CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Extreme Value Behavior in Cryptocurrency Market

by

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A dissertation submitted in partial fulfillment for the degree of Doctor of Philosophy

in the

Faculty of Management & Social Sciences
Department of Management Sciences

2023

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2023

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The Unprecedented Dedication to my Parents

A parents' love is something that no one can explain, It is made of deep devotion, and of sacrifice and pain. It is endless and unselfish, and enduring come what may, For nothing can destroy it or take that love away.

It is patient and forgiving when all others are forsaking, And it never fails or falters even though the heart is breaking. It believes beyond believing when the world around condemns, And it glows with all the beauty of the rarest, brightest gems.

It is far beyond defining, it defies all explanations. And it still remains a secret, like mysteries of creation A many-splendored man cannot understand, And special wondrous evidence of Life's tender guiding hand.

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This is to certify that the research work presented in the dissertation, entitled "**Extreme Value Behavior in Cryptocurrency Market**" was conducted under the supervision of **Dr. Nousheen Tariq Bhutta**. No part of this dissertation has been submitted anywhere else for any other degree. This dissertation is submitted to the **Department of Management Sciences, Capital University of Science and Technology** in partial fulfillment of the requirements for the degree of Doctor in Philosophy in the field of **Management Sciences.** The open defence of the dissertation was conducted on **October 31, 2023**.

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List of Publications

It is certified that following publication(s) have been made out of the research work that has been carried out for this dessertation:-

1. Qureshi, G. K., & Bhutta, N. T. (2022) Bivariate Hedging Between Crypto-Currency And Traditional Assets. *Journal of Positive School Psychology*, 6(11), 545-568.

(Ghazia Khoula Qureshi)

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Acknowledgement

All Praise is due to Allah, Whose Endowments are Countless

Glory to **Allah**, the Creator, He created Hell and Heaven. Good and Bad. He gave us a mind and Ability to Choose. Al-hamdulilah! First and foremost thanks to Almighty Allah for blessing me with wisdom and strength to complete the dissertation successfully.

Essentially, I would like to pay the profound respect to the esteemed **Dr. Arshad Hasan** (Dean of Faculty of Management and Social Sciences) for providing a healthy learning environment.

I am obliged to **Dr. Nousheen Tariq Bhutta** for her supervision and providing the knowledge of finance all through the way to accomplish the degree. I am grateful to my colleagues for their invaluable assistance to bring this report in the presentable form.

Last but not the least; I owe my deepest gratitude to my family, especially my parents **Muhammad Sajid Qureshi and Tahira Qureshi**, my husband **Salman Qureshi**, and friends for their believe in me, for their unprecedented prayers and indispensible motivation throughout this time. Thank you all for making me believe in dreaming, striving, and finally achieving it.

(Ghazia Khoula Qureshi)

Abstract

The study intends to analyze the extreme value behavior in cryptocurrency market, it specifies that cryptocurrency market follows fat tailed distribution. Initially to analyze extreme value behavior in cryptocurrency market Generalized Pareto Distribution (Peak over Threshold- POT) is applied. Secondly to measure the time varying volatility Bivariate DCC-GARCH model is used to find the relationship between previous and present correlation and presence of conditional correlation rolling from previous to present period. Thirdly ARMA-GJR-GARCH model is employed for mineable and non-mineable crypto-currencies and specifies that mineable crypto-currencies are volatile than non-mineable crypto-currencies and supply effect does affect volatility. To define dependence structure Copula family has been applied, and T-Student Copula turns out to be the bestfitted model. The heavy tails of a distribution de nes movements towards left and right which may possibly surge due to extreme variability in returns. Bivariate analysis of cryptocurrency market with other asset classes has been observed by using static and dynamic hedge ratio among countries where cryptocurrencies are being traded most frequently over 2013 to 2019. The findings of the study denotes the long term causal relationship running from traditional assets to cryptocurrency market, co-movements are observed. The change in cryptocurrency returns may not affect returns of traditional assets yet any change in traditional assets upsurge cryptocurrency market in the long term which indicates opportunities for cryptocurrencies to hedge. Theoretically the study intends to provide substantial support for risk management and academia. Practically it aims to provide empirical justifications for investors, managers and policy makers to figure out exactly where cryptocurrencies stand along with other asset classes, and what actually it brings to the nancial system.

Keywords: Cryptocurrency; Extreme Value Behavior; Supply E ect; Time Varying Volatility; Copula; Hedge Ratio.

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Abbreviations

ARCH	AutoRegressive Conditional Heteroskedasticity
ARMA	Auto Regressive Moving Average
BEKK	Baba, Engle, Kraft, and Kroner
CM	Crypto-currency Market
DCC	Dynamic Conditional Correlation
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GJR	Glosten Jagannathan and Ruckle
MNC	Mineable Crypto-currencies
NMC	Non-Mineable Crypto-currencies
RBBR	Returns of 10Y Government Bond of Brazil
RBCA	Returns of 10Y Government Bond of Canada
RBGR	Returns of 10Y Government Bond of Germany
RBJP	Returns of 10Y Government Bond of Japan
RBKO	Returns of 10Y Government Bond of South Korea
RBRU	Returns of 10Y Government Bond of Russia
RBTR	Returns of 10Y Government Bond of Turkey
RBUK	Returns of 10Y Government Bond of United Kingdom
RBUS	Returns of 10Y Government Bond of United States
RBVN	Returns of 10Y Government Bond of Vietnam
RCM	Returns of Cryptocurrency Market
REXBR	Returns of Exchange Rate of Brazil
REXCA	Returns of Exchange Rate of Canada
REXGR	Returns of Exchange Rate of Germany
REXJP	Returns of Exchange Rate of Japan

REXKO	Returns of Exchange Rate of South Korea
REXRU	Returns of Exchange Rate of Russia
REXTR	Returns of Exchange Rate of Turkey
REXUK	Returns of Exchange Rate of United Kingdom
REXUS	Returns of Exchange Rate of United States
REXVN	Returns of Exchange Rate of Vietnam
RGM	Returns of Gold Market
RSMBR	Returns of Stock Market of Brazil
RSMCA	Returns of Stock Market of Canada
RSMGR	Returns of Stock Market of Germany
RSMJP	Returns of Stock Market of Japan
RSMKO	Returns of Stock Market of South Korea
RSMRU	Returns of Stock Market of Russia
RSMTR	Returns of Stock Market of Turkey
RSMUK	Returns of Stock Market of United Kingdom
RSMUS	Returns of Stock Market of United States
RSMVN	Returns of Stock Market of Vietnam
VECM	Vector Error Correction Model

Chapter 1

Introduction

The first chapter opens the study to the reader with the background description and steadily leads toward the interior of the research. Furthermore, it continues and exposes the problem statement, along with the explanation and the objectives of the study.

1.1 Background of the Study

1.1.1 Fintech- The Beginning of Digital Finance

FinTech movement is a long-awaited advancement in finance and its regulations. In 2007-09 the worldwide financial crisis triggered various innovative regulatory initiatives and enhanced existing ones. The existing framework of finance industry has indeed been valued yet, it has been running its course and it is unlikely to bring significant structural changes in the coming future. Therefore, to cope with the emerging era of integration, it seems the need to consider alternative approaches in finance and technology that stand possible to integrate Fin-Tech.

It includes digital revolutions and technology driven business modelled innovations in the financial sector. These novel innovations may possibly disrupt prevailing structures and blur industry boundaries, assist strategic disintermediation, revolutionize the current practices to produce and supply products and services, offer unique doorways for entrepreneurship, democratize financial services, yet also generate substantial privacy, governing and legal challenges. Likewise, the inventions that are dominant to Fin-Tech today embrace new digital advisory and trading systems, machine learning, peer-to-peer lending, artificial intelligence, mobile payment systems, equity crowdfunding, cryptocurrencies and the block-chain.

1.1.2 Storage of Coins in Bits and Bytes

Bits and bytes are commonly known as the digital storage of information in binary digits. A self-published white paper written by an anonymous person (Nakamoto, 2008) introduced Bitcoin, the first digital storage of coins in bits and bytes, a decentralized, peer to peer system of payment. Before Bitcoin, online disbursements used to be dependent on financial institutions to facilitate electronic dealings as trusted intermediaries. This digital asset is categorized as cryptocurrency, which refers to the medium of exchange that includes internet based financial transactions using cryptographic functions. It is driven by block-chain technology. that ultimately eliminate the need of an intermediary and transformed it with a peer-to-peer networking. He also explained the tracking of all transactions on a marked ledger called as the block-chain. All transactions regarding Bitcoin are confirmed by a network node, such as computers that are connected to the network. These networking nodes are called as the "miners".

1.1.3 The World of Digital Coins

Due to the growing interest and popularity of Bitcoin and the advancement of block-chain since 2009, many other cryptocurrencies have come into existence. There are more than 3,000 cryptocurrencies and around 2300 total crypto markets currently being traded across the globe. The aggregate market capitalization of the entire crypto market is nearly $$332,694,134,760, trading volume as $$83,309,629,531. An apparent outcome of this entirely new industry is its trading that emerged globally, which block-chain centered applications are integrally facilitating and following the use of cryptocurrency worldwide.

1.1.4 Defining the Building Blocks

Economists express the definition of money by its nature and functions; that it may possibly be anything that satisfies the following necessary functions;

1. Medium of exchange means, it essentially should be a standard value known and accepted by its users. It is an important function to measure value. With respect to this function, money should possess a continuous purchasing power and constant intrinsic value on average.

2. A store of value can be anything, that is non-perishable or does not depreciate over time. Basically, a store of value means money must preserve purchasing power for the future. It denotes those liquid assets that can be certainly being exchanged for goods and services since that are the greatest store of value.

3. To be a unit of account, it should hold a monetary unit to measure the market value of goods, services, and related transactions. In simple words, money is something that can be used to value transactions and make calculations. The unit of account function is also required to be divisible, countable, and fungible.

Accordingly, what gives money a value depends on what kind of money is it, generally the various kinds of money are categorized as;

Commodity money which originates its value from that product, or commodity of which it is made up of. This type of money can be exchanged upon demand for any particular commodity. Commodities used as a medium of exchange nclude barley, gold, copper, silver, cocoa beans, alcohol, large stones etc.

Another type of money is fiat money that government declares as a legal tender, yet it is not back by any material commodity. However the value is driven by demand and supply forces, rather than the value of the substance it is made up of. The present paper currencies are the best example of fiat currencies.

The hybrid of the ideal features of commodity as well as fiat money, yet with no intrinsic value however possesses an artificially unconditional scarcity. This type of money is free of any monetary authority control and avoids politically-motivated alterations. Selgin (2015) viewed this potential in elastic synthetic money, specifically emerging cryptocurrency.

1.1.5 Cryptocurrency

Cryptocurrency relies on the rules of mathematics as compared to fiat currency, which is backed by the trusted issuing authority. It is designed on the basis of manifold mathematical procedures centered on cryptography. Although currently due to high volatility and diverse features, cryptocurrency does not satisfy the traditional definition of money. Cryptocurrency as a medium of exchange, store of value and unit of account is still under question. However holding unique features and scarcity makes it an interesting notion to study in financial academia. Although there is an ongoing debate among different schools of thought, on whether take it as a currency or a viable addition to the existing financial asset classes.

1.1.6 Cryptography

Before the beginning of modern age cryptography was used as synonymous with encryption. Cryptography is an exercise of developing protocols by means of secure and protected communication to impede malicious parties from accessing private data. Cryptography applies an algorithm to transform input that is original text or plain text (readable and understandable) into encrypted output that is cipher text (scrambled) to secure from unknown recipient if somehow they managed to get hands on the information. Thus through this process of encryption the shared information is considered as coded and hence locked. This coded information is then unlocked by recipient and restored it into its original binary form while using another key.

Cryptography plays an integral role in the prime working of block-chain technology. The mathematical ciphers are used to conceal information, based on algorithms to verify and protect cryptocurrency transactions. Cryptography is used in block-chain technology in several different ways, such as key encryption serves basis for block-chain transactions and wallets, cryptographic functions provides feature of immutability and, Merkle trees manage transactions and ensure efficient block-chains.

1.1.7 Encryption

The cryptographic technique used to mask information to impede malicious and unauthorized access during its transmission, and keeping it secure and protected is termed as encryption. It is a practice to generate ciphers from original information. The techniques employed for encryption are Symmetric encryption that is all recipients have the same key for encryption and decryption and Asymmetric encryption that is two dissimilar keys for encryption and decryption are utilized. In block-chain technology, encryption is used for securing identity of source contributor of transactions and confirming that previous records of transactions are not interfered.

1.1.8 Electronic Payment System

The system that utilizes cryptographic technique to offer secure transactions over internet and ensures protected medium to transfer money, such that to facilitate electronic commerce. Though secure means of electronic transactions requires, ensuring private communication, verifying transmission of communication, certifying the server and the client and to confirming the information, is as generated originally. In order to compliance with these requirements, electronic transactions depend on encryption and digital certifications. The encrypted algorithms transform original information into ciphers, which is then decrypted by the recipient and thus retransforms into original information.

1.1.9 Block-chain

The decentralized public ledger to record all transactions of cryptocurrencies primarily initiated with the advent of best known cryptocurrency that is Bitcoin, to execute peer to peer networking is termed as the Block-chain. This technology allows participants to make financial transactions deprived of any intermediary authority. It permits the existence of cryptocurrency, such as the digital asset applies on the techniques of encryption in order to control the formation of financial units and to ensure the transfer of funds and other potential applications such as settling of trade and voting etc.

1.1.10 Exchanges

The online platforms to serve exchange of one cryptocurrency with another on the basis of the market value of the cryptocurrencies are known as cryptocurrency Exchanges. Currently, the best known cryptocurrency exchanges are Binance and GDAX. Usually these exchanges do not restrict trade of cryptocurrency for cryptocurrency, but also allow trade of between fiat currency and cryptocurrency. For instance Kraken, accepts fiat currency such as CAD, GBP, JPY and USD, and allows trade with Bitcoin, Ethereum, Litecoin, Monero and Ripple.

1.1.11 Peer-to-Peer Networking (P2P)

The peer to peer networking group devices that store and share information collectively. Each device in the network is a node (individual peer), where at least two nodes participate in highly interconnected decentralized interactions. In blockchain technology, peer to peer is an electronic payment system and refers to the exchange of cryptocurrencies by the use of distributed network. This networking is employed at the very core of cryptocurrencies and serving up to a greater extent in the block-chain industry. Thus it is an open network where anyone can set a node and participate in the process of generating, authenticating and confirming blocks.

1.1.12 Wallets

An application that allows cryptocurrency holders to stock and retrieve their cryptocurrencies is named as secure digital cryptocurrency wallet. When cryptocurrency is acquired it is stocked in the wallet in order to start further transactions.

These wallets generally permit buying and selling range of cryptocurrencies and allow referring to different exchanges to initiate trade for other cryptocurrencies. Currently various cryptocurrencies employ their official wallets. However the pioneer wallet for cryptocurrency was presented by Satoshi Nakamoto when the first bitcoin protocol released yet other cryptocurrencies that emerged on the same block-chain technology can be stocked on the cryptocurrency wallet. Hence, wallet employs the security keys related to the addresses of cryptocurrencies and the block-chain contains the record of the amounts related to such addresses.

1.1.13 Supply Effect - Miners and the Process of Mining

Miner is a network node that assembles transactions from memory to organize into blocks and hence whenever transactions are completed, miners get rewards for the consumption of computing power for verifying transactions' blocks. Whereas mining refers to the art of applying powerful computing hardware in order to decipher complexed cryptographic problems, labeled as Proof of Work. However, the process of mining for cryptocurrencies is the course of generating new crypto-coins within the network confirms the transaction and registers it into the block-chain. This process allows cryptocurrencies to exert in a peer to peer decentralized network, deprived of any intermediary, thus in this way miners generate new crypto-coins and add into the existing supply (circulating supply). In point of fact, proof of work is a process of encryption, to ensure transactions to be correct on the block-chain. The mining model benefits in making it difficult to attack cryptocurrency network where various nodes are involved in the process to attack, even in cloud mining prevalence.

1.1.14 Inflationary Supply Effect - Mineable Cryptocurrency

As the name suggests, cryptocurrencies that are mineable are acquired through the mining process that require Proof of Work (PoW) and Proof of Stake (PoS). Mineable coins are treated as incentive since the miners operates to solve complexed mathematical algorithms and hence in turn, verify the transactions and uniquely created block is added into the block-chain. For instance, Bitcoin, Ethereum and Litecoin etc. are mineable cryptocurrencies.

1.1.15 Deflationary Supply Effect - Non-Mineable Cryptocurrency

In contrast to the above, non-mineable cryptocurrencies are not directly mined yet are bought through cryptocurrency wallets. These cryptocurrencies are in circulation, stored in wallets and interest is earned by holding these cryptocurrencies in wallets; higher chances of getting higher interest depend on higher number of coins in the wallet. Since there is no mining process, so there are no coins incentives for miners, no Proof of Work (PoW) is required and no increase in existing circulating supply. Hence, transactions' validity depends on trusted validators through consensus system following Proof of Stake (PoS). In addition to this, these types of cryptocurrencies are typically pre-mined. For instance, Cardano, IOTA and Ripple etc. are non-mineable cryptocurrencies.

1.1.16 Pre Mined Cryptocurrency

Under this type of cryptocurrencies, mining process takes place before making them available on cryptocurrency exchanges for trade. Miners allocate certain amount of credit to cryptocurrency wallets prior than launching codes to other miners. The process of pre-mining occurs when miners pay for certain unique features in development or during Initial Coin Offerings (ICO). These cryptocurrencies benefit the miners, investors and token holders that are involved during the stages of development and ICO. Several cryptocurrencies are pre-mined to a certain level in the market, for instance, AuroraCoin, Bitcoin and Ripple etc.

1.1.17 Crypto Coins

Cryptocurrencies with separate and independent block-chains are referred as Coins. These cryptocurrencies include bootstrapping from scratch with a broad network explicitly designed to achieve certain objectives. For instance, native coin of Bitcoin, bitcoins (BTC) holds highest liquidity in the market with highest realized market capitalization in the cryptocurrency market, moreover Ethereum's native coin ether (ETH) is based on the platform for generating programs to run the decentralized block-chain. Instead aiming financial data, Ethereum emphases on arbitrary data program, whereas ether is employed in transmission of data, assets management, payments and DAPP interactions on the network.

1.1.18 Crypto Tokens

The unique disbursement of cryptocurrency platforms that enables miners to generate, supply and manage derivatives of the prime block-chain are termed as crypto-tokens. They acquire distinctive place in the cryptocurrency market and function as utility tokens within application of ecosystem. For instance, token ERC-20 is a part of MakerDAO DAPP on the platform of Ethereum. where Maker DAO is a process to access credit instruments like borrowing and lending while using Dai. Moreover similar to Dai, ERC-20 token can easily be exchanged for any ERC-20 token or any other protocols based on Ethereum platforms like ERC-721 and ETH coin. Consequently crypto tokens exist as application specific tokens within block-chain network. For instance, Augur, Dai, Golem, Komodo, Maker and Ox etc., exist within ecosystem of Ethereum.

1.1.19 Initial Coin Offering (ICO)

Initial Coin Offering is a form of crowd-funding. This crowd sale is revolutionary of its type and managed to provide paths by which developers of decentralized applications (DAPP) acquire funds for the projects. In addition to this, it enables easy investment by anyone in any project of their interest, simply by investing in tokens of the particular DAPP to become part of the project. Since 2013 development of cryptocurrencies is done under ICOs, and pre-mined cryptocurrencies (tokens) are frequently traded on the exchanges of cryptocurrencies. After 2014 ICOs have established as de-facto system of generating funds for crypto projects by releasing integrated tokens of the projects.

1.1.20 Cryptocurrency Users

Though the system distinctively designed to eliminate the intermediary from transactions, yet the adaption of cryptocurrency as a unique instrument for payments still relies on trust. However it is difficult to get accurate number of cryptocurrency users due to its featured anonymity, the users are classified differently as they perceive it differently. Firstly, several businesses accept cryptocurrencies as a unique medium of payments and several do not accept it completely due to its limited user base. Likewise a group of customers do not use cryptocurrencies since it is not broadly accepted. This vicious cycle is present and restraining the opportunities for its progress since certain incidental evidences make the cryptocurrency users perceive as criminals.

Secondly, there is a group that uses cryptocurrency as a medium of exchange and establishes payment systems, provide guarantee of accounts and transactions. This group also contains online business dealing in illegal products on cyberspace (dark markets). Thirdly, another group that is inspired by cryptocurrencies is investors of ICO. These investors seek to invest in new projects of block-chain purchase cryptocurrency coins and cryptocurrency tokens. Such projects aim to develop user base of cryptocurrency market by gaining confidence of potential users for instance, the users from developing countries who seek to shelter against increasing inflation domestically and find ease in access to banking free system. Many large scale businesses also find it interesting to infer the use of cryptocurrency system into unique and innovative applications and smart contracts. Moreover, a group of users exchange into cryptocurrency from domestic currency and find it a speculative asset rather merely a new form of currency. They hold cryptocurrency without any intent to practice it as medium of exchange. Therefore as cryptocurrency is treated as an option for investment, it does not pose any economic, monetary or financial stability risk to the alternative fiat currencies.

1.1.21 The Possible Potentials

Right after the inception of cryptocurrency, it is gradually accepted by many users though online illegal financial activities also get up for instance, Silk Road. In such relation, it is being scrutinized by central authorities and public, with the perception that majority of the early adopters of cryptocurrency uses the anonymity for the purpose of money laundering and other illegal trade, and hence are lawbreakers and criminals, (Slattery, 2014). Therefore such applications overshadowed the unique structure and innovative opportunities for decentralized block-chain system. However, in recent years this perception is started fading and cryptocurrencies are now perceived to be widely accepted as innovative medium of investment with astonishing value gains.

1.1.21.1 Applications for Business, Financial and Other Institutions

Cryptocurrencies assist small businesses, since the cost to develop a new system is cheaper than traditional payment system (Churilov et al., 2016). Cryptocurrencies provide opportunity to start with micro transactions. It provides faster, low cost and more efficient method for international transactions without any business account and payment terminals, low entry barriers and competition in market. Since it excludes, concept of intermediary so there is no storage cost involved.

The system creates environment for cheap and easy trading in absence of regulations yet is the main hindrance in its broader adaption, as many large scale businesses do consider block-chain industry but do not put their confidence in cryptocurrencies. The law varies in different countries, considering it as commodity, currency or security, whereas some countries ban the use of cryptocurrencies completely. Although block-chain technology provide many opportunities and the use of its applications grow substantially like smart contracts, crowd-source mechanism of voting, future contracts and market speculations.

Moreover, these applications may possibly affect daily life of a common user by implementing Internet of Things devices, for instance to serve data transfer anonymously, sale and purchase of cars on the block-chain that eliminates the role of car dealers, which directly reduces the cost of a car, interested user deposits money which automatically approves the car key and payments are instantly authorized before getting access to the car. Block-chain applications may possibly extent their utility from merely simple transactions to complex reconciliations and settlements cases. With the help of this system royalties for intellectual properties, piracy issues and track of digital content may also be exercised and content writers may get their reward for their literary work in exchange without ads. In addition to the system may assist governments to use block-chain technology in automation of voting mechanism, registration of properties and assets. Barratt and Aldridge (2016), Georgia utilized the system in a development project the land registry in the block-chain in 2016. The appealing concept of the block-chain provides mechanism to regulate ownership and information systems, which is inexpensive and independent of government solutions. Similarly, the technology may possibly be helpful in issuing birth certificates, reducing charges for immigrants in sending remittances to their families, providing access to economic, administrative and social inclusion, and proving identities for political asylums. The applications of block-chain may also be useful in the domain of law and other legal services by reducing burden of courts and stream lining litigation mechanism (Hegadekatti, 2017). The cascading effect of the block-chain technology is really appreciated by financial institutions; for instance NASQAD implements the system in Linq. Moreover, the future of the financial institutions and infrastructure under control of central and commercial banks may possibly get inspired by the decentralized system of block-chain (Alimbek, 2016). Hence, far-reaching applications of the block-chain technology may improve systems of transactions, dealing of contracts, registration and distribution of information, financial services, voting regulations, and healthcare, economic, governmental and other industrial procedures. Such improvement of inefficient systems may possibly reduce infrastructure cost for banks; however they may possibly face greater downscaling.

1.1.22 The New Model of Raising Capital

ICO is a new module for raising capital at early stage for block-chain based start-ups with drastically diverse opinions, gaining praises from some users as an integral component for decentralized system whereas some users compare it with a speculative bubble like tulip mania back from 17th century (Koenker & Xiao, 2002).

The mechanism is originally traced back to the idea of conventional IPO (Marshall 2017). As IPO functions, the tokens are purchased in ICO with some voting power, deprived of high costs and strict regulations like crowdfunding websites (work online without any identity and residency check).

During ICOs the trading tokens are different in nature, some are featured as securities, some as currencies and other exhibit completely different properties, since no default definition is been provided yet. These tokens are acquired through auctions and profits are utilized to develop platforms. However the prices of these tokens at the time of auction are not backed with anything except trust in the providers. Some tokens appreciate in value and earn return on investment (ROI) and others stay useless.

Conley et al. (2017) suggested that if token is a kind of money, it should comply with anti-money laundering and know your customer laws. Whereas if token is a kind of security, it should follow regulations of Securities and Exchange Commission (SEC). This is one of the first studies that try to evaluate tokens, their economic value, and mechanisms of effective ICOs and effects of crowd-funding investment in such unique yet ambiguous assets.

With the development in the block-chain technology ICOs are growing in numbers. It is becoming great opportunity of funding block-chain based start-ups, such as new applications of social networks, cloud avenues of computing and speculative markets. Moreover ICOs may also be done through cryptocurrencies. For instance, Agrello is a crowd-funding project that provides grounds for dealing in smart contracts without using codes or any legal experience. It is deemed to fuel the development of new ventures based on block-chain technology.

ICOs may offer exceptionally high returns for investors in terms of value and liquidity rather than traditional investments and this may appeal potential investors who resist due to its regulations and uncertainty issues (Kastelein, 2017). Many ICOs offer more discounts on the trade of cryptocurrencies prior to make them available of exchanges independent of any authority. However some investors look for protection and structural reforms to mitigate their risks, whereas some investors believe that this framework enable investment with less capital in such accredited system. Hence, above the system of block-chain technology and value exchange, cryptocurrencies provide a unique model of funding, which may possibly be valuable for non-profit organizations, networks and start-ups for a rapid development in various industries by using decentralized technology of cryptography.

1.1.23 The Possible Risks

Cryptocurrency market lacks in independent standards and regulations and the feature of anonymity makes it to consider fallacious. Since it eases multiple illegal activities especially over cyberspace, frauds like money laundering and tax falsifying, financing illegal activities and facilitating terrorism and contributing in developing dark web markets including online markets for prohibited trades.

1.1.23.1 Money Laundering and Tax Falsifying

There are three levels in money laundering that is, placement occurs when illegal funding is presented by depositing usually small amounts of money into different accounts, then there comes layering where multiple transactions are made to hide the source of this money and then integration, here this money is reverted back into legal circulation in the market (Brown, 2016).

Cryptocurrencies may possibly be used in each of these levels, and it may simply be integrated with different types of digital currencies. Whereas at second level, layering is the circulation on the cyberspace. The market of dark web for money laundering activities and cryptocurrency handling that reflects the activities available on surface web. Similarly, cryptocurrency laundering activities increase the movement of money by mixing the wallets due to anonymity, and transfer the cryptocurrency of a user in micro-transactions through the network, which is hard to catch (Ciancaglini, Balduzzi, McArdle, & Rösler, 2015). The users may access services of making payments that allow them to exchange cryptocurrencies for any currency through ACH, Western Union, Paypal and cash, similar mixing services are also available over the surface web. These services are utilized to mix user's money with others and stop any third party to track transactions generating from a certain address (Gruber, 2013).

Most commonly, online token purchase and gambling activities are executed. In cryptocurrencies the block-chain technology is able to track the transactions record in order to figure out the malicious addresses through analysis of the transactions beside the timings of criminal activities. Yet linking a fake name to the original name seems impossible to prove, by such means cryptocurrency provides a safe way to money launders and criminals.

In addition there are some institutions that use this system for money laundering and tax evasion since there are no regulations. These services are utilized without validating the identity of users, which makes it easy to open anonymous and fictitious accounts that allow money laundering and tax evasion across borders. That is the reason; law-making authorities put pressure to categorize these institutions to take legislative measures internationally.

Hence, the decentralized nature of cryptocurrencies lack centralized body to monitor and control suspicious activities. Marian (2013) argued that cryptocurrencies are probably becoming tax haven for users by choice. Cryptocurrencies provide assurance that the profits are not exposed to tax and anonymity of the users is preserved. Since it does not rely on any intermediary or financial institution and thus, independent of any inquiry of government and regulators.

1.1.23.2 Financing Illegal Activities

The anonymity of the users and instant transfer of funds across the globe are the profound features of cryptocurrencies that opens many opportunities for different kinds of criminal and illegal activities. Irwin and Milad (2016) claimed that the scope is difficult to estimate due to anonymous user base but cryptocurrencies may possibly be the easiest method of financing, since stable cash-flows and financing for criminal activities are the challenging tasks for terrorists and criminal groups.

Similarly, dealing with cryptocurrency brokers, payment providers like Paypal and one to one exchanges are some other methods for terrorists and criminal groups. With the development of cryptocurrencies online dark markets and illegal economy flourish simultaneously. The conventional search engines (Google) on the surface web are not able to access dark markets; therefore these markets operate on the cyberspace which is called as deep web (Ciancaglini et al., 2015). Stroukal et al. (2016) stated that dark web is a part of darknet markets, that provide limited access to networks by using special software like The Onion Routed (TOR), which provided maximum security and anonymity and cryptocurrencies allowed emergence of such market places.

In 2011, Silk Road appeared as the first dark net market, right after two years of the inception of the first cryptocurrency (Bitcoin). Initially only Bitcoin is used for making payments for purchases, yet in subsequent years several other cryptocurrencies emerged like Monero and Dash (Greenberg, 2017). According to Ciancaglini et al. (2015) about 86.14% of the users of the dark markets purchased pharmaceuticals, drugs and seeds (the size of drugs trading is greater than the size of the network), about 6.93% buy games and 6.93% buy stolen accounts.

Furthermore, cryptocurrencies are used in malicious trades and multiple cyber-attacks (ransomware) like CryptoLocker. For instance, the Armada Collective attack in 2015 on Greek banks Brown (2016) and the WannaCry attack in 2017 on multiple organizations across the globe (McGoogan, Titcomb, & Krol, 2017) are known examples of ransomwares where Bitcoin (cryptocurrency) is used as payment method.

Additionally, cryptocurrencies provide easy way to purchase fake money, stolen details, replicated credit cards, passports, citizenships, pornography, weapons, and other services like assassination and leakage of personal identifiable information of officials, government and celebrities (Paxton 2017). While apart from such services, it is projected that block-chain technology may contribute in the development of sophisticated contracts based transactions and decentralized malicious attacks (malware attacks) systems.

Regardless of many profound advantages offered to terrorists and criminals, cryptocurrencies are not recognized as a substantial threat by legal and law enforcement authorities in 2016 (Brown, 2016). Whereas in 2015, National Risk Assessment of Money Laundering and Terrorist Financing UK, regards it as low risk for money laundering, and indicates that the use of cryptocurrencies is limited to online markets, yet it is probable to become a viable weapon in hands of terrorists in future. Hence, cryptocurrencies are potential threat and technological challenge for authorities. Levin, O'Brien, and Zuberi (2015) stated that the administrations, governments and central authorities are managing to acquaint legislations against the imposed challenge. Investigatory Powers Act 2016, UK and Digital Economy Bill 2016/17, UK etc. are such a response, and several other countries are still trying to define the grounds.

1.1.24 Designing Grounds for Execution of Cryptocurrencies

Nevertheless cryptocurrencies proved to be valuable with distinct integration into financial markets, while currently targeting niche class of the users. However the prime idea of the cryptocurrency is its adoption on the large scale as alternative form of money and unique payment system. The academic literature catches equally negative reviews about cryptocurrencies to become widely accepted form of money. As discussed earlier, the potential to recognize cryptocurrency as money, it is deemed to compare it against the neoclassical functions of money such as, medium of exchange, unit of account and store of value. Alimbek (2016); Evans (2014); Yermack (2015); Weber (2016) shared that the cryptocurrencies are unable to perform the stated functions due to low governance, high risk, lack of regulations, and lack of concern to manage supply so as to reduce high volatility. Sachs (2014) reported that cryptocurrency, on the boundaries between commodities, currencies and financial assets, is best defined as a speculative financial asset which can be used as medium of exchange. However, the difficulties to consider it as a store of value are the main roadblocks to its scope to be adopted as a medium of exchange.

Consequently, despite of the prime idea of the creation, cryptocurrencies are not perceived as money and there are certainly no chances to replace it with fiat currency. Though this does not indicate that cryptocurrency would die, yet there is the potential in the governance arrangements and technology of the cryptocurrencies to stay alive in the system to gain wide acceptance. In addition, the idea is brought forward by the Bank of England that an issuance of cryptocurrency by central banks to apply block-chain technology to redundant the need to manage accounts for commercial banks.

1.1.25 Spotting Cryptocurrency in the Financial System

The significance of the newly established technology is determined by considering the elementary module of the completely new model of financial structure that is Digital Finance. It is obvious that until recent the three fundamental models of financial structure include, the Classical Finance, the Corporate Finance and the Islamic finance, and now the Digital Finance constitutes the fourth structure.

Initially, the Classical Finance counts from the time of issuance of banknotes. This system specifies that the value of money does not change over time, for instance the value of one unit of currency remains same in value over a year. Secondly, the Corporate Finance counts since the start of the time of rapid growth in financial markets. The system specifies that the value of money depreciates over time. In addition, the Islamic Finance counts since the rapid growth in economic development of Muslim countries. The system specifies the exceptional principle of impermissible interest. Moreover each of the three models assumes central authority of central banks and strict control of state over the domain of financial structures. Therefore, these models are generally categorized as centralized structures of finance.

These financial structures are allied with the development of the economic and political spheres of a country. The Classical finance set the grounds for financial systems, whereas Corporate Finance relates with the development of finance systems. This pace of development creates wide horizons for alternative means for investments that emerged into different ways of establishing business specifically in case of increasing cost of capital. In the meantime, the Islamic Finance finds room to flourish with the rapid economic growth and development among certain Muslim countries. The system permits the Muslims countries to make Shar'iah compliant investments. Subsequently, as the time heads towards virtual and cloud avenues. The rapid development of financial systems and inherent internet in financial sectors embellishes Block-Chain, Big Data, Smart Contracts, Peer to Peer

Networking, Space distribution etc. Such development opens incredibly enormous opportunities for business over the internet. It allows evolution of an entirely unique and novel financial system that is the Digital Finance. Hence, one of the revolutions of Digital Finance is the best known cryptocurrencies, primarily the decentralized structure of finance.

1.1.26 From the Lenses of the World

The distinguishing characteristic of cryptocurrencies is the absence of regulations to address the use, which is explicitly the basis of its implementation extensively, (Barrdear & Kumhof, 2016). Deprived the regulations, it requires struggle to ensure legitimacy for its wide acceptance, or else its unrecognized status is supposed to provide benefit illegal activities and prevents adaption by legal businesses and trade activities. The decentralized governance attracts many users to gain confidence in cryptocurrencies since they value anonymity as compared to fiat currencies. Yet on the other hand it is likely insecure if hacked. Resultantly, victims turn towards legal and central authorities to retrieve. Therefore, many countries do not permit the use of cryptocurrencies, and many others do not prohibit the use, though the legal interpretation significantly varies under various authorities and administrations.

Marshall (2017) reported that, Bitcoin (cryptocurrency) is used as private money in United Kingdom, since value added tax (VAT) is charged on the commission earned but not on the exchange of cryptocurrency for sterling Pound. The HM Revenue and Customs (HMRC) releases policy paper stating the use of cryptocurrency and how taxes are imposed on the transactions depending upon the circumstances. Legally regulations are not imposed on the users. The Bank of England states in an official statement that currently digital currencies (cryptocurrencies) do not pose any material threat to financial and monetary stability in the country.

There is a substantial advancement towards forming a workable framework for digital currencies (cryptocurrencies) in United States. It is treated as property for taxation purpose (Barrdear & Kumhof, 2016). Slattery (2014) proposed to enfold Bitcoin (cryptocurrency) in the existing tax regime is US. In 2013, the exchange of cryptocurrency indicted under the definition of a money service business (MSB) announced by the Financial Crimes Enforcement Network (FINCEN). This means the users of cryptocurrencies are required to follow the existing requirements provided for the MSBs.

California and New York lead in providing regulatory framework. Fargo (2015), California Assembly Committee approved a bill in 2015 for regulation of cryptocurrencies and in the same year BitLicense regulatory framework is implemented by New York State Department of Finance in order to adopt cryptocurrencies' businesses. This regulation however faces many critique and threats of closure of operations in New York from existing digital currency businesses. Khidzev (2016) stated, since the regulations imposed the obligation to hold reserves of the same size, and the same size of cryptocurrency as the amount deposited by the customers of the company along with the provision of the real name of the customers and reporting central authority for every transaction that exceeds $10,000 or equivalent.

Either from legal or economic perspective cryptocurrency or any other digital currency is not recognized as money by the European Central Bank. According to the law, euro bank-notes and coins are considered legal and any electronic money is not considered as legal, yet it is accepted as payments of any kind by choice. Currently, cryptocurrencies are not regulated in European Union, therefore it is not subject to the Earnest Money Deposit regulations or Payment Services Directives as ECB does not aim to change or expand EU financial legal framework. However the bank alters the former definition of any virtual currency by dropping the words money and unregulated in order to avoid any misunderstanding.

In 2014 the Financial Action task Force (FATF) released a report directing to provide conceptual framework for cryptocurrencies in order to address financing of terrorism and anti-money laundering risks postured by the system. Baillie and Bollerslev (1990) stated that cryptocurrency is also been under discussion by European Commission and EUROPOL, since EC proposed implementation of the database constituted the real identities of the cryptocurrency users and the addresses of the providers of the online cryptocurrency wallets. However the opponents of cryptocurrencies viewed it as an attempt to harm the existing system.

Firstly, Singapore is one of the countries that enable launch of the block-chain system and use of cryptocurrencies nationwide. In 2017 the report of Monetary Authority of Singapore released an outline of their project Ubin, which is a prototype of Distributed Ledger Technology (DLT) for inter-bank payments and cooperation with financial institutions and other banks. Their token is based on Ethereum, which is used for transactions among customers of banks and exchanges the part of their fiat money. Moreover the electronic currency that is being used in their project Ubin is totally backed by the Singapore dollar as it is the tokenized version of their fiat currency.

Secondly, in terms of cryptocurrencies and framework of regulations Canada turns out to be progressive country. Barrdear and Kumhof (2016) claimed that Canada is the foremost country to establish tax system on any virtual currency. Arnfield, Harper, Doyle, Bickers, and Smith (2015) stated that the parliament of Canada approves a bill that amends their existing laws of anti-money laundering and financing terrorism to make it applicable for users of cryptocurrencies. In another report Pearson (2017) confirmed the National Bank of Canada adjoins the Ethereum Alliance Enterprise to develop unique applications of business on Ethereum based block-chain. Hertig (2017) reported the Bank of Canada launches inter-bank payment system based on block-chain technology in their project Jasper likewise Singapore, yet later the plan is postponed.

In 2017, the government of Japan starts recognizing and accepting Bitcoin (cryptocurrency) as legal tender of making payments. The cryptocurrency exchanges follow anti-money laundering as well as know your customer regulations to classify it as prepaid instrument of payments.

The government of Australia set plans to position their country as the global leader by investing billions of Australian dollars into Fin-Tech industry. In 2015 Bitcoin's world market is controlled by Australia. The central authority eliminates digital currencies from taxation as goods and services since 2017 and treats cryptocurrency as money.

Whereas in case of Marshall (2017) stated that inflation predicted by IMF hit the highest and several companies accept Bitcoin as sole way of making payments.

Rands (2017) claimed that the President of Venezuela Nicolas Maduro accepts policies that allow Bitcoin on a broader scale.

Developing countries like Nigeria and India report rise in the use of cryptocurrencies. Rivlin and Gebron (2016) stated that the implementation of Ethereum based block-chain is India is considered as alternative of currency and a system to solve many issues like voter fraud, broken identity system and exceptionally high remittance charges. Campbell (2017) confirmed the report of the inter-government committee provided by Ministry of Finance India to design the legal framework of cryptocurrency market to make it open for public.

Contrary to the above, there are several countries that pursue otherwise, for instance, Carata et al. (2017) stated that Thailand stood the first country to ban the trade of cryptocurrencies and any transaction while using this system of payment, since the absence of appropriate laws to cope with the system.

Similarly, Russia adopts the same stance yet government of Russia applies the law that forbids use of anything as substitute for the Ruble. The representative of the Central Bank of Russia stated the plan to develop their national cryptocurrency (RT 2017). The testing set on the Hyperledger and Materchain platforms and one of their stock exchanges plan to permit trade of virtual currencies. The Ministry of Finance, Russia confirms to recognize and accept cryptocurrencies by the year 2018.

In case of China, the People's Bank of China warned the financial institutions to use and trade in cryptocurrencies (Hern, 2013). Yet the government modified the stance and rather prohibiting the use imposes regulations on the cryptocurrencies and the exchanges (Arnold & Chen, 2017) Tian, 2017). Though in 2017, the decision reverts back to the earlier position and the cryptocurrencies market put back to disarray. However, He et al. (2016) refered to the report of IMF that states policy and regulatory challenges in order to legalize cryptocurrencies for countries. The report claims that virtual currencies do not fulfill legal interpretation of money and hence, holds risks for financial systems. Moreover, it depicts regulatory challenges and troubles in monitoring the projects, the transactional reach and the absence of abiding laws to formulate strategies for such decentralized system.

1.1.27 Regulation of Cryptocurrencies

From the above discussion, different countries employ exotically different interpretations towards legal classification and application of cryptocurrencies. The academia is also divided in their stances to draw legal definition of cryptocurrency. Srokosz and Kopciaski (2015) claimed that cryptocurrencies should be categorized as private money, whereas Enyi and Le (2017) argues to classify it as personal property especially securities and money. Such differences are resultant of the dependency of each country on their common and civil laws.

Enyi and Le (2017) stated when cryptocurrencies are considered as securities; generally it refers to crowdfunding sales by means of ICOs. According to the US law specifically the Jumpstart Our Business (JOBS0 Act and the securities Act 1922, the definition covers cryptocurrencies. Therefore, subject to the Commodity Futures Trading Commission (CFTS) most of the cryptocurrencies qualifies as commodities for making ICOs.

However, cryptocurrency is defined distinctively depending upon the context due to the structure of the block-chain technology and the governance. Since the lack of legal recognition as equivalent to cash, as there is no increase or decrease of money between the wallets actually, it just place indicators in the block and records the transaction on the block-chain.

Therefore, it seems difficult to regulate the entire system, though exchanges are easier to control. The countries that formulate explicit regulations may possibly concentrate primarily on such exchanges. International Monetary Fund (IMF) 2016 stated, regulators may execute regulations for market participants from providing interface or restrict regulating entities (banks) from interacting with cryptocurrencies and the market participants while providing legal framework for cryptocurrencies.

In another study Chambers (2016) suggested that English law interprets the trade of cryptocurrencies on exchanges as securities; hence the regulations of securities should be drawn down to cryptocurrencies.

Even though, if cryptocurrency is regulated following appropriate laws, cryptocurrency exchanges and cryptocurrency wallet regulators may possibly be perceived legally uncertain since they hold users' key. Meanwhile if any case of hack occurs on any such institution, the effective solution is to report contract claim or proprietary restitution claim against such institution regarding breach of terms and conditions. For such a system, it is important to define and execute self-imposed standards and regulations by cryptocurrency exchanges themselves.

1.2 Theoretical Grounds of the Study

The research integrates Theory of Portfolio and Theory of Extreme Values to analyze extreme value behavior in crypto-currency market. By assessing the high volatility and risk inherent in crypto-currencies the study seeks to refine hedging strategies, while incorporating extreme value theory to allow for a deeper understanding of tail risk. It enables more robust risk management in crypto-currency investments. This holistic approach aims to enhance the resilience of portfolios against extreme events, contributing valuable insights to the evolving landscape of digital assets like crypto-currencies and its integration along with traditional asset classes in traditional framework of investment.

1.2.1 Theory of Portfolio

Since, value at risk refers to the class of measures of probabilistic market risk, where value at risk metrics is a function of probability distribution and current market value. By this means assigning values of returns, variance, standard deviation that are different types of value at risk metrics. Initially measures of value at risk are developed in two parallel dimensions that are portfolio theory and adequate capital computations, though this study revolves around discussion about portfolio theory. Accordingly, Bernstein (1993) afterwardsMarkowitz (1999) briefly documented their contributions in the line of portfolio theory which primarily focused on the development of the measures in the line of adequate capital computations.

The theory of portfolio provided framework for construction of a portfolio to maximize returns for a certain level of risk while sound diversification. It states that investment is the weighted average of estimated returns and how each security in a portfolio move together, rather individual estimated returns of any investment. Markowitz (1952) introduces the notion of covariance in order to quantify movement of securities along each other. He proposed investors to measure variances in returns as well as expected returns and rate first the combination that offered greater expected returns at certain level of risk, such portfolios are deemed to be efficient. However value at risk and the measure of expected shortfall provided complementary and suitable estimates for construction of a portfolio to measure risk associated with assets in a portfolio.

1.2.2 Theory of Extreme Values

In addition to this, until recent studies the debate of value at risk is extended to focus on extreme values which are being applied to anticipate the probabilities under given market conditions. The model of extreme value theory is driven by Embrechts, Kluppelberg, and Mikosch (1999), which emerged as an essential statistical discipline for the research specifically in applied sciences over past decades, however it also captured the attention of researchers of other fields like finance in recent years. The considerable attribute of extreme value theory is to measure the stochastic performance at usually large or small levels of a portfolio construction. Precisely extreme value theory involves assessment of the possibility of market conditions, generally more risky and extreme rather other formerly perceived events.

However this approach is subjected to various criticisms, for instance common parametric techniques to estimate normal distribution though, the estimation underestimates the risk of high quantiles particularly related to fat-tailed data series which is very usual in financial data. In addition to these, the non-parametric techniques did not apply any assumption related to the empirical normal distribution, yet they failed to solve out of sample quantiles and to apply same weight on all the observations. Therefore, an interesting notion to test the prediction based on extreme returns of a portfolio lied in the application of extreme value theory. The distinguished characteristic between the two is that conventional value at risk approaches emphasized on the center of the distribution, whereas extreme value theory approach to value at risk weighs the tail of the distribution. Extreme value theory contributed a meaningful complementary risk measuring approach that offered very appropriate normal distributions suitable in extreme conditions and to explain high quantiles that are essentially desired to predict such conditions.

1.2.3 Revolutions of Value at Risk Estimates over Time

The foundation of portfolio theory is traced back to the non-mathematical thoughts to structure portfolio. Firstly the virtues of diversification are discussed by (Hardy, 1923; Hicks, 1935). However the first ever published quantitative model of value at risk is offered by (Leavens, 1945). The study focused on binominal distribution of the values which comprised of a portfolio constructed with ten bonds over certain horizon. However it did not explicitly identify the value at risk metric, yet repeatedly mentions "spread between gains and losses", which explained standard deviation of the portfolio.

Surprisingly, two independent yet similar contributions Markowitz (1952) and intuitively Roy (1952) worked to develop ways for portfolio construction to maximize gain for certain level of risk and thus publish value at risk measures that integrate covariance between factors of risk to demonstrate diversification of portfolio and hedging of risk. Though Markowitz (1952) applied variance in simple average returns, whereas (Roy, 1952) used risk that represented upper bound probability gross returns less than catastrophic returns. However both studies lined in order to specify probabilistic assumptions for a distribution. Markowitz (1952) estimated covariance matrix for given risk factors and proposes procedures to construct the matrix that ought to join statistical techniques and common practical judgments, that is being called Bayesian nowadays. Besides Roy estimated mean vector as well as covariance matrix for the given risk factors and observes these estimates from information available from the past. Moreover Markowitz (1959) elaborated the entire chapter in a book about constructing subjective probabilities broadly for non-technical users, developed by (Savage, 1954).

Afterwards Sharpe (1963) described the value at risk measure that engaged diagonal covariance matrix proposed by Markowitz (1952) in his PhD thesis. The measure is not similar yet it motivates CAPM, (Sharpe, 1964). Although due to lack of processing power, most of the measures from that period are generally theoretical and based on emerging theory of portfolio. This period embraced value at risk estimates that are best fitted and designed for equity portfolios specifically (Tobin, 1958; Treynor, 1961; LINTNER, 1965; Mossin, 1966), and very few cover other asset classes since application of value at risk to these classes raises certain modeling issues, for instance real estate, debt and future contracts make value at risk impracticable. However Schrock (1971); Miller (1972) explained modest value at risk methods for portfolios of futures, but neither speak about the term structure and seasonality problems, whereas Lietaer (1971) defined a useful value at risk estimate for structuring foreign exchange risk and proposed a sophisticated technique to optimize ongoing hedges in case of devaluation of currencies, with a conditional magnitude being normally distributed. It incorporated value at risk estimate along with the variance of market value, since computations are streamlined using model Sharpe (1963), thus it is considered as the earliest example of the Monte Carlo method of value at risk estimation.

The decade of seventies threw far reaching reforms for financial markets and technology advancements. Specifically, expanded the horizons of asset classes for value at risk applications, changes risk taking behavior of individual and institutional investors and, establishing means and newer contexts to relate value at risk. In early 70's as exchange rate floated foreign forward exchange market, emerged following two major oil crises, deregulation by US government that opened ground to compete among marketing and distribution companies. Similar liberalization experienced world electricity markets and European gas markets and several events spin interest rates which led the market of US dollar roved overseas. Subsequently the country shocking budget deficits. Thus the situation pushed a surge towards US securities and numerous financial markets for US as well as Euro MTN's (medium term notes) grew rapidly along with markets for similar instruments like high yield bonds and collateral mortgage obligations. Chicago Mercantile Exchange launched future contracts, currency futures 1972, US Treasury Bills futures 1975, and future on bonds, currencies, deposits and indices come on board afterwards. Merton (1973) published the revolutionary model of Black and Sholes for pricing options and in the same year Chicago Board Options Exchange – CBOE, the first options exchange is being registered.

In early 80's simple interest rate swaps initiates, staring Solomon Brothers 1981 to arrange currency swaps between IBM and World Bank. Following this, Chase Manhattan Bank 1986 comes up with commodity swap and Bankers Trust 1989 with equity swap. Meanwhile first asset back security introduces, Boston 1985,which is a vibrant sweep for leases, securitized loans and rotating debts. At the beginning of 1980's over the counter market – OTC is formed and, unique experiments for exotic settings begin including caps, floors, swaptions, Asian options, and barrier options. Since then possibilities for compounding risk are limited. Yet the utmost consequence of this decade in the series of financial innovations is propagation of leverage. The thriving leveraged terms included securities lending, commodity leasing, short sales and repos. This led institutions to find diverse ways to deal with risk which in turns motivates looking for new risk measures, since conventional metrics for financial accounting seemed inadequate, particularly when dealing with derivatives. Thus gradually but widely accepted risk metrics includes Convexity, Duration, Delta, Gamma and Vega, yet these metrics are largely of strategic value. However financial institutions kept looking for such enriched risk metric consistent across various asset classes.

Though the term value at risk is not explicitly used before mid of 1990's however, its origin lied back to the time. In early 90's financial institutions established elementary measures of value at risk with broad variations to measure it. As the outcome of various crises associated to the application of leverage and derivatives between 1993-95 comprehensive risk measures are introduced. Morgan (1995) provided data access to public regarding variances and covariance among different asset classes to measure risk and names this service as Risk Metrics and related the term Value at Risk to explain the risk emerged from the data. It is readily accepted by investment and conventional banks, and regulatory controls, hence value at risk emerged as an established method to deal with risk exposures for financial institutions and began finding acceptance for non-financial institutions. Another remarkable development is a rapid evolution of financial data industry, compilation of databases and historical information. The development facilitated data required to state probabilistic assumptions for estimation of value at risk metrics. Since financial markets become recurrently volatile and often experiences extreme shifts, financial institutions become more leveraged, thus the urge for financial risk estimates, more deliberate metrics flourished over all these years. (Holton, 2002).

1.2.4 Research Gap

The concept of value at risk is first applied by financial risk managers since 1970-1980 in order to quantify risk for portfolios, and the applications of value at risk exploded since then. It is a set of statistical measures that quantifies the degree of financial risk associated with particular investment or a portfolio of investments over a given time period, commonly used by risk managers to determine the extent of a potential loss and risk exposure. Since value at risk is considered as a science of risk management and the most common value at risk estimate is volatility. Apparently, in case of cryptocurrencies, where cryptocurrencies are distinguished as mineable and non-mineables according to the supply effect, volatility alone cannot be enough to measure risk because cryptocurrency in a portfolio may be volatile and may suddenly jump towards positive as well as negative extremes. Logically risk managers and investors don't get anxious for positive extremes that may lead them to higher returns. They consider risk as odds of losing, so they are only concerned about the jumps towards negative to secure against potential losses. Therefore value at risk measures generally cover three key elements like time, confidence level (likelihood) and percentage of loss to evaluate risk associated with portfolio of investment that includes cryptocurrency.

Hence value at risk denotes the value that is likely at risk over a certain time, additionally value at risk measures the expected shortfall that is the actual loss occurs during the specified time. As such volatile investment requires risk managers and investors an ability to limit their downside risk through hedging since they pour huge sum of money into various assets in a portfolio. This helps them to keep value of portfolio from falling, yet the value fall if there are extreme conditions in a market and how risky are the assets including cryptocurrency and traditional assets added up to make up a portfolio and by taking into account the chance of occurrence of such extreme conditions in returns of highly volatile assets. The research gap is pointed as there is absence of detailed exploration of how Value at Risk (VaR) is specifically applied to the unique characteristics of cryptocurrencies, particulary considering the distinction between mineable and non mineable cryptocurrencies.

1.3 Problem Statement

The time of mainframe is fading and use of personal computers is ruling. Since financial markets are espousing technology, machine learning progressions, and beginning of cryptocurrency and the block-chain requires pricing risk and return of such complex and volatile securities. There is a controversial argument among financial experts and economists that cryptocurrency could actually outclass existing fiat currency and traditional commodities yet this would entail a complete overhaul of the economic system as we observe it today. Though its practice as a sole system of making investment is not likely to be appearing in the very near future but cryptocurrency remains a fascinating notion for imminent exploration. Therefore it is likely to say that cryptocurrency has potential to do to finance what internet has done to information. In the contemporary age of information, people like the idea of holding such as asset that is decentralized (e.g., like gold) and can be stored digitally but not physically, besides proficient to be sent round the world within no seconds. This, in essence stands the value proposition for the emerging cryptocurrencies which may be called as tele-portable gold. Since cryptocurrencies empower direct transmission of economic value completely over the internet, in absence of any trusted intermediary, thus this can be an exceptionally valuable thing.

However the market is yet not completely developed. A comprehensive evaluation of cryptocurrency and its market is yet untried water. A very limited literature has been found and a few empirical studies have been on the board. There is still a disagreement among many countries whether the use of digital investment is really a safe haven or it is merely to welcome another major disaster to the financial market. Since the market is not stable, facing high volatility issues and this lead to a high risk. On the other hand as the market of cryptocurrency is growing, the categories within the market are emerging as well, initially category of mineable (number of coins increase with every mining process) and non-mineable (number of coins does not increase due to limited supply) cryptocurrencies and then category of coins and tokens differently. Therefore it is not difficult to believe that cryptocurrency will stay regardless of experiencing high volatility issues. The high volatility is due to diving trust and speculations. Yet, it seems interesting to find out volatility dynamics, which type of cryptocurrencies between mineable and non-mineable are facing more volatility issues and its role in hedging for considering it as a workable investment choice. Therefore, the rapid evolution of cryptocurrency market, lack of comprehensive evaluation pose a challenge, and lack of empirical evidences hinder a clarity in understanding about its financial wellbeing of cryptocurrencies. High volatility driven by lack of trust and speculations, complicates identifying its dynamics, particularly between mineable and non-mineable cryptocurrencies, and impact their role in hedging along with other asset classes.

1.4 Research Questions

In accordance with the discussion, extensive evaluation of cryptocurrency seems necessary. The openness of cryptocurrency along with other asset classes as a unique investment choice made it even complex. In this section the problem statement that needs to be studied, is pointed down into the following research questions.

1. Whether cryptocurrency market returns exhibit extreme values?
2. What is the performance of cryptocurrency market if volatility is time dependent?
3. Whether supply effect influences volatility among cryptocurrencies?

4. Whether cryptocurrency can be a viable alternative for investment as compared with other asset classes?

5. What is the role of Crypto-currency in hedging along with other asset classes?

1.5 Research Objectives

The dissertation is carried to investigate the cryptocurrency market and a comparison between recently established cryptocurrency along with other asset classes as a unique choice of investment. Therefore the above research questions are deemed to be explored to serve the following objectives.

1. To observe extreme values in the returns of cryptocurrency market.

2. To investigate the performance of cryptocurrency market if volatility is time dependent.

3. To illustrate if volatility among cryptocurrencies is affected by supply effect.

4. To evaluate the performance of cryptocurrency as a diversified avenue for investment along with the other asset classes.

5. To examine the role of Crypto-currency in Hedging along with other asset classes.

1.6 Significance of the Study

1.6.1 Theoretical Contribution

There is extensive literature to estimate value at risk by applying various approaches including sets of non-parametric, parametric and semi parametric measures etc. Since cryptocurrency market experiences fat tailed distributions due to extreme values driving from extreme volatility, and this volatility is supposed to be time dependent. Thus the dissertation focuses on the categorization of cryptocurrencies as mineable and non-mineable to find the influence of supply effect and then to check its role in portfolio diversification as a workable choice for investment. Therefore it is deemed to be effective and interesting aspect of the theory. It intends to provide substantial arguments for risk management particularly the estimation of value at risk for investing point of view as well as academia.

1.6.2 Practical Contribution

It is foreseeable that use of digital currency will apparently mainstay where everything is heading towards cyber and digital commands. Since we are already wandering around digitalization yet the probable question is what kind of digital asset will survive. Presently government, policy makers, practitioners and financial institutions seem skeptical about legalization of cryptos which is absolutely obvious. Since they are controlling the entire economy and are interrogating the possibility of any other parallel economy. Its implications for business and economy require clarity about legalization and legislation of such technologies and understanding the meaning and nature of cryptocurrencies and the regulations. The most imminent and apparent objection is as it is not as simple as it seems to simply invent a completely different type of asset. Its nature plugs to the source of its value that is obviously the network of people who catches interest to hold and transact in an entirely new type of asset due to its scarcity. They appreciate the idea of possessing digital asset under their ultimate control. Therefore the dissertation aims to provide empirical grounds for investors, managers and policy makers to figure out exactly where cryptocurrencies stand along with other asset classes, and what actually it brings to the financial systems. The study frames the empirical grounds on the countries where currently cryptocurrencies have larger user base and intends to draw lines for countries still working on such grounds.

1.7 Organization of the Study

Cryptocurrencies are in the beginning stages, and there are voluminous factors that can influence the evolution of the cryptocurrency ecosystem. This dissertation presents a neutral assessment of available information on the cryptocurrency landscape. All information within this report is valid as of the time of writing but is subject to change, given the rapidly evolving nature of the technology.

The structure of this report is distributed into five chapters. At first, the chapter commenced with the opening part of the study. It composes the introduction, problem statement, significance and contribution of the study along with the research questions and objectives to be addressed. Subsequently, the second chapter establishes theoretical support to the underpinned study and development of hypotheses to be tested. Addition to this, the third chapter explains the methodology employed in the study. It comprises the data description and data processing measures. Here comes the core of the study, the fourth chapter that contains the illustration and the results brought forward through various econometric measures. The concluding chapter holds final discussion of the research, limitations, future directions and implications of the study.

Chapter 2

Literature Review

The chapter sets up frame of references to amplify theoretical soundness of the thesis. It intends to congregate facts essential for relevance of the analysis instigated by the author, and assists to propose hypotheses of the study.

2.1 Theoretical Framework of the Study

2.1.1 Cryptocurrency and Extreme Values

Yu, Davidson, and Nurullah (2005) estimated risks, which is a vital topic in financial institutions (Mulvey, Rosenbaum, & Shetty, 1997; Bouchaud, 2000). The financial intermediaries involve the; management and risk pricing strategies (Cornett & Saunders, 1999). The financial intermediations facing risk, in wider sense, contain credit risk, liquidity risk, market risk, gearing risk, operational risk, sovereign risk and solvency risk (Santomero & Babbel, 1997). Out of these different types of risk categories, market risk is the most crucial risk measure faced by the financial institutions (Heffernan, 1996; Santomero, 1997; Cornett & Saunders, 1999). Besides this there are numerous models that are presently applied by different financial institutions in order to quantify risk.

The conventional GARCH model and the two of its non-linear variations to estimate stock market's volatility on weekly basis Franses and Van Dijk (1996) discovered that the QGARCH model is superior when sample does not hold any extreme values as observed in stock market crash in 1987 however, the GJR model is not recommended for predicting volatility.

McNeil and Frey (2000) combined pseudo-maximum likelihood of GARCH methods in order to calculate volatility and extreme values while considering the tail of the distribution. They estimate tail risk with conditional quantiles, back-testing of daily historical returns reveals one day better estimates than those methods that disregard the heavy tails of the distribution and the stochastic pattern of the volatility, Moreover Monte Carlo (MC) method is also applied to estimate conditional quantiles and conclude that it outperforms the square root of simple time scaling approach.

Additionally, Suarez (2001) practiced non-parametric historical simulation, estimation of Generalized Extreme Value Distribution with Mixing Unconditional Disturbances constant volatility model and Generalized Pareto Distribution. Whereas the back-testing provided higher correctness in under and upper bound confidence interval for the Peak-Over Threshold and Block Maxima approaches. Meta-heuristic method is applied to explain investor‘s program and to figure out the uncertainty related to future returns. MCS (conditional copula and Generalized Hansen skewed-t distribution) supported to consider the necessary features of time varying dependence and volatility, departure from Gaussian World and Extreme joint movements of financial markets.

The Value-at-Risk estimates with Markov Switching ARCH (SWARCH) methods Leon Li* and Lin (2004) observed structural changes non-normality in series of stock return distributions. The SWARCH models disclosed parameters to device structural changes in the appraising periods that moderate tail fatness, kurtosis and skewness difficulties while dealing with value at risk.

Other Bekiros and Georgoutsos (2005) conducted a relative valuation of value at risk models for the analytical performance allied to extreme value theory outcomes like Block Maxima and Peak over Threshold techniques that are based on results for the excess distribution.

(Kao, Changchien, Lin, & Chen, 2009) proposed a method that combines the exponentially weighted moving average (EWMA) approach to measure conditional volatility and EVT approach to measure the tail-risk behavior of the given distribution. They also used kurtosis measurements to measure the parameters of the exponential weighted approach and applied nominal assumptions regarding the underlying modelling of tail with non-parametric Hill approach to shape the parameter of the given distribution.

Karmakar (2013) paper provided estimations related to tail risk processes by utilizing conditional EVT two stage methods which is formerly suggested by McNeil and Frey (2000) in order to evaluate the dynamics of value at risk and ES estimations. Girardi and Ergün (2013) applied methodology of CoVaR which is originally introduced by Adrian and Brunnermeier (2011), the method uses value at risk conditional to the financial system of an institution which is facing financial distress. They explained systematic risk associated to the institution from its benchmark CoVaR stated to the financial distress in order to back-test the approach and to expand its stability with the dependence of the parameter.

The rational modified bubble measures for cryptocurrencies including Bitcoin that integrate probability of a total downfall in prices of assets and heavy tails of the distribution. Experimentally it proves presence of bubble in cryptocurrencies like Ethereum and Bitcoin. However, it revealed that liquidity risk may possibly be a reason that causes heavy tails in the market, since the market is prone to serious booms and crashes without exposure of any bubble (Fry, 2018). Whereas Gkillas and Katsiampa (2018) also observed the tail behavior with EVT analysis and use value at risk and expected shortfall methods to estimate risk measures associated with tail of the distribution.

Katsiampa, Gkillas, and Longin (2018) used bivariate extreme value theory (peaks-over-threshold method) to examine the extreme dependence between returns and trading volumes in the cryptocurrency market. They found the evidence of asymmetric return-volume relationship in the cryptocurrency market. In mark with the theoretical framework, the statistical findings of Ciaian, Kancs, and Rajcaniova (2018) endorsed that the transaction demand and speculative demand of Bitcoin have substantially significant power to form Bitcoin price movements. They evaluated the price factors by applying GARCH and these prices replied negatively to the velocity of Bitcoin, though positive movements in the Bitcoin stock prices, size of the Bitcoin market and the interest rate exercise an increasing force to the prices.

Another study characterized extreme volatility and bubbles behavior among cryptocurrencies. Although it is hard to weigh an intrinsic value to any cryptocurrency thus Hafner (2020) worked with the newly suggested tests for bubbles behavior that are based on recursive uses of conventional tests for unit root. This study also covered time-varying volatility while supposing a deterministic longer-term element that may possibly consider a decline in unconditional volatility when the cryptocurrency develops with higher market distribution. Moreover a more stochastic shorter-term element to build volatility clustering is also included in volatility assessment.

Trucíos, Tiwari, and Alqahtani (2020) estimated the risk of cryptocurrency market with VaR and Expected Shortfall to find outliers and presence of correlation in the market. The study proposed vine copula and volatility models to measuer seven-dimensional portfolio of the market. Jeribi and Fakhfekh (2021) studied relationship between cryptocurrencies, oil and US indexes and found appropriate hedging strategy by applying FIEGARCH-EVT Copula and hedge ratio. The crypto-currency market showed positive and asymmetric volatility effects. Bruhn and Ernst (2022) suggested cryptocurrency market entails greater risks rather other assets by examining EVT for extreme risks, and applied GARCH-EVT. Moreover t-copula investigated diversification effects for a portfolio of cryptocurrencies. Moreover, (Tenkam, Mba, & Mwambi, 2022), focused on optimum selection of cryptocurrency for a portfolio, by clustering algorithm and model of GARCH C-Vine from copula family along with differential algorithm.

Contrary to this, Jia, Shen, and Zhang (2022) investigated the investor sentiments by applying novel proxies in cryptocurrency market to explain extreme movements. It also highlighted that investor herding behavior is significantly strong in prominent cryptocurrencies and stated that investor sentiment in one of the dominant factor factors in exhibiting extreme movements in cryptocurrency market. Kim, Lee, and Assar (2022) examined market conditions (bullish and bearish) to identify extreme movements in cryptocurrency market by Hidden Markov Model (HMM) and concluded that investor sentiment is more relevant during bullish conditions through different sequences of heterogeneity in cryptocurrency market. Catania, Grassi, and Ravazzolo (2019) explained the behavior of time series of cryptocurrencies (Bitcoin), where they observed complex extreme movements and applied a dynamic model to study the volatility, time dependent skewness and kurtosis. The results confirmed time dependent skewness can improve density, volatility and forecasting.

Thus, this study intends to observe extreme value behavior in the cryptocurrency market, secondly, the study is first to study mineable and non-mineable cryptocurrencies separately and highlights the dependence structure of cryptocurrencies with the traditional asset classes over the countries with most frequent users.

In a normal probability distribution, values are located around the mean of the distribution; however extreme values are either extremely small or extremely large values that lie on the tail of the distribution. It is defined by the literature that cryptocurrency is experiencing high volatility issue. Subsequently not only a lot of speculations are following its trading yet its high volatility is not allowing it to be taken as a serious mode of investment but merely a speculative bubble. Since its values have extremely diverged from its mean value. Therefore to study the tail behavior of the probability distribution of cryptocurrencies, the study establishes the following hypothesis;

H1: Cryptocurrency returns experience extreme values.

2.1.2 Cryptocurrency and Volatility

The time-varing volatility in stock markets focus on an asymmetric volatility process called "the leverage effect." Black (1976) illustrated the market's asymmetric response to news in the way that the returns become more volatile, especially following a negative price movement shock. It is important to note that the first empirical studies that explicitly modeled to capture the leverage effect later embrace the A-GARCH model by (Engle, 1990), E-GARCH modelled by (Nelson, 1990), and following switching GARCH model by (Glosten, Jagannathan, & Runkle, 1993). A natural generalization about the process that let the past conditional variances in the current conditional variance equation to evaluate the maximum likelihood and various tests allied to the uncertainty in the inflation rate is proposed by (R. F. Engle, 1982). However Bollerslev (1986) derived the model of GARCH for the class of parametric models to facilitate stationarity settings as well as autocorrelation structure of the models.

The correlation arrangement for squares with the generalized autoregressive conditional heteroskedastic (GARCH) process introduced by (Bollerslev, 1986). The study focused on simulation experimentations to find the applicability of the hypothetical results for the order identification and diagnostic checking of the model. It exposed that the performance of the correlations matrix for the squares simulated the performance of typical correlations of a properly explained ARMA process.

However, Hodrick (1989) attempted to measure the extent to which deviations in the exogenous conditional variances vary with the degree of exchange rate by applying ARCH models. While Baillie and Bollerslev (1990) assumed the second moment conditional matrix to demonstrate generalized multivariate ARCH model. This estimated model is applied to check the hypothesis about the risk premium as a linear function of the given structure of conditional variance plus covariance.

The prominence of non-linearity existing in return behavior of stocks that are not addressed by conventional ARCH or GARCH approaches and the non-stationarity of stock volatility are compared by Pagan and Schwert (1990) with the help of various statistical methods for the data of monthly stock return-volatility.

Lamoureux and Lastrapes (1990) measured the GARCH model to investigate the persistence of the varianceon data of stock market returns. The analysis of daily returns and Monte Carlo Simulation endorsed the hypothesis that suggested measures to check persistence in variance turns out to be sensitive to such form of model misspecification.

Nelson (1990) measured with basic and sufficient settings for the stationarity and ergodicity of the given GARCH (l .l) process. This study also examined the similar persistence of shocks with respect to conditional variance in the given GARCH (l .l) model and improved necessary and adequate settings for the finiteness of absolute and complete moments of any order. However, Lin (1992) introduced four estimates to factor GARCH models, these included; 2SUE (two-stage univariate

GARCH), 2SML (two-stage quasi-maximum likelihood), RMLE (quasi-maximum likelihood with known factor weights), MLE (quasi-maximum likelihood with unknown factor weights). Moreover a Monte Carlo Simulation (MCS) plan is intended for bivariate GARCH one-factor models to test the set of sample characteristics.

The likelihood of transitional regimes (González-Rivera, 1998) considered with the introduction of a distinctive smooth-transition tool in a simple GARCH specification. The results of Monte Carlo (MC) simulation displayed that the experiment has good scope and power. However, the smooth-transition GARCH specification estimated exchange rate and stock returns data. Whereas a threshold model is favored for stock returns, yet smooth-transition model is likely to test for exchange rates.

A Markov chain Monte Carlo method is developed by Nakatsuma (2000) to facilitate linear regression model with the help of ARMA and GARCH. In order to generate a MCS model from the combined posterior distribution, the study used a Markov chain sampling in addition to Metropolis–Hastings algorithm.

(Gokcan, 2000), applied ARCH and GARCH models substantially for exhibiting volatility in a given time series. It related the linear model of GARCH (1, 1) and non-linear model of EGARCH and stated that in case of emerging stock markets GARCH (1,1) model achieved better rather EGARCH model, though if series of stock returns show skewed distributions.

Haas, Mittnik, and Paolella (2004) illustrated Markov-switching models Haas, to find the volatility dynamics related to the financial time series, drove the dynamic features and the effects for the given volatility process. The suggested approach represents that a capable volatility model is an independent process of switching GARCH with possibly skewed conditional density mixture. Furthermore, Hillebrand (2005) applied GARCH model on a given time series that held parameter variations in the process of conditional volatility. The total estimated autoregressive (AR) parameters related to the conditional variance congregates to one, therefore this conjunction held for all simulators of GARCH follow realistic parameter variations and sample size for the given financial volatility data series.

Additionally, Liu (2005) applied value at risk forecast combinations using Artificial Neural Networks (ANNs), including Mean Loss Comparison, Violation Ratio and Christofferson's conditional coverage test. The study reported the ANNs combinations have superior forecast performance than the individual VaR models and showed significant positive bias in Historical Simulation and significant negative bias in GARCH (1, 1).

(Aussenegg & Miazhynskaia, 2006) set for parametric and non-parametric value at risk modeling to compute the uncertainty in the estimates. It also proposed a different value at risk method which is based on Bayesian approach in a simple GARCH volatility structure. This approach is associated with various parametric methods including bootstrap resampling and quasi-maximum likelihood as well as non-parametric HS volatility adjusted approaches. Silvennoinen and Teräsvirta (2009) reviewed multivariate GARCH models including non-parametric and semi-parametric models to compare the results of numerous multivariate GARCH models tailored in the given data series.

In order to evaluate value at risk and other extensions, Aloui and Mabrouk (2010) considered cases with asymmetry, long-range and fat-tailed volatility in energy markets. They computed value at risk with three well-established models of ARCH/GARCH comprising FIAPARCH, FIGARCH, and HYGARCH. These approaches estimated in the presence of three substitute innovation's distributions including normal Student and skewed Student. Furthermore, the suggested FIAPARCH model outstripped the other given models to predict value at risk. Agarwal and Ramakrishnan (2010) stressed to quantify risk with value at risk approach by using historical simulation including Kernel approach (also known as support vector machine of machine learning approach.

Hoogerheide and van Dijk (2010) considered adaptive significance sampling technique which is known as the Quick Evaluation of Risk using Mixture of t estimates (QERMit). Although the results designated that this approach overtook alternative methods, in the way that it created more exact expected shortfall and value at risk estimations while giving the equal amount of calculating time, or, evenly, that it involved less calculating time for the similar numerical correctness. Yet Liu and Lux (2015) worked with the extension of the exclusive bivariate Markov-switching multifactor approach to value at risk advised by Calvet, Fisher, and Thompson (2006) and permit correlations among volatility modules to be non-homogeneous with the help of two dissimilar factors leading the volatility correlations at frequencies of high and low. The model is applied for calculating value at risk statistics for various groups of financial assets to link the outcomes with the homogeneous bivariate multifactor model, the bivariate DCC-GARCH and baseline.

However, Choi and Min (2011) tried to figure out the main factor affecting the variances in the performance of value at risk valuation by associating the effects of conditional and unconditional methods. The empirical findings emphasized the significance of the flexibility of the distribution function to estimate value at risk models.

According to the conditional and unconditional coverage back-testing methods the skewed generalized t-distribution (SGT) volatilities (categorized as skewed and leptokurtic) to give better estimations of value at risk with respect to number of total rejections (Cheng & Hung, 2011). The results followed non-parametric, normal and generalized error distributions.

Regarding evidence on disaggregated value at risk forecasts and profit/loss method Berkowitz, Christoffersen, and Pelletier (2011) assumed a broad study on Monte in order to weigh which of the tests exhibited the finest power features and finite-sample size. However the Engle and Manganelli (2004) stated that conditional autoregressive value at risk performs overall better than all other tests, yet time-based approaches also turn out well in some cases.

While by applying Variance targeting estimate to improve the arithmetical troubles regarding test of QMLE (univariate GARCH models) (Francq, Horvath, & Zakoïan, 2011) relied on the model re-parameterization and step first estimate of the variance (unconditional). However in the step second QML estimates the outstanding parameters. Precisely, it proved that in case of miss specified model, long-term estimation of value at risk, VTE model is a better choice than QMLE model. In the article Gaglianone, Lima, Linton, and Smith (2011) intended to focus on value at risk measures, by using back-testing (test specifications) from the literature, including (Christoffersen, 1998) (conditional coverage) and (Engle &

Manganelli, 2004) (conditional auto-regressive value at risk). This study proposed another way to back-test that offers necessary conditions to evaluate performance of finite sample quantile model. It also allowed recognize times where risk exposure increases on the basis of quantile regression model (Koenker & Xiao, 2002).

The application of GARCH which incorporated realized volatility for quantile forecasting in the data of financial returns, Watanabe (2012) evaluated value at risk and expected shortfall measures for normal, Student-t and skewed Student-t distributions.

An extensive GARCH models in order to quantify value at risk in times of stress are compared as well as assessment of realized returns with value at risk with back-tests including (Kupiec et al., 1995) (unconditional coverage), and (Christoffersen, 1998) (conditional coverage). Orhan and Köksal (2012) also measured quadratic loss with specifications of GARCH to quantify value at risk and report that GARCH non-linear power is a weak performer with STATA for MLE model.

An adaptive, unique and efficient way to forecast volatility and value at risk (Gerlach, Lu, & Huang, 2013) extended exponential smoothing and GARCH specifications formally adaptive from Laplace asymmetric distribution in which heavy tailed distribution, time dependence and skewed nature is considered.

While combining traditional GARCH estimated with the presently emerging machine learning approach for volatility evaluation (Peng, Albuquerque, de Sá, Padula, & Montenegro, 2018) applied mean and volatility calculations by using Support Vector Regression (SVR) and links the GARCH models. The predictive ability of suggested models is calculated with Diebold-Mariano and Hansen's Model Confidence test. It exhibited SVR-GARCH achieved to beat models including GARCH, EGARCH and GJR-GARCH under; normal, student and skewed student distributions, and time frequencies. The model SVR-GARCH emerged statistically significant and more efficient over other GARCH extensions.

In support to VaR estimates Zhang et al. (2018) proposed a non-parametric online sequential learning model entitled as OS-GELM, which is a cognitive autonomous system and GARCH to estimate value at risk. This proposed method to value at risk not simply acquires data chunk-by-chunk or one-by-one yet it also determined value at risk by extending OS-ELM in real time from machine learning to the traditional non-parametric GARCH measure. The OS-GELM model achieved more perfect outcomes and is improved model for forecasting risk, turned out to be a better device for online risk management strategy.

(Ardia, Bluteau, & Rüede, 2019) tested the occurrence of regime changes in the volatility GARCH dynamics of Bitcoin returns by applying MSGARCH. The study related MSGARCH model with single regime specifications in GARCH. The Bayesian approach is utilized to estimate the parameters of the model and to forecast value at risk estimates. The strong evidence is reported with respect to regime changes in GARCH process, further revealed the outperformance of MSGARCH over single regime specifications.

Guesmi, Saadi, Abid, and Ftiti (2019) investigated volatility spillover and conditional cross effects among Bitcoin and other financial indicators by utilizing various multivariate specifications of GARCH. The study advised that all the given models approved the significant relationship of returns and volatility spillovers. However, prominently, VARMA (1, 1)-DCC-GJR-GARCH turned out the finest model designed for modeling the combined dynamics for a range of financial assets. It revealed that taking short position (buying position) in the Bitcoin market agreed hedging for taking riskier investment in various financial assets. However hedging approaches contained equities, oil, gold and Bitcoin noticeably reduce the risk associated with portfolio as compared to the risk associated with the portfolio comprising equities, oil and gold except Bitcoin.

In addition to this Blau (2017) observed the level of unusual volatility in Bitcoin which is attributed to speculations in trading, though the findings do not approve that speculations in Bitcoin trading contribute in exceptional increase and consequently crash in its value. Moreover it also stated that level of unusual volatility in the value is not necessarily associated to trading speculations. However Chu, Chan, Nadarajah, and Osterrieder (2017) the foremost modelling of seven famous cryptocurrencies with twelve GARCH models and each model fitting for every cryptocurrency which is evaluated with respect to five criteria to forecast volatility in selected cryptocurrencies. .

Furthermore the preprocessing of forecasting the volatility in prices of the most commonly traded and largest in market capitalization cryptocurrency that is Bitcoin (Kristjanpoller & Minutolo, 2018) constituted a review at both national and corporate levels by proposing a hybrid of Artificial Neural Network-Generalized Auto Regressive Conditional Heteroscedasticity (ANN-GARCH) model.

Sigaki, Perc, and Ribeiro (2018) observed a unique methodology of statistical complexity and permutation entropy over gliding windows of time-varying log returns to compute the dynamic efficiency of crypto market where about 400 cryptocurrencies. This research concluded some of the selected cryptos as efficient over time but some of the cryptos are only efficient informationally, though this efficiency did not correlate with the market capitalization of these cryptos.

For currency risk and to capture the conventional evidences of financial returns, different methodologies are used to calculate value at risk for one day. These approaches included GARCH models and its extensions and conditional approach based on EVT that joins the GJR-GARCH method to take the asymmetric movements and time dependent volatility under consideration (Omari, Mwita, & Waititu, 2017). However in comparison of each method with back-testing results, it revealed that the conditional approach based on EVT overwhelmingly beat all the given conventional models under estimation. Gangwal and Longin (2018) studied the extreme movement in prices of Bitcoin that indicate dramatic volatility related to striking crashes and booms.

The study focused on predictability in time series of cryptocurrencies to associate numerous alternative approaches including univariate as well as multivariate for point and density forecasting. Catania et al. (2019) statistically found substantial developments in point forecasting by means of combining univariate models, and density forecasting by means of selecting multivariate models. However a study explored the effects of structural breaks on the structural changes and long memory on the cryptocurrency markets by utilizing four distinct models of generalized autoregressive conditional heteroscedasticity including GARCH, FIAGARCH, FIPARCH, and HYGARCH. Moreover Catania et al. (2019) also stated the degree of persistent decrease for returns and volatility once accounting for switching states and long memory.

According to Yu, Kang, and Park (2019) the microstructure for Bitcoins market is exceedingly established about generation of information and its transfer. For empirical testing GJR-GARCH model is found appropriate to study volatility dynamics. Initially, the volatility asymmetry is found as the market showed more market efficiency rather the conventional financial market, yet the volatility persistence is higher. Furthermore, the market aided the arrival of sequential information hypothesis in trading volume for a day that exhibited statistical significance on that day's volatility in returns. Subsequently, among proxies for user interest such as growth rate of viewed on Wikipedia and Google Trends, find effects of Google Trends only as statistically significant with relationship of returns and volatility regarding Bitcoin.

Moreover, Omane-Adjepong, Alagidede, and Akosah (2019) explored class of models such as ARFIMA-FIGARCH about two different distributions. They focused on uncovered informational efficiency (inefficiency), a modified log-periodogram method, the estimate of returns and volatilities, persistence in volatility persistence (extremely sensitive responsive to time-scale), and regime shift. Precisely, evidence about persistence in volatility is reported to be covered under conditional returns plus a break regime; however, the crypto markets observed features conflicting to the Efficient Market Hypothesis.

A paper revisted the stylized facts of cryptocurrency markets and porposed various approaches for modeling the dynamics governing the mean and variance processes. Segnon, Bekiros, et al. (2019) adopted two loss functions and the model confidence set (MSC) tests to evaluate the predictive ability of the models and the likelihood ratio test to assess their adequacy. The results confirmed that cryptocurrency markets are characterized by regime shifting, long memory and multi-factuality and find that the Markov switching multifractal (MSM) and FIGARCH models outperformed other GARCH-type models in forecasting bitcoin returns volatility.

Moreover, Yaya, Ogbonna, Mudida, and Abu (2021) assumed persistency of both volatility and market efficiency during periods of pre-crash and post-crash and discover that Bitcoin and most of Altcoins can be taken as efficient, while these cryptocurrencies are extremely volatile mainly in the post-crash period and hence their volatilities may possibly continue for shorter time period while in the pre-crash time period.

While Chai and Zhou (2018) evaluated the model of multivariate stochastic volatility along with the irregular jumps to average returns and volatility, which let to excerpt average shared time-varying volatility and explained for possible great outliers. Furthermore, the components of stable volatility seem determined by developments in major market, and the level of general interest in holding cryptocurrencies. Standardized simulation practices proposed the features of long memory dependence in cryptocurrencies which are well repeated by using stationary models along with jump components.

Fakhfekh, Jeribi, Ghorbel, and Hachicha (2021) studied dynamic and persistence in correlations among top five crypto-currencies with Gold, VIX, WTI, S & P 500, NIKKIE, FTSE and MSCIEM, for optimal hedging strategies by DCC, ADCC and GO GARCH models. They reported Bitcoin along with gold display tremendous features for optimal hedging. Shalini (2022) examined the co-volatility of crypto-currencies along with traditional assets and analyzed time-varying correlation and covariance by using models of multi-factor volatility, and found mixed results for various countries. Koutmos, King, and Zopounidis (2021) developd analytical model to find optimal weights for 11 crypto-currencies by using conditional correlation model and regression model to find connection between weights and economic uncertainty. The study found better hedging under uncertain conditions. Murty, Victor, and Fekete-Farkas (2022) stated volatility dynamic connections between Bitcoin and other assets by EGARCH model. It observed DCC GARCH model to check time dependent co-movements among the markets. Since positive movement between gold and Bitcoin showed, that Bitcoin is safe option for investment.

Agyei et al. (2022) presented time frequency analysis and lead lag relationship among different cryptocurrencies and their index by using various Wavelet techniques. The study reported interdependencies among cryptocurrencies and the index, long term dynamics in comovements, where co-movements are influenced by different shocks, and suggested investors to hedge against volatilities due to predictive quality of the index. Similarly, (D'Amato, Levantesi, & Piscopo, 2022) checked the volatility spillover between cryptocurrencies and financial markets and found that volatility forecasting in cryptocurrency market underperforms in the market dynamics. The study is based on Deep Learning to produce better results than traditional methods of forecasting. In the same manner, (Salisu & Ogbonna, 2022), tested how news effect risk and return volatility predictions during pandemic by using GARCH MIDAS technique on hourly time series data. The study stated increase in volatility during the pandemic rather the time earlier to the pandemic.

In addition another condition of parametric testing of value at risk is the assumption of time dependence. Since time varying volatility defines how volatility shifts over a given period of time. However financial models are used to solve statistical variations in price fluctuations for given different time periods. The study develops the first hypothesis as;

H2: Cryptocurrency market experiences time varying volatility.

2.1.3 Cryptocurrency and Supply Effect

Stoffels (2017) suggested incorporating different characteristics to analyze cryptocurrencies such as supply effect which may potentially affect the prices. However there has no empirical study found to capture the supply effect of cryptocurrencies Almeida and Gonçalves (2022) conducted a broad bibliometric analysis by using VOS Viewer from 2009 to 2021 to summarize the dynamics of risk management for investment in cryptocurrency market. The analysis indicated that predictive ability of volatility, risk management, and speculations may possibly be entertained by the leverage effects and the persistence in volatility. Sukarno et al. (2020) intended to find the use of cryptoucurrency to replace conventional form of money by applying Silogism analysis. This study refuted since it violates the rules to be applied as a medium of payment and provided basis for negative use of cryptocurrency that may turn out detrimental to the any state. Charfeddine, Benlagha, and Khediri (2022), analyzed the factors that affect volatility interconnectedness among mineable, non-mineable coins and tokens. They reported that mineable coins are great transmitter of volatility rather than non-mineable coins. The study stated that macroeconomic and financial factors affect interconnectedness that may improve risk management for investors for diversification. Therefore, the study proposes the following hypothesis;

H3: Supply effect does influence volatility among cryptocurrencies.

2.1.4 Cryptocurrency as Viable Investment Asset Class

To propose the advanced parametric Lagrange multiplier (LM) and similar tests to LM without parameter constancy, linearity and ARCH in standardized errors Lundbergh and Teräsvirta (2002) applied an integrated framework to analyze the competence of the GARCH model estimated. Since ARCH and GARCH frameworks turned out as imperative tools for the analysis regarding time series data, mainly in applications of financial settings (Engle, 2001). This group of models is specifically suitable to forecast and estimated volatility and provided the inspiration to the easiest GARCH to simplify its utility in observing portfolio risk.

For a perfectly differentiated portfolio in order to model daily value at risk the performance of a broad family of ARCH is assessed and to discover leptokurtic distributions that are capable to create one step ahead of VaR forecasted well (Angelidis, Benos, & Degiannakis, 2004). However the selection of sample is essential for accurate forecast, yet ARCH models accuracy of forecasts differently for each portfolio and particular for every equity index.

A research work to deal with portfolio optimization when distribution is non-elliptical, firstly Avouyi-Dovi, Morin, and Neto (2004) compared Mean-variance with Mean-CoVaR methodologies. In addition to this, it applied an unconventional method Keating and Shadwick (2002) to the different performance valuation method which is termed as Omega.

Another paper introduced model of GARCH–EVT-Copula to find foreign exchange portfolio risk. Z.-R. Wang, Chen, Jin, and Zhou (2010) also used Multi-variate Copulas like Clayton and Gaussian, to define a risk structure of portfolio, besides extended the inquiry ranging from the bivariate to the n-dimensional problem related to the asset allocation. In addition, the study found that optimal asset allocation focused on the dollar investment. It reported that Copula-t and Copula-Clayton represented better correlation among multiple investment assets rather Copula-Normal.

Various researches emphasized that CoVaR being a measure of risk for portfolio to test the permanence and potential consistency of optimal portfolio under CoVaR (Tokpavi & Vaucher, 2012), besides it also related the effects of the measure with Minimum Variance of portfolios.

The first detailed look at analysis of extreme value estimation of the Bitcoin returns Osterrieder and Lorenz (2017) focused the tail risk characteristics and carry comprehensive univariate EVT analysis. They compared the characteristics of dollar and exchange rates of traditional G10 currencies. They concluded that it is imperative for individual as well as institutional investors to understand these characteristics in order to take cryptocurrency, Bitcoin particularly as an investable class of mainstream assets.

Swami, Pandey, and Pancholy (2016) discovered the appropriate risk models to measure risk associated with foreign exchange in portfolios of banks and empirically find the suitable VaR models. The methods included non-parametric HS, parametric variance–covariance and Back-testing effects for different value at risk estimation models based on the Kupiec's proportion of failures (KPOF) and regulatory 'traffic light' approach.

One of the major contributions is construction of cryptocurrency index CRIX Chen, Chen, Härdle, Lee, and Ong (2018) which is constructed on the basis of approximately 30 cryptocurrencies that captured high exposure of accessible market capitalization. The suggested index covers a wide range of cryptocurrencies on the basis of various model selection standards and different liquidity rules.

Furthermore, (Mba, Pindza, & Koumba, 2018) proposed two novel approaches originated from the classical differential evolution (DE) technique to GARCH-differential evolution (GARCH-DE) and to GARCH-differential evolution t-copula (GARCH-DE-t-copula). The analysis showed that the GARCH-DE-t-copula outperformed the DE and GARCH-DE approaches in both single and multi-period frameworks. For these notoriously volatile assets, the GARCH-DE-t-copula showed risk-control ability, hereby confirming the ability of t-copula to capture the dependence structure in the fat tail.

While comparing the association between dollar, gold and Bitcoin the study defined that Bitcoin as something in that lies in between dollar and gold. Baur, Dimpfl, and Kuck (2018), the findings on the basis of original sample as well as extended sample showed that Bitcoin exhibited distinctively different return, volatility and correlation characteristics compared to other assets including gold and the US dollar.

Tan, Chan, and Ng (2020) proposed measuring volatilities of about 102 cryptocurrencies by utilizing the measures of Garman and Klass volatility, and models asymmetric bilinear Conditional Autoregressive Range (ABL-CARR) method. They depicted the outcomes that revealed persistence of volatility and presence of leverage effects which may possibly improved the predictability of volatility, lessen the degree of speculations and hence reduced risk in the cryptocurrency market.

To examine the volatility Cermak (2017) also applied GARCH (1, 1) model along with various macroeconomic indicators of different countries where Bitcoin (cryptocurrency) is being in trade more frequently. The study revealed that Bitcoin acted similarly to fiat currencies in countries including U.S, European Union and China except Japan. Though the volatility is gradually declining and if it goes with the similar pattern six years further of its existence, it would extend its volatility level to fiat currencies nearly in 2019-2020 thus, would possibly become a effectively functioning alternate to various fiat currencies.

In line with previous studies, Katsiampa (2017) assessed the volatility with comparison of GARCH models and found that the ARCH GARCH models offered the optimal fit. It is emphasized that the market of Bitcoin is highly speculative. ElBahrawy, Alessandretti, Kandler, Pastor-Satorras, and Baronchelli (2017) observed behavior of the entire crypto market including 1469 cryptocurrencies from April 2013 to May 2017. This study stated that the cryptocurrencies in the market appeared and disappeared constantly yet the market capitalization is growing exponentially; numerous statistical characteristics of the crypto market are noticed being stable for years.

To summarize, Poyser (2017) put forward the categories of price drivers for cryptocurrencies as forces of supply and demand (the main internal aspects that directly influence on the market price) as internal drivers, however attractiveness (such as popularity), legalization (means adoption), and various macro-finance factors (including gold prices, interest rate and stock markets) as external drivers.

Koutmos (2018)) measured interdependencies and expressed Bitcoin as leading in returns and volatility spillovers among the selected cryptocurrencies. The spillovers gradually gained attention, however there are spikes in return and volatility spillovers during important events related to cryptocurrencies. The results of the study reported a greater amount of contagion risk in the market. In addition to this, the time-varying feature of spillovers exposed certain dimensions of ambiguity concerning the imminent future of these decentralized digital currencies.

In line with the above study, the research initiated by Yi, Xu, and Wang (2018) assumed spillover index method and its modifications to observe the connectedness in both static and dynamic volatility among eight common cryptocurrencies. Moreover in the variance decomposition method a volatility connectedness network is constructed in order to discover those cryptocurrencies that are closely interrelated and mega-cap cryptos that are most likely to proliferate volatility shockwaves to others cryptocurrencies.

Nasir, Huynh, Nguyen, and Duong (2019) evaluated the predictability of returns and volume of Bitcoin by using values taken from Google search. They worked with a broad set of recognized empirical models that included framework of value at risk, a copulas model, and non-parametric illustrations in order to build a dependence structure of Bitcoin returns and volume.

Whereas Zhang, Chan, Chu, and Nadarajah (2019) investigated the stylized facts in regard of the Hurst exponent, while using both the R/S and the DFA approaches, capturing the top four popular cryptocurrencies on the basis of the market capitalization. This analysis showed high frequency data returns with multiple varying lags. Additionally along with the Hurst exponent characteristics of dependence among different cryptocurrencies is also considered. In order to explore the capability of various econometric models for forecasting value at risk for a sample data of daily returns of given time series of cryptocurrencies Pele and Mazurencu-Marinescu-Pele (2019) employed a high frequency time series data for Bitcoin to assess the entropy of intraday distribution of log sample returns by using symbolic time series analysis (STSA) for constructing low resolution from high resolution data. Their findings displayed robust explanatory power of entropy for the quantiles distribution of the daily sample time series returns. On the basis of Christoffersen's tests (1998) for back-testing value at risk forecast is most appropriate which is built upon the entropy of intraday of sample returns, in contrast to the value at risk forecasts that classical GARCH family offered.

The application of vine copula methodologies to structure the portfolio value at risk and the co-dependence of six selected cryptocurrencies by employing daily periodic data, Boako, Tiwari, and Roubaud (2019) formed proof of robust dependences among the virtual digital currencies with a highly active dependency structure. The study revealed that among the selected set of cryptocurrencies, the most economical risk reward and best optimal trade-off is comprised by Ethereum by means of the efficient frontier of Markowitz.

By the use of CoVaR for the evaluation of conditional tail-risk in the markets, Borri (2019) discovered that the idiosyncratic risk may possibly be reduced for the portfolios of selected cryptocurrencies that offered good conditional returns and risk adjusted estimates rather each cryptocurrency individually. The results of the study specified that the portfolios may provide potentially attractive hedging characteristics and returns if investors include cryptocurrencies in a portfolio. Yet if liquidity is concerned, the share of cryptocurrencies in the optimal selection of portfolio is less.

The classical GARCH may not provide correct estimation for value at risk and predictions for ES, thus results in inappropriate portfolio management, pricing of securities and risk management etc. According to (Caporale & Zekokh, 2019) suggested that the results can be possibly upgraded by applying other models with specifications that allow regime switching and asymmetries which can benefit regulators and investors simultaneously. Symss (2023) attempted to find features of cryptocurrency to take it as a financial asset, and suggested that cryptocurrency market is independent of conditions of financial markets since it depicted weak correlation with other financial assets, and hence can be used as an alternative. Keeping the growing interest of investors prices of are trusting cryptocurrencies to provide solution to liquidity issues and financial constraints to any company.

Ecer, Böyükaslan, and Hashemkhani Zolfani (2022), stated that cryptocurrency is a technological innovation which attracted investors expectations of earning high by investigating cryptocurrencies with highest market capitalization with sixteen indicators. However, the study showed that investors don't encourage doubts in while making investments, and found that big cryptocurrencies like Bitcoin, Ethereum and Tether are suitable for investment that provided stability in investments in cryptocurrencies. Mo, Meng, and Zheng (2022), investigated the frequency-time dynamics connectedness of cryptocurrencies and commodity market. It found that cryptocurrency short-term and long-term spillover to the commodity market during COVID-19 pandemic. Hence after the pandemic the market turned out to be an interesting hedging instrument into a portfolio for an investor. Pereáñez (2022) that cryptocurrency market is strengthening appearance in the international market. There are certain regulatory, characterization and identification issues attached to it as compared to other currencies; however, cryptocurrency (Bitcoin) has become a desired asset in the market of North America. Xi, O'Brien, and Irannezhad (2020) discussed socio-economic features of cryptocurrency investors by conducting a web based survey applying a Logit model to study the choice of investors between cryptocurrency coins and other ICO tokens. They concluded with differences in the choice of investors among Austrialian and Chinese investors on the basis of various demographic factors. On the other hand, Hacioglu, Chlyeh, Yilmaz, Tatoglu, and Delen (2021) described the mining strategies (home mining and cloud mining) for cryptocurrencies as essential for cryptocurrency investment. It suggested that home mining strategy turned out to be the best strategy on the basis of highest performing service providers in terms of cost of operations and the payout measures.

Literature indicates cryptocurrency as speculative asset rather than being used as mode of payment, since its volatility is high and it has not yet achieved to satisfy the requirements to be considered as potential form of currency. Yet due to its intangible scarcity it is deemed to be considered as another form of a financial asset which has grasped the attention of investors and their volume is continuingly growing. Therefore the study designs the following hypothesis to test the potential of cryptocurrency to be a viable alternative for investment in comparison with the set of other conventional asset classes.

H4: Cryptocurrency can be a viable alternative for investment similar to other asset classes.

2.1.5 Crypto-currency and Hedging

(Von Hayek, 1976) described the concept of competition in currency markets, not merely between the countries but competition within the countries alike. It urged people to be free to pick any currency they want to use. The Austrian School of economics found Bitcoin (cryptocurrency) an intriguing currency, since it introduced the probability of disrupting the expropriation about issuance of fiat currencies as it held potential to deteriorate the powers of authorities like central banks. It is believed that if Bitcoin (cryptocurrency) continued on the same pace to attract interest of masses and may become widely used by them, it may possibly become alternate option practically, and they would start switching to it to uphold against increasing inflation in domestic currencies.

The economists from Austrian school of economics Korda (2013); Graf (2013) criticized Bitcoin (cryptocurrency) and their criticism relies on the belief that it violated the Mises's regression theorem (Mises, 1912; Von Mises, 1949) of money, since cryptocurrency did not back any tangible commodity. Though other economists including Graf (2013) and Surda (2014) from the same school of thought specialized in Bitcoin and interpret the regression theorem differently. They argued that although Bitcoin did not back any tangible commodity, yet it is a uniquely designed scarce intangible good that fulfills the requirements as to be a commodity. Consequently, Bitcoin did satisfy the Austrian definition of a currency since it is likely to work as a medium of exchange.

Moreover a noble memorial prize laureate (Krugman, 2013) famously wrote a post on blog entitled "Bitcoin is Evil", where he questions ability of a Bitcoin (cryptocurrency) to be taken as a reliable store of value. Delong (2013) seemed skeptical since Bitcoin did not support by a "too-big-to-fail entity" that it would be bought back if necessary. However, ultimate deflationary nature of Bitcoin is a point of concern among Keynesian economists.

Gronwald (2014) used GARCH, an autoregressive jump intensity model and concluded that price of Bitcoin is strongly characterized by extreme movements, which indicated it as an immature market. However, Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) explained that the users commonly treat Bitcoin as a speculative asset, rather means of payment. (Baek & Elbeck, 2015) reported robust proof that volatility of Bitcoin is driven internally though buying and selling forces, led to the inference that presently its market is greatly speculative. Moreover the interest rates are historically low, which indicated investments are risky yet have potentially high returns; so it is assumed if interest rates are lower, Bitcoin would become ultimate choice of risk-tolerant investors.

Dyhrberg (2016) explored bitcoin's capabilities as a financial asset using GARCH models. With the help of asymmetric GARCH model, the author found the evidence that bitcoin may possibly be beneficial in the risk management strategies and perfect choice for risk averse investors in expectation of the negative extreme shocks in the market. In addition to this Bouoiyour, Selmi, et al. (2016) studied daily prices of Bitcoin by using the optimal GARCH model and express that its volatility illustrated decreasing trend while comparing pre to post 2015 data. They observed substantial asymmetries in the Bitcoin market as the prices are determined more towards negative than positive shocks.

Bouri, Gupta, Tiwari, and Roubaud (2017), another study investigated that Bitcoin can serve as an effective diversifier but it did not function as a hedging instrument. Whereas volatility of Bitcoin and its forecasting ability by applying GARCH model is also examined (Urquhart, 2017). The study found that the realized volatility in Bitcoin price is relatively high in the sample initially (first half), however declined afterwards (recent years) and no evidence to support leverage effect is reported. Moreover, (Lamoureux & Lastrapes, 1990; Alam, 2017) tested the weak form of efficient market efficiency in cryptocurrency using time series data for the cryptocurrencies Bitcoin and Litecoin. They reported weak form of efficiency and concluded that cryptocurrency reacted instantly to new information, which is consistent with the EMH, thus cryptocurrency held a higher predictability power than the stock market due to this sensitivity to information.

Baur and Dimpfl (2018) analyzed effects of asymmetric volatility for leading cryptocurrencies, They stated the distinctive asymmetry relative to equity markets where positive movements result raised in the volatility more as compared to negative movements. The conclusions are consistent with FOMO (fear of missing out) of unsophisticated investors and the presence of pump and dump patterns in the prices of cryptocurrencies.

The distinctive illustration of stylized facts about the variance measures of cryptocurrencies are employed by using log of daily returns, thus these results are then related to their corresponding cryptographic schemes for instance intended transaction speed (Lukianenko & Rud, 2018). The overarching inference of these results is the volatility of the given cryptocurrencies that can be better assumed and measured by means of functions of fast moving autocorrelation.

However in a review Corbet, Lucey, and Yarovaya (2018) offered a systematic analysis of the literature of empirical studies that comprised the main areas about the market of cryptocurrencies since its inception as a financial digital asset in 2009. Even though surprising increase in price in most recent years, cryptocurrencies are subjected to allegations of financial pricing bubbles, its potential for illegitimate practice because of its anonymity, and infrastructural ruptures from conventional means of financial dealings that influenced by means of growing cyber criminality.

On the other hand, Corbet et al. (2018) also focused on the presence and periods of financial pricing bubbles in the prices of Bitcoin as well as Ethereum by employing the methodological approach initially proposed by Phillips and Yu (2011) in order to inspect the key fundamental indicators of the bubbles in the prices. The study concluded presence of clear behavior of bubbles in Bitcoin prices which is now certainly existing in a bubble phase.

By applying the GARCH-MIDAS model Conrad, Custovic, and Ghysels (2018) extracted the short-term as well as long-term volatility elements of cryptocurrencies. To potentially strong drivers that exist in Bitcoin volatility, they pondered approaches of risk and volatility of the US stock market along with the approach to global economic activity. Lastly, they concluded with the strongly positive relationship between the long-term Bitcoin volatility and Baltic dry index and stated that global economic activity influences Bitcoin volatility thoroughly.

However, Tu, D'Odorico, and Suweis (2020) study cryptocurrencies that are increasingly popular digital assets/cashes programmed to exert as a medium of exchange, which is "secure" by design for example through block-chains and cryptography). As the year 2017 seems the rise and fall of the cryptocurrency market, followed by high volatility in the price of each cryptocurrency, therefore the study critical transitions in cryptocurrency residuals through the phenomenon of critical slowing down.

The semi-parametric method along with the Cornish-Fisher extension that estimates quantile by using high moments in the distribution which is provided to assess hedging proportions with CoVaR (Chai & Zhou, 2018). They also compared the conventional Minimum-Variance model and the Minimum CoVaR model, where later outperforms in-sample criteria but is not consistent with out-sample. The CoVaR approach captured the structures of high moments along with high kurtosis and the heavy and fat tailed distribution.

Whereas Shintate and Pichl (2019) provided the framework of random sampling measure (RSM) to predict trend based on deep learning (DL), to compare the performance of the two traditional baseline approaches for non-stationary time series data of cryptocurrencies. The turnover rates on the basis of RSM beat the methods based on long short-term memory (LSTM), though the estimation did not exceed the buy and hold plan during the period, thus did not offer a base for algorithmic exchange.

The three pair wise bivariate BEKK approaches in order to inspect the dynamics of conditional volatility with the interconnection and conditional correlations among the sets of cryptocurrencies. The price volatility of cryptocurrency deemed to be reliant on the past and past volatility and shocks. Katsiampa, Corbet, and Lucey (2019) classified bi-directional volatility effects of spillovers between the three sets of cryptocurrencies and put forward the evidence regarding time dependent conditional correlations present that are generally positive.

In addition to this, the hypothesis that hedging abilities and volatility spillovers abilities are present between Ethereum and Bitcoin by using multivariate BEKK-GARCH approach analysis for impulse response applied in value at risk estimates (Beneki et al., 2019). This study illustrated the unidirectional volatility transference from Ethereum to Bitcoin which suggested that cost-effective trading schemes may possibly be recognized for a recently established derivative market by the significances beside market efficiency. In the light of the literature cryptocurrency has a dynamic role and can be an effective hedging instrument for a well-diversified portfolio. (P. Wang, Zhang, Li, & Shen, 2019), that cryptocurrency market is not a safe investment against international financial markets, however the cryptocurrencies with highest market capitalization and liquidity may possibly provide better hedging capability and lastly, it may turn out to be safe hedging in developed markets particularly.

Bouri, Shahzad, and Roubaud (2020), exhibited the hedging and safe investment characteristics of cryptocurrencies against downside movements of S & P 500 and ten related equity sectors. This study showed cryptocurrencies potential to be a valuable asset class and investors may improve the efficiency of their portfolio by including cryptocurrencies along with different equity sectors.

Okorie and Lin (2020), observed relationship between cryptocurrencies and crude oil by considering cryptocurrency market a commodity market. By applying VAR, MGARCH, GJR and BEKK approaches, and Wald estimates, it showed the presence of bi-directional and uni-directional spillover between the cryptocurrency market and crude oil. It also found hedging capability of crude oil with cryptocurrencies. Susilo, Wahyudi, Pangestuti, Nugroho, and Robiyanto (2020), related to the previous literature to find hedging capability of cryptocurrencies with equities. The technique of Asymmetric Generalized Dynamc Conditional Correlation GARCH (AG DCC) facilitated to find index of cryptocurrency may possibly be significant and consistent to hedge against other equities rather each cryptocurrency separately. However Minimum Variance Model expresses that cryptocurrency can be added into a portfolio to improve its efficiency instead of hedging.

Karim, Naeem, Mirza, and Paule-Vianez (2022) confirmed the hedging characteristics between bond market and cryptocurrency market by applying Baur and

McDermott (2010) and AGDCC GARCH approaches. This study stated that SKUK and SPGB offered safe investment for cryptocurrency market and provided significant diversification during economic instability. Maitra, Rehman, Dash, and Kang (2022), examined volatility spillover and hedging capability of cryptocurrencies and different equity markets. It provided comparative analysis of pre-COVID and COVID period data by using Copula approach. It found that the pandemic increases the volatility spillover from cryptocurrencies to the stock markets, and thus investment during the period reduced as the cost of hedging increases. Yet it confirmed that cryptocurrencies did not provide excessive returns by hedging against stock market during the period.

Nekhili and Sultan (2022), compared equities, bonds, commodities, currencies, and derivatives to hedge against cryptocurrency (Bitcoin). The study endorsed hedging capability of the assets against cryptocurrency market by using Wavelet Dynamic hedging approach. Almeida and Gonçalves (2022), performed bibliometric analysis of cryptocurrencies with respect to diversification, hedging and safe investment characteristics. It found the increasing academic interest in cryptocurrency's capacity to hedge against other asset classes, and hence it possessed characteristics of diversification and safe investment. Since cryptocurrency exhibits extreme movements, therefore investors may consider Gold and Crude Oil along with cryptocurrency market for hedging. In the light of the literature cryptocurrency has a dynamic role and can be an effective hedging instrument for a well-diversified portfolio. Therefore, the study designs the following hypothesis; Therefore the study designs the following hypothesis;

H5: Cryptocurrency plays dynamic role in hedging of investment.

Chapter 3

Research Methodology

In this chapter, the techniques and procedures espoused to address the problem statement are presented. It endeavors to serve each step involved to precede with the study, besides that it attempts to illuminate the intents of the thesis to the reader.

3.1 Methodological Framework

3.1.1 Sources of Data Collection

The study applies secondary source of data collection, the list of cryptocurrencies and the data is collected from Coinmarketcap and the data for all other variables is collected from Investing.com.

3.1.2 Time Frame

The underlined study is quantitative in nature and captures market data. The statistical data for cryptocurrency is recently established therefore it covers time from July 2013 to June 2019. Since it is ut-most important to select cryptocurrencies from the same time horizon, therefore the year in which any requisite information regarding any cryptocurrency omit, is excluded. Moreover, cryptocurrencies are selected on the basis of survivorship bias.

3.1.3 Sample Size

There are total 3047 cryptocurrencies out of which 2353 are active with total market capitalization of $233,094,030,968, comprises 857 coins and 1496 tokens. The Purposive Sampling Technique is applied in the selection of cryptocurrencies, since cryptocurrency coins with market capitalization of USD 100,000 and above covers the sample size. There are about 498 cryptocurrencies (list of cryptocurrencies is given in annexure) with market capitalization of USD 100,000 and above while writing the thesis.

3.1.4 Selection of Countries

The following list of countries is taken from Congressional Research Service (2018) and Library of Congress (2018). This list depicts complete picture of the regulations of cryptocurrency around the globe. The **Table 3.1** categorizes countries as banned (absolute and implicit), regulated (by tax laws and by anti-money laundering and anti-terrorism laws), and the countries that are trying to develop hub of cryptocurrencies;

However, as per the report submitted by the company of cryptocurrency analysts the DataLight.me (2019) provides the geographical distribution of cryptocurrency traders by examining 100 most popular exchanges of cryptocurrency. The top 10 countries with highest cryptocurrencies traders are selected, **Table 3.2**;

Table 3.1: Countries with Highest Crypto-Currency Traders

S. No	**Country**	**Country Symbol**	**Number of traders**
1	United States	US	22260554
2	Japan	JP	6142686
3	South Korea	KO	5731772
4	United Kingdom	UK	3898222
5	Russia	RU	3183839
6	Brazil	BR	3108640
7	Germany	GR	2528541
8	Vietnam	VN	2482579
9	Turkey	TR	2414148
10	Canada	CA	2027280

3.1.5 Description of Variables

Following are the variables of interest;

Cryptocurrency Returns – CR: Cryptocurrency returns by creating index of 461 coins trading on Coin market cap. Exchange Rate – ER: Currency exchange rate of the selected countries. Fiat currency is one of the important areas where investors invest money. Generally along with other assets investors tend to invest in appreciating currencies as well as they tend to divert from investing in currencies in times of devaluation to safeguard against inflation.

Stock Returns – SR: Stock market is another avenue for investment where institutional as well as individual investors put their money in shares of various companies. However with changing macro-economic conditions and integration of stock markets, sole investment in stock market is not ideal. 10 Years Government Bond Rate – GB: Investment in bond means providing money to a company or government against periodic payments in the form of interest with certain maturity, and interest is the rate at which bond is being sold or purchased. Investors invest in bonds since stream of periodic payments are predictable and it is a simple way to preserve money as bondholders receive back the principal amount after maturity.

Gold Rate – GR: Gold is one of the most important traditional choices available to investors. It is believed as the precious and desirable metal, and hence it is perceived as reliable and safest form of wealth, rather than stocks and bonds. Investing in gold means diversifying risk since other investment choices are unpredictable. The gold price is stated per ounce. The variables are summarized in **Table 3.3**.

All prices will be taken in terms of USD.

3.2 Fundamentals of Analysis

The definition of risk is merely anything that diverges from normal, but actually breaking down into its components is crucial thing. Defining what is called normal and what is called abnormal, and the measures to estimate deviations are what academic researchers are trying to explore since the debate of value at risk begin. Over past decades researchers come up with different measures of value at risk and this field of study is continually evolving. To build the methodological framework of the dissertation the following measures for risk estimation are applied.

TABLE 3.2: List of Variables under Study

Variables/	**CR**	**Index of 461 cryptos on the basis of market capitalization.**	
Countries	**GR**	**Gold price per ounce.**	
	ER	SR	GB
US	USD	S&P-500	USGB10Y
JP	JPY	Nikkei-225	JPGB10Y
KO	KOW	KOSI	KOGB10Y
UK	GBP	FTSE-100	UKGB10Y
RU	RUB	MCX	RUGB10Y
BR	BRL	BOVESPA	BRGB10Y
GR	EURO	DAX	GRGB10Y
VN	VND	HNX-30	VNGB10Y
TR	TRY	BIST-100	TRGB10Y
CA	CND	TSX	CAGB10Y

3.2.1 Econometric Framework

For analysis of the study daily data has been used. Firstly the returns Returns of each series are defined as below, where i denote the name of variable; t represents present day price and t-1 price of the previous day for each series as;

$$R_i = log\left(\frac{R_t}{R_{t-1}}\right)$$

Initially normality of the data is checked with skewness and kurtosis. Theoretically cryptocurrency market deemed to be highly volatile and experiencing extreme values. Such values fails to make normal distribution and most of the values lies on both extremes of the distribution which makes heavy tails of the distribution. Taking measure for value at risk which holds assumption of non-normal distribution and assumes student t-distribution, is appropriate to explain risk and return in fat tails distribution. Eq 3.7 illustrates as below; where v=5 as the degree of freedom for empirical explanation of fat tails, and the maximum likelihood ratio.

$$VaR^{StTD}_{(t+1,\alpha)} = \mu + \sigma\sqrt{\frac{v-2}{v}t^{v}_{1-\alpha}} \tag{3.1}$$

3.2.2 Confidence Interval

The study plans to study at 95% and 99% confidence levels.

3.2.3 Value Weighted Index of Cryptocurrency Market

Set of 498 cryptocurrencies on the basis of market capitalization are selected. The weights against each cryptocurrency based on their respective market capitalization are determined. Hence by summing the product of each cryptocurrency price and its weight the index is created for further analysis of the analysis.

3.3 Extreme Value Theory – EVT

In order to observe extreme values in cryptocurrency market, Extreme Value Theory proposed by Embrechts (1997) and Coles et al., (2001) refers to deal with the extreme deviations away from the median value of the probability distributions. These extreme values are center of attention for risk management since; they are associated with shattering events such as market crash and extremely large losses. Though, the rate of occurrence of such extreme events is unusual. Unlike some research which assume certain distribution which may not be identical to the real distribution and give rise to error, EVT does not assume specific distribution, but deal with extreme value specifically, to describe the tail area of the distribution more exactly. It considers three parameters for estimation that is location, shape and scale.

3.3.1 Generalized Pareto Distribution (Peak over Threshold - POT)

The independent observations of a random variable with distribution function known as f(x), where, xf is the finite and infinite endpoint of the cumulative distribution function, and the excesses that is Xi over certain threshold u illustrate as, Eq 3.2

$$fu(y) = p_r(x - u \leq y \Big| x > u) = \frac{f(y+u) - f(u)}{1 - f(u)}, 0 \leq y \leq x_f - u \tag{3.2}$$

EVT is effective for VaR estimates about the tail of the distribution, since modeling for extreme values is applied into two different manners such as modeling the maximum variables and modeling the extreme values over certain threshold. The model Peak over Threshold – POT is generally more efficient to estimate parameters with limited observations above the threshold. Hence GDP models the behavior of the distribution, Eq 3.3 expresses as; where σ is scale parameter and ξ shape parameter (if ξ <0 the distribution is Weibull, if ξ=0 the distribution is Gumbel and if ξ >0 the distribution is Frechet).

$$G_\xi = \begin{cases} 1 - \left[\left\{ 1 + \frac{\xi}{\sigma} \right\}^{-\frac{1}{\xi}} \right] \xi \neq 0 \\ 1 - \exp\left(\frac{-y}{\sigma} \right) \ \xi = 0 \end{cases} \tag{3.3}$$

3.3.2 Generalized Pareto Distribution

The GDP static measure applies to observe fat-tailed behavior with constant parameters of the distribution and uses parameter of location as threshold. The static function expresses Eq 3.4; where location parameter denotes the minimum value of the given variable, whereas scale and shape parameters should be greater than 0.

$$VaR_{t+1}^S = \gamma + \frac{\hat{\sigma}}{\hat{\xi}} \left[\left\{ \frac{n}{N_\gamma} (1-p) \right\}^\xi - 1 \right] \tag{3.4}$$

Moreover GDP dynamic is another measure of value at risk estimation for a probability distribution at a given confidence level that applies forecasting of conditional variance at dynamic one day above estimates of value at risk. It illustrates as follows, Eq 3.5;

$$VaR^{D}_{t+1} = U_{(t+1)} + \sigma_{(t+1)} \times VaR^{S}_{t+1} \tag{3.5}$$

3.3.3 Expected Shortfall of GDP

The expected shortfall of GDP is the expected loss which exceeds value at risk, mathematically, written as Eq 3.6;

$$ES^{S}_{q} = VaR_q \frac{\sigma + \xi(VaR_q - u)}{1-\xi} = \frac{VaR_{(q)}}{1-\xi} + \frac{\theta - \xi u}{1-\xi} \tag{3.6}$$

3.4 DCC GACRH Model

For measuring time varying volatility Dynamic Conditional Correlation, commonly known as DCC GARCH by Engle (2001) is applied, it belongs to the set of models to measure conditional correlations and variances, Eq 3.7;

$$H_t = D_t R_t D_t \tag{3.7}$$

It simply decomposes the covariance matrix into conditional correlations and standard deviations, where correlations and standard deviations are time time-varying. The DCC GARCH model defines H_t as the covariance matrix and R_t is the correlation matrix. D_t, represents univariate GARCH, however this univariate model can incorporate other variables as, Eq 3.8;

$$D_t = diag\left\{\sqrt{h_{i,t}}\right\} \tag{3.8}$$

Here D_t represents the univariate GARCH model where limitation on non-negative variance and condition of stationary of the variables apply, Eq 3.9:

$$h_{i,t} = c + \sum_{p=1}^{p} \alpha_{i,p} r_{i,t-p}^{2} + \sum_{q=1}^{q} \beta_{j,q} h_{i,t-q} \tag{3.9}$$

Similarly R_t of the model defines Eq 3.10;

$$R_t = Q_t^{(*-1)} Q_t Q_t^{(*-1)} \tag{3.10}$$

It expresses Q_t and Q_t^* as, Eq 3.11;

$$Q_t = \left(1 - \sum_{m-1}^{M} a_m - \sum_{n-1}^{N} \beta n\right) \bar{Q} + \sum m - 1^M a_m(\in t - 1 \in t - m) + \sum_{n-1}^{N} \beta n Q t - n \tag{3.11}$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 \\ 0 & \sqrt{q_{22}} & 0 \\ 0 & 0 & \sqrt{q_{33}} \end{bmatrix} \tag{3.12}$$

Eq 3.12; $\overline{Q}$ denotes the unconditional covariance of standardized residuals at initial stage of the estimation. Theoretically and empirically the dynamic conditional properties (2001) depicts that if Q_t is positive, R_t is also positive. Additionally scales of α and β should be greater than zero yet $\alpha + \beta < 1$ (Orskaug; 2009 and Andersson & Lindskog; 2019).

3.4.1 Selection of the Model

To select the model, it is assumed that model reduces loss of information and captures maximum information to be tested. Therefore the first measure is the Akaike Informtion Criterion (AIC) that maximizes the conditional likelihood of ARCH (p, q) and rationalizes the model, Eq 3.13;

$$AIC = -2Log(L) + 2k \tag{3.13}$$

However it is the relative measure in order to relate with other models (Burnham et al. 2004). So, there is another model in relation to that is Bayesian Information Akaike (BIC) model (Schwarz, 1978), Eq 3.14;

$$BIC = -2Log(L) + KLog(n) \tag{3.14}$$

As with the value of AIC compares the value of BIC for each model and hence model with the lowest value applies.

3.5 ARMA - GJR GARCH

Autoregressive (AR) model assumes linear dependency between present day returns and past day's volatility whereas moving average (MA) model signifies that the returns are dependent not only on the present day volatility rather on past day's volatility. It happens when new information gradually absorbs and circulates in market at different time. Resultantly, the new shock generated in the market holds past as well as present shock. These two concepts of AR and MA join to form Autoregressive Moving Average (ARMA) model. The ARMA (p,q) model symbolizes, Eq 3.15;

$$r_t = c + \sum_{i-1}^{p} \phi_i r_{t-1} + \sum_{j-1}^{q} \phi_j \varepsilon_{t-1} + \varepsilon_t \tag{3.15}$$

Here ϕ_i represents the AR (p) model and θ_j represents MA (q) model. Setting P = 0, eliminates AR (p) model and reduces to the MA (q) model whereas q = 0 sets out MA (q) model and reduces to AR (p) model. In combination to this measure for clustering volatility GJR-GARCH model is derived by Glosten, Jagannathan and Runkle (1993) that draws asymmetry in the simple GARCH process.

This model asserts observations process by using GJR-GARCH where volatility is high due to negative shocks than positive shocks and includes leverage effect (caused at the point where negative returns generate greater effect on future volatility rather do positive returns) composed of lagged squared of negative observations. The model Eq 3.16; allows conditional volatility to depict different shocks to past variations depending on their signs, where ϕ_k is the parameter to measure new information in a generalized error distribution.

$$h_t = c_o + \sum_{i=1}^{p} \alpha_i h_{t-1} + \sum_{j=1}^{q} \beta_j u_{t-1} + \gamma_k u_{t-j}^2 D_{t-1} + \varepsilon_t \tag{3.16}$$

D_{t-i}, defines the dummy variable for supply effect. This dummy variable applies if past day shock is negative $\mu_{t-j} < 0$, and allows GJR GARCH model to activates leverage effect,Eq 3.17;

$$D_{t-1} = \begin{cases} 1\, if\, u_{t-1} < 0 \\ 0\ otherwise \end{cases} \tag{3.17}$$

3.6 Measure of Dependence

Linear correlation or Pearson correlation widely applies to measure dependence between two or more random variables, such as given below; where x_1,x_2 are random variables in a joint function with positive finite variances.

$$\rho(x_1, x_2) = \frac{n(\sum x_1.x_2) - (x_2 - \bar{x}_2)}{\sqrt{\sigma^2(X_1)}\sqrt{\sigma^2(X_2)}} \tag{3.18}$$

Whereas the measure to estimate the degree of change in one variable predicts the degree of change in another variable is defined by the statistical term correlation coefficient, Eq 3.19;

$$r = \frac{n\left(\sum x_1.x_2\right) - \left(\sum x_1\right)\left(\sum x_2\right)}{\sqrt{\left[n\sum x_1^2 - \left(\sum x_1\right)^2\right]\left[n\sum x_2^2 - \left(\sum x_2\right)^2\right]}} \tag{3.19}$$

The dependence of random variables is instinctively apparent; however Pearson correlation seems invariant while strictly increasing linear transformations, which may not possibly lead to similar correlation. Therefore in case of strictly increasing function this correlation may not give appropriate measure of dependence unless variables are elliptically distributed jointly.

3.6.1 Dependence Structure – Copula Approach

Copula is defined as a joint function of random variables in standard multivariate uniform distribution. Initially this concept is put forward by (Ward, Glorig, & Sklar, 1959)Sklar (1959) commonly known as Sklar's theorem, yet Rank and Siegl (2002) introduce the said technique to quantify dependency in computation of VaR estimates. It tends to measure the level of association or dependence among various random variables, in the manner given below, Eq 3.20; where $U_1 \sim U$ (0, 1) for number of variables i = 1, 2. . . ., n. Copula modelling allows to describe the structure of dependency of set of random variables independently from the marginal distribution. If set of random variables is X_1,, X_2,. . . . . X_n with joint function denotes as f and continuous marginal functions as fi, Eq 3.21;

$$C(u_1, u_2, u_3, \ldots u_n) = p_r\{U_1 \leq u_1, \ldots U_d \leq u_d\} \tag{3.20}$$

$$C(u_1, u_2, u_3, \ldots u_n) = f\{f_1^{-1}(u_1), \ldots, f_d^{-1}(u_d)\} \tag{3.21}$$

3.7 Conditional Value at Risk (Expected Shortfall)

The Conditional expected shortfall (ES) Acerbi and Tasche (2002) determines the expected value of the loss when it exceeds value at risk. It is a risk valuation measure that deals with the average loss conditional to the point larger than value at risk over a given time period. Mathematically, Eq 3.22 drives f_{VaR} (x)dx is the probability density function for returns x and c refers to the breakpoint of the distribution.

$$Co_{VaR} = \frac{1}{1-c}\int_{-1}^{VaR(p)} x f_{VaR}(x)dx \tag{3.22}$$

Expected shortfall illustrates Eq 3.23; where σ^2 refers to variance, ϕ represents the distribution. The minus sign with VaR shows loss. Thus modeling of ES falls similar for every measure value for the term σ changes with change in distribution.

$$Co_{VaR} = -\frac{\sigma^2\phi\{-VaR(p)\}}{p} \tag{3.23}$$

3.8 Delta Conditional Variance - Delta CoVaR

The ΔCoVaR is a measure of systematic risk that focuses on the tail dependency among cross sections. This method seems useful in order to detect which asset is at risk as it measures directional dependency at tails of variables under study. ΔCoVaR is estimated by using quantile regression as well as GARCH. ΔCoVaR is defined in terms of value at risk and conditional value at risk. As value at risk is a measure to estimate potential loss expected in a value of highly volatile asset over a specified time at a given confidence level as given Eq 3.24. Here x is the return of asset of distribution f and (1- q) VaR is the confidence level, that indicates the probability of returns of an asset i, which must not be less than VaR.

$$p\left(X^i \leq VaR_q^i\right) = q\% \tag{3.24}$$

In Eq. 3.25 X^i represents the returns of an asset i. The following equation defines conditional value at risk (CoVaR) at q% confidence level. $\mathrm{CoVaR}_q{}^{c|c(x^i)}$ is the VaR of an asset c, defined by the q%-quantile of a conditional probability distribution, conditional to extreme shifts, C(X^i).

$$P\left(X^c|C(X^i) \leq CoVaR_q^{c|c(x^i)}\right) = q\% \tag{3.25}$$

According to Adrian and Brunnermeier (2011), ΔCoVaR is estimated by taking difference between VaR of a financial asset conditional on the extreme shifts (left or right) of asset i, and VaR of a financial asset conditional on the average (median) of asset i, given, Eq 3.26; as:

$$p\left(X^i \leq VaR_q^i\right) = q\% \tag{3.26}$$

3.9 Hedge Ratio

In order to determine the relationship between cryptocurrency and each of the assets in a portfolio hedge rati. is used. It is a measure to determine the optimal proportion of a traditional asset to offset the risk in other traditional assets under study, in order to reduce overall volatility. For static hedge ratio VECM model and for time varying hedge ration bivariate GARCH are applied (Ederington, 1979).

3.9.1 Vector Error Correction Model -VECM

Vector error correction model provides the dynamic estimation of correlation in returns and insight about the lead lag relationship between two variables (Alexander, 2001). It structures the short run and long run variations from the equilibrium to be corrected. The model Eq 3.27 is given as below; where ΔC_t the change in crypto currency returns and ΔK_t is the change in comparative asset returns.

$$\begin{aligned} \Delta C_t &= \alpha_1 + \sum_{i=1}^{m_1} \beta_{1i} \Delta C_{t-1} + \sum_{i=1}^{m_2} \beta_{2i} \Delta K_{t-1} + \gamma_1 z_{t-1} + \varepsilon_{1t} \\ \Delta K_t &= \alpha_2 + \sum_{i=1}^{m_3} \beta_{3i} \Delta K_{t-1} + \sum_{i=1}^{m_4} \beta_{4i} \Delta K_{t-1} + \gamma_2 z_{t-1} + \varepsilon_{2t} \end{aligned} \tag{3.27}$$

3.9.2 BEKK Garch Model

BEKK GARCH R. F. Engle and Kroner (1995) models the vigorous structure in defining correlations and covariance matrices between two variables. The general form of the model is given Eq 3.28, where M_0 represents the lower triangular matrix, A_{ik} and $B_i k$ represents T*T matrix.

$$H_t = M_0^T M_0 + \sum_{k=1}^{k} \sum_{i=1}^{q} A_{ik} \varepsilon_{t-i} \varepsilon_{t-1} A_{ik} + \sum_{k=1}^{k} \sum_{i=1}^{p} B_{ik} \sum\nolimits_{t-1} B_{ik} \tag{3.28}$$

3.9.3 Optimal Hedge Ratio

The optimal hedge ration between cryptocurrency and traditional assets depending on the correlation between them, aims to strike a balance between risk reduction and maintaining exposure to potential returns.

Whereas, hedge ratio is estimated as, Eq 3.29;

$$h_t = \frac{Cov(\Delta C_t \Delta K_t)}{Var(\Delta K_t)} \tag{3.29}$$

Chapter 4

Results

This chapter covers empirical demonstration of the evaluation measures. Moreover findings of the study are summed up to analyze and discuss in accordance with the research questions and objectives of the study

4.1 Extreme Values in Cryptocurrency Market

4.1.1 Student's t Distribution

Initially Student's t distribution for a probability distribution with tails heavier than the normal distribution is applied which allows greater chance to incorporate extreme values to employ the confidence interval. The one sided p-value with degree of freedom (df) =5 is 0.05097 and two-sided p=value with degree of freedom (df) = 5 is 0.10194. Confidence interval is reported 2.57058 at 95% and 3.36493 at 99%.

4.2 Generalized Extreme Value – EVT

The analysts of Extreme Value Theory provides the Generalized Extreme Value distribution which consists of three types of continuous probability distributions that deals extreme values; Gumbel, Frechet and Weibull.

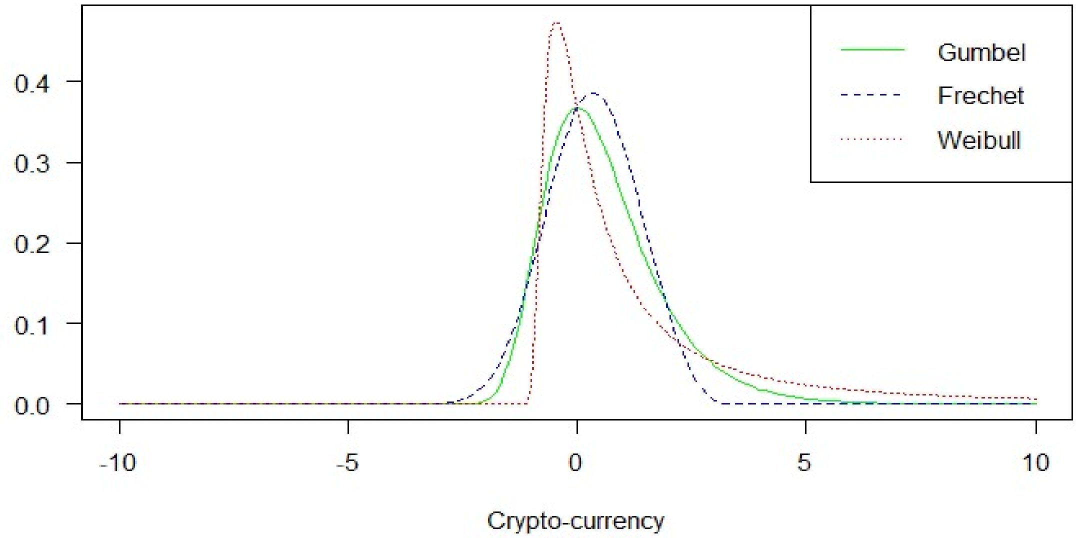

FIGURE 4.1: Generalized Extreme Values Distribution

4.2.1 Estimation of Value at Risk (VaR) Measures

For Value at Risk estimation following diagnostic tests are performed, like ARCH test, normality test and values to fit the correlation to predict next 8 days values that traditional VaR estimates are inadequate for the analysis of Extreme Value distributions. **Table 4.1**; reports the Value at Risk estimates of the three distributions Gumbel, Frechet and Weibull. Gumbel distribution exhibits measures of Chi-square ARCH 353.09 (0.0000) and Kurtosis 158836 (0.0000), Frechet distribution with ARCH 259.12 (0.0000) and Kurtosis 211127 (0.0000), and Weibull distribution with ARCH 365.21 (0.0000) and Kurtosis 158808 (0.0000) at df 45. Whereas Gumbel distribution with Kurtosis 158836 (0.0000), Frechet distribution with Kurtosis 211127 (0.0000), and Weibull distribution with Kurtosis 158808 (0.0000) at df 2.

TABLE 4.1: Diagnostic Testing

Distribution	**Measures**	**ARCH Test**	**Kurtosis**
Gumbel	Chi-squared	353.09	158836
	P-value	0	0
Frechet	Chi-squared	259.12	211127
	P-value	0	0
Weibull	Chi-squared	365.21	158808
	P-value	0	0
	df	45	2

Table 4.1, captures the diagnostic test including chi-squared p-value, for ARCH test and Kurtosis, with degree of freedom, of Gumbel, Frechet and Weibull distributions of GPD.

4.2.2 Conditional Drawdown

Following, **Table 4.2**; exhibits estimates of Gumbel, Frechet and Weibull distributions at 95% and 99% confidence interval. Drawdown risk measures downside risk, whereas conditional drawdown risk defines the cumulative drawdown for the events where drawdown exceeds the threshold (Chekhlov, Uryasev, & Zabarankin, 2005). Gumbel, Frechet and Weibull distributions show 9.2 CDD at 95% confidence interval and 9.84 CDD at 99% confidence interval.

4.2.3 Expected Shortfall

Secondly the **Table 4.2**; examines the expected shortfall of Gumbel, Frechet and Weibull distributions at 95% and 99% confidence interval. It measures sensitivity of the shape parameter of a distribution and measures the average shortfall in case where Value at Risk (VaR) exceeds the threshold. It infers Value at Risk (VaR) for Gumbel -0.3634259, for Frechet -0.6492217 and for Weibul -0.4096232 under 5% worst cases where value at Risk (VaR) exceeds the threshold at 95% confidence interval. Whereas the Value at Risk (VaR) for Gumbel, Frechet and Weibul is -1 under, 1% worst cases where value at Risk (VaR) exceeds the threshold at 99% confidence interval.

Conditional drawdown measures the decline in the value of asset below a previous peak, under certain conditions. Whereas Expected Shortfall estimates the average of the worst potential loss beyond a specified confidence level, providing a more comprehensive risk assessment than VAR in the analysis. Conditional drawdown and expected shortfall at 95% and 99% confidence intervals provide insights into tail risk for the three distributions Gumbel, Frechet and Weibull. CDD measures the decline in cryptocurrency market from a peak under extreme conditions. Expected shortfall assesses the average loss beyond the given confidence levels, providing a more comprehensive risk evaluations for the market especially in the extreme events where drawdowns are significant.

TABLE 4.2: Presents, the Parameters of Maximum Likelihood Estimation, Includes Threshold, Scale and Shape Parameters

Distribution	**Gumbel 95%**	**Frechet 95%**	**Weibull 95%**
Conditional Drawdown	9.2	9.2	9.2
Expected Shortfall	-0.3634259	-0.6492217	-0.4096232
conf.inf.scale	0.002667761	0.02435046	0.008982837
conf.sup.scale	0.022090121	0.13408869	0.037852127
	99%	**99%**	**99%**
Conditional Drawdown	9.84	9.84	9.84
Expected Shortfall	-1	-1	-1
conf.inf.scale	-0.000383713	0.007109335	0.004447143
conf.sup.scale	0.025141595	0.151329821	0.042387821

***Table 4.2**, defines the conditional drawdown and expected shortfall of Gumbel, Frechet and Weibull distributions of GPD at 95% and 99% confidence interval.*

4.2.4 Generalized Pareto Distribution for Crypto-currency Market

The Generalized Pareto Distribution covers fat tailed distributions which an integral condition in extreme value behavior of crypto-currency market. The shape parameter (ξ) helps to define the distribution;

- If $\xi > 0$, the nature of distribution is Pareto; Frechet Distribution of GPD.
- If $\xi = 0$, the nature of distribution is Exponential; Gumbel Distribution of GPD.
- If $\xi < 0$, the nature of distribution is Pareto type II (distribution on a bounded interval); Weibull Distribution of GPD.

4.2.5 Peak Over Threshold

The Peak over Threshold function of GPD model tails of the distribution, i.e., the values of crypto-currency that exceeds the predetermined threshold. To illustrate POT selection of threshold and parameters need to be determined.

4.2.6 Selection of Threshold

Firstly, selection of a suitable threshold is important in Peak over Threshold modeling. Scarrott and MacDonald (2012) describe the graphical representation for selection of a suitable threshold. This method requires association of data while picking a threshold in order to analyze the model. Therefore the threshold tends to be reliant on the data to measure the parameters.

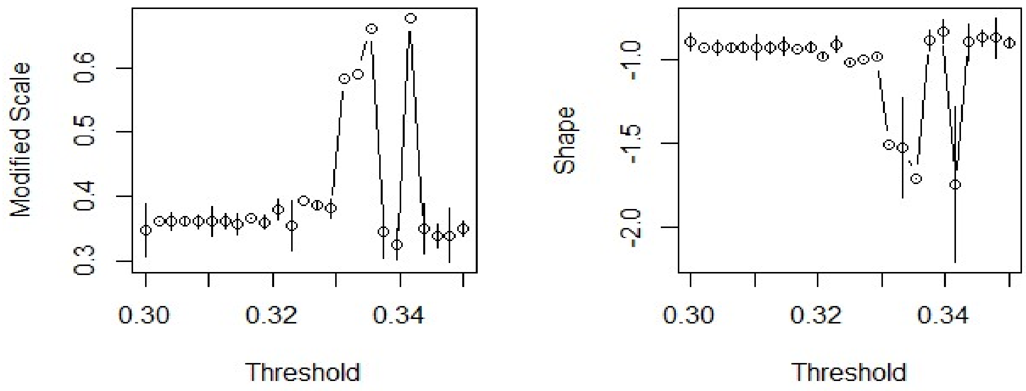

FIGURE 4.2: Threshold Selection

Scarrott and MacDonald (2012) draw the threshold stability plot to select the suitable threshold by estimating parameters of scale (σ) and shape (ξ). The two plots, plot the estimates at a given confidence interval to find the threshold which is the lowermost value and the plots are constant in fitted GPD. Above **Figure 4.2**; signifies that the parameters of σ and ξ are stable where $\mu \geq 0.33$, therefore the suitable threshold appears to be 0.33 as suitable.

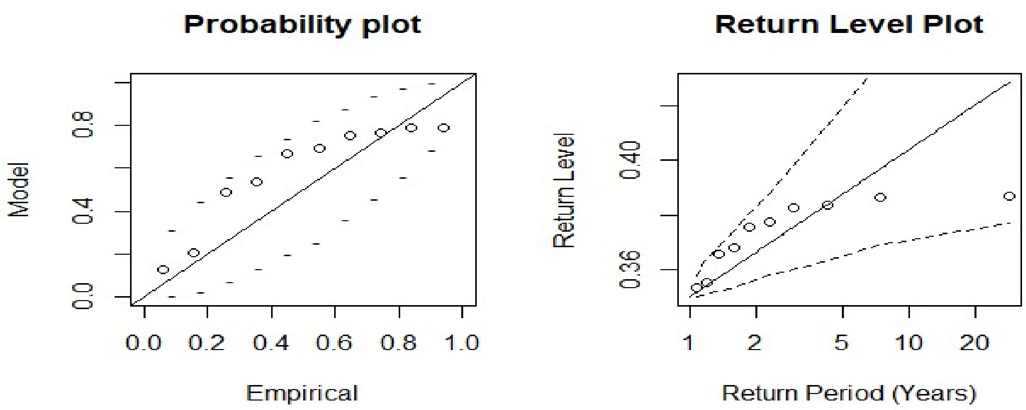

FIGURE 4.3: Probability and Return Level Plot

Figure 4.3; expresses the graphic diagnostics of a fitted model where Maximum Likelihood Estimation appears to be appropriate.

4.2.7 Exceedance Probability

A measure to find the value that is likely to exceed in future in order to predict extreme shifts (Lambert & Hill, 1994; Kunreuther et al., 2002) is referred as exceedance probability. The estimation of exceedance probability measures the possibility that a pre-defined threshold is likely to exceed in a time series for a pre-defined future.

4.2.8 Estimation of the Parameters by Maximum Likelihood Estimation

Maximum Likelihood Estimation determines the parameters to explain the distribution. As from the dataset of a crypto-currency market the MLE defines the distribution by indicating the following parameters in **Table 4.3**;

Table 4.3: Parameters by MLE

Parameters	**Estimates**
Threshold	0.33
Exceedance Probability	0.4783
Deviance	440.1989
Scale σ	9.3722
Scale Standard Error	0.027694
Shape ξ	-0.9707
Shape Standard Error	0.000002

Table 4.3 *Presents, the Parameters of Maximum Likelihood Estimation, Includes Threshold, Scale and Shape Parameters.*

The threshold is 0.33 which gives the predicted probability of a distribution, the exceedance probability as 0.4783 which shows that there are 47.83% possibility that the prices of crypto-currency tends to exceed the threshold in future. The Deviance shows that the response variable predicted by the model is good fit. The Scale (σ) parameter is 9.3722 and Shape (ξ) is -0.9707. The MLE specifies that the crypto-currency market follows Weibull distribution as -0.9797 $<$ 0 since $\xi <$ 0 applies in Weibull distribution.

4.2.9 Estimates of Forecasted Volatility (Dynamic GPD)

Generalized Pareto Distribution is a measure to estimate Value at Risk (VaR) for a fat tailed distribution that applies forecasting of conditional variance at one day above risk.

TABLE 4.4: Volatility Forecasting

Forecast	**Gumbel**	**Frechet**	**Weibull**
Mean	0.00003453	0.0074699	0.000001795
Mean Error	0.000100276	0.00117062	0.000107233
Standard Deviation	0.000100276	0.00117062	0.000107233

Table 4.4*, defines the conditional drawdown and expected shortfall of Gumbel, Frechet and Weibull distributions of GPD at 95% and 99% confidence interval.*

Table 4.4 above, examines the mean, mean error and standard deviation for Gumbel distribution as 0.000034530, 0.000100276 and 0.000100276 respectively. For

Frechet distribution mean 0.00746990, mean error 0.00117062 and standard deviation 0.00117062. Whereas for Weibull distribution mean is 0.000001795, mean error is 0.000107233 and standard deviation is 0.000107233 for one day above forecasting of Value at Risk (VaR).

H1: Cryptocurrency returns experience extreme values.

The analysis of the study supports the above hypothesis, that crypto-currency market exhibits extreme values which indicates fat tailed distribution,in line with the findings of (Catania et al., 2019; Kim et al., 2022; Bruhn & Ernst, 2022; Trucíos et al., 2020). The three continuous distributions of extreme value theory i.e., Gumbel, Frechet and Weibull are compared and the study directs that the crypto-currency market follows Pareto II distribution, which is referred as Weibull distribution of the extreme value theory. It refers that Pareto II distribution is a heavy tailed frequency distribution and such a distribution is known as Lomax distribution, (Lomax & McGee, 1987).

4.3 Time Dependent Volatility in Crypto-Currency Market

For analysis of the study daily data has been used. Returns of each series are defined as below, where i denote the name of variable; t represents present day price and t-1 price of the previous day for each series as;

$$R_i = \frac{R_t}{R_{t-1}}$$

Firstly before employing estimations of the DCC GARCH model, **Table 4.5** captures the descriptive statistics. The returns of crypto-currency market show highest variability in mean 44.83%, maximum value 684.3026, minimum value -0.5818 and standard deviation as 17.3045%. Moreover skewness and kurtosis for all variables imply non-normal distribution. The mean series of each variable is used for further analysis of the study. The unit of measurement of all variables in USD.

TABLE 4.5: Descriptive Statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
RCM	0.4483	-0.0001	684.3026	-0.5818	17.3045	39.4995	1561.472
RGM	0.0001	-0.0001	0.1546	-0.1185	0.0168	0.6603	25.1899
REXBR	-0.0003	0	0.061	-0.0687	0.0102	-0.0134	6.157
RBBR	-0.0002	0	0.1707	-0.0508	0.0119	2.0174	31.2999
RSMBR	0.0006	0	0.066	-0.088	0.0141	-0.0089	4.8546
REXCA	-0.0001	-0.0003	0.0198	-0.019	0.0047	0.1225	4.0536
RBCA	0	0	0.1418	-0.0985	0.0239	0.395	5.0805
RSMCA	-0.0004	0.0004	0.0294	-1	0.0262	-35.7319	1365.805
REXGR	-0.0001	-0.0001	0.0307	-0.0238	0.0051	0.1454	5.6557
RBGR	-0.0119	-0.003	13	-32.6667	0.9995	-21.3178	754.7405
RSMGR	0.0003	0.0005	0.0497	-0.0682	0.0108	-0.2827	5.4154
REXJP	-0.0001	-0.0001	0.0303	-0.0806	0.0057	-1.7398	30.2198
RBJP	0.0145	0	30	-21	1.2582	6.755	356.6985
RSMJP	0.0004	0.0001	0.0771	-0.0792	0.0123	-0.1591	7.9915
REXKO	0	0	0.0333	-0.0326	0.0064	0.2144	5.4594

Continued Table: 4.5 Descriptive Statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
RBKO	-0.0004	0	0.0826	-0.0822	0.0132	0.0451	6.4823
RSMKO	0.0001	0	0.0353	-0.0444	0.0073	-0.4064	5.6813
REXRU	0.0044	-0.0017	9.1477	-0.0326	0.2314	39.4892	1560.931
RBRU	0.0001	0	0.2303	-0.1687	0.013	2.5475	86.7226
RSMRU	0.0005	0	0.0526	-0.1079	0.0108	-0.7325	12.574
REXTR	-0.0003	0	0.137	-0.1163	0.0123	0.2002	21.8553
RBTR	-0.0001	0	0.1031	-1	0.0297	-24.4186	826.4488
RSMTR	-0.0004	0	0.0644	-1	0.0286	-27.424	960.0243
REXUK	-0.0007	-0.0003	0.0826	-0.1375	0.01	-1.5432	31.5384
RBUK	-0.0002	-0.0007	0.1397	-0.2093	0.0311	-0.0689	7.0067
RSMUK	-0.0005	0.0002	0.0358	-1	0.0266	-33.9343	1275.236
RBUS	0	0	0.113	-0.1044	0.0192	0.2241	5.3253
RSMUS	0.0004	0.0003	0.0496	-0.041	0.008	-0.3908	6.9893
REXVN	-0.0001	0	0.0166	-0.0158	0.002	-0.2337	22.6908
RBVN	-0.0004	0	0.0727	-0.0586	0.0071	0.0359	27.3634
RSMVN	0.0004	0.0006	0.0423	-0.1041	0.0107	-1.0772	11.2752

Table 4.5, *captures the descriptive statistics, mean returns, maximum value, minimum value, standard deviation, skewness and kurtosis for all variables.*

Secondly for analyzing time series data in financial studies, the research begins with the unit root test to check if data is stationary. The standard Augmented Dickey Fuller- ADF test is applied on all the return series to check null hypothesis of unit root against alternate hypothesis for stationary series. **Table 4.6** presents the unit root tests, all series are stationary at 1st difference and hence significant at 1%. **Figure 4.4** presents the Q-Q plots of all the variables under study; **Table 4.6**: Stationary Test

TABLE 4.6: Stationary Test

Variables	**Level**		**1st Diff.**	
	t-Stat	**Probs.**	**t-Stat**	**Probs.**
RCM	-6.87	0	-26.14	0
RGM	-2.63	0.0878	-39.67	0
REXBR	-1.49	0.5396	-43.38	0.0001
RBBR	-0.66	0.8542	-40.01	0
RSMBR	-0.02	0.9558	-40.66	0
REXCA	-1.93	0.3204	-39.95	0
RBCA	-1.79	0.3864	-40.36	0
RSMCA	-2.36	0.1545	-36.69	0
REXGR	-1.47	0.5503	-40.82	0
RBGR	-1.47	0.5484	-40.07	0
RSMGR	-2.19	0.2092	-40.13	0
REXJP	-2.04	0.2683	-45.99	0.0001
RBJP	-2.06	0.263	-34.26	0
RSMJP	-1.9	0.3328	-41.37	0
REXKO	-1.6	0.4843	-39.4	0
RBKO	-1.26	0.6486	-40.29	0
RSMKO	-1.95	0.3096	-39.84	0
REXRU	-2.01	0.2807	-40.37	0
RBRU	-1.75	0.4077	-44.33	0.0001
RSMRU	-0.28	0.925	-40.11	0
REXTR	-0.99	0.7575	-39.06	0
RBTR	-1.08	0.7252	-39.22	0
RSMTR	-1.68	0.4399	-39.59	0
REXUK	-0.88	0.7939	-39.67	0
RBUK	-1.36	0.6048	-41.83	0
RSMUK	-2.36	0.1548	-39.25	0
RBUS	-2.02	0.2783	-42.76	0
RSMUS	-0.88	0.7947	-39.03	0
REXVN	-0.61	0.8663	-30.47	0
RBVN	-1.24	0.6583	-13.66	0

Table 4.6 *Presents the Unit Root Tests, all Series are Stationary at 1st Difference and Hence Significant at 1%.*

4.4 Dynamic Conditional Correlation GARCH

Thirdly to check presence of time varying dynamic conditional correlation, DCC GARCH model is implied. The DCC GARCH verifies the volatility in crypto-currency market as compared to traditional assets. The model (GARCH, GJR-TARCH, EGARCH) is identified by comparing Akaike Information Criterion, the model with minimum AIC value is reported in **Table 4.7**.

Table 4.7: DCC GARCH Analysis

	Model	**Theta 1**	**Prob.**	**Theta 2**	**Prob.**	**AIC**
RGM	GJR-TARCH	-0.00283	0	0.761656	0	4.736176
REXBR	GARCH	0.07492	0.8162	0.723841	0.368	3.261269
RBBR	GARCH	0.018087	0.655	0.980273	0	3.606995
RSMBR	EGARCH	-0.00193	0	0.842949	0	4.598363
REXCA	GARCH	0.360351	0.1238	0.435046	0.2043	1.731818
RBCA	GARCH	0.242531	0.4598	0.476479	0.4983	4.828123
RSMCA	EGARCH	0.120832	NA	0.879126	NA	5.826146
REXGR	GARCH	0.224569	0.5003	0.695029	0.0908	1.804123
RBGR	GARCH	0.068128	0.4072	0.924723	0	8.247447
RSMGR	GARCH	0.270843	0.8007	0.506147	0.7964	3.286499
REXJP	GARCH	0.441297	0.0205	0.444367	0.0305	2.24164
RBJP	EGARCH	0.280554	0.3001	0.605954	0.0076	10.74477
RSMJP	GJR-TARCH	-0.00174	0.2175	0.952141	0	4.304377
REXKO	EGARCH	0.200908	0	0.799073	0	8.517075
RBKO	GARCH	0.382722	0.0051	0.571764	0.0002	3.695862
RSMKO	GARCH	0.308986	0.1251	0.60188	0.0599	2.613648
REXRU	GJR-TARCH	-0.00277	0	0.791143	0	3.957018
RBRU	GARCH	0.81072	0	0.009495	0.9605	3.201578
RSMRU	GARCH	0.328502	0.2059	0.555349	0.1434	3.37852
REXTR	EGARCH	-0.00134	0	0.963709	0	3.626375
RBTR	EGARCH	-0.00205	0	0.140853	0.9904	5.342916
RSMTR	-	-		-		-
REXUK	GARCH	0.129535	0.2776	0.817006	0	1.993661
RBUK	GARCH	0.086478	0.2666	0.898433	0	5.351779
RSMUK	GARCH	0.478072	0.1701	0.488995	0.1961	5.345875
RBUS	GARCH	0.041287	0.8999	0.596582	0.4988	4.457524
RSMUS	GARCH	0.126809	0.3917	0.853682	0	2.591015
REXVN	GARCH	0.177747	0.4333	0.770005	0.0066	-0.57408
RBVN	GARCH	0.213712	0.1730	0.75819	0.0001	2.034458
RSMVN	GARCH	0.37976	0.3861	0.266759	0.714	3.21252

***Table 4.8**, examines the descriptive Statistics of Crypto-currency Market, Mineable and Non-Mineable.*

The results of $\theta 1$ are significant for crypto-currency market with RBRU and RBTR which means previous period's shock is flowing to the present and the present period's correlation is predictable yet no relationship between previous and present period's correlation is reported. However results of $\theta 2$ for crypto-currency market with RBBR, REXGR, RBGR, RBJP, RSMJP, RSMKO, REXUK, RBUK, RSMUS, REXVN and RBVN turns out to be significant.

It specifies the relationship between previous and present correlations between them yet previous period's shock is not found which means present period's correlation is not predictable through previous period's correlation since $\theta 1$ is insignificant. RSMTR does not meet the stability condition.

H2: Cryptocurrency market experiences time varying volatility.

To support the above hypothesis, the results are reported for crypto-currency market with other assets, correlations are associated with each other but previous correlations do not predict present day's correlations. Salisu and Ogbonna (2022); Murty et al. (2022); Koutmos et al. (2021) found similar findings. The correlations within crypto-currency market are predictable since previous and present correlations are time dependent. Hence, it is a highly volatile market and the volatility is time dependent and correlation of crypto-currency market and other assets are associated yet not predictable.

4.5 Supply Effect Influences Volatility in Cryptocurrency Market

Table 4.8, captures the descriptive statistics of cryptocurrency market. The returns of crypto-currency market show variability in mean 32.1%, maximum value 684.3026, minimum value -0.582 and standard deviation as 14.624%. Returns of mineable crypto-currency display highest variability in mean 34.8%, maximum value 742.604, minimum value -0.585 and standard deviation as 15.870%.

Table 4.8: Descriptive Statistics of Crypto-currency Market, Mineable and Non-Mineable

c	**Mean**	**Median**	**Maximum**	**Minimum**	**Std. D**	**Skewness**	**Kurtosis**
Crypto-currency	0.321	0.000	684.303	-0.582	14.624	46.753	2187.222
Mineable	0.348	0.000	742.604	-0.585	15.87	46.754	2187.302
Non-Mineable	0.007	0.003	1.798	-0.971	0.098	4.949	86.767

Table 4.8, examines the descriptive Statistics of Crypto-currency Market, Mineable and Non-Mineable.

Whereas returns of non-mineable crypto-currency exhibits variability in mean 0.07%, maximum value 1.798, minimum value -0.971 and standard deviation as 0.98%. Moreover skewness and kurtosis for all variables imply non-normal distribution. The mean series of each variable is used for further analysis of the study.

4.6 ARMA GJR-GARCH Model

The ARMA GJR GARCH model is used to improve volatility dynamics in crypto-currency market, mineable crypto-currencies and non-mineable crypto-currencies. ARMA covers the time series autocorrelation and moving average effects, whereas GJR-GARCH extends by incorporating asymmetric effects in volatility allowing the model to respond differently to positive and negative shocks. The is particularly useful for capturing the impact of extreme events in financial markets. The inclusion of asymmetric provides a more balanced representation of volatility dynamics, offering improved risk management and forecasting capabilities between mineable and non-mineable crypto-currencies. The model which is used to check asymmetric volatility is Glosten Jagannathan and Ruckle (GJR-GARCH) model. **Table: 4.9** shows the descriptors of crypto-currencies (CM), mineable crypto-currencies (MCM) and non-mineable crypto-currencies (NMCM). Firstly, mean model (Mu) for CM, MCM and NMCM is significant with coefficients of 0.006172, 0.012923 and 0.007586 respectively. The Autoregressive model AR (1) reports significant coefficients of CM (-0.629379), MCM (0.959445) and NMCM (-0.97844) which means that the present prices of CM, MCM and NMCM is based on their immediate preceding prices respectively. The negative coefficient of CM and NMCM implies that large positive values are likely to be followed by negative vales, whereas for MCM the effect of a shock is likely to disperse over time. The moving average model MA (1) shows linear dependency of present day price on present day and past day error terms. The MA (1) is significant yet coefficient for MCM is negative -0.938043. Additionally, Omega (C) is the intercept of the variance equation. The, α (1) examines the ARCH (1) model which is positively significant for CM 0.180908 (0.000546) and MCM 0.307501(0.0000). This depicts that either good or bad news comes in the market, it captures short term volatility. Moreover, the β (1) applies for GARCH (1) model which is positively significant for CM 0.318092 (0.0000) and MCM 0.864627 (0.0000) which indicates that there is persistence in long term volatility. The level of persistence is the sum of α, β and $\gamma/2$ which should be less than 1, therefore it calculates $0.999 < 1$ for CM, $0.999 < 1$ for MCM and $0.0000375 < 1$ for NMCM.

Table 4.9: ARMA GJR-GARCH Analysis

Descriptors	**CM**		**MCM**		**NMCM**	
	Co-efficient	**P-Value**	**Co-effiient**	**P-Value**	**Co-efficient**	**P-Value**
Mu	0.006172	0.000	0.012923	0.000	0.007586	0.000
AR (1)	-0.629379	0.000	0.959445	0.000	-0.97844	0.000
MA (1)	0.937505	0.000	-0.938043	0.000	0.97857	0.000
c	0.000222	0.000	0.000095	0.000	0.001218	0.000
α (1)	0.180908	0.000546	0.307501	0.000	0.000	0.99999
β (1)	0.318092	0.000	0.864627	0.000	0.008949	0.81359
γ (1)	1.000	0.000	-0.346256	0.000	-0.017823	0.24581
LogLikelihood	1644.643		913.0393		2915.827	
AIC	-2.0928		-1.1579		-3.7174	
BIC	-2.0689		-1.1339		-0.6934	

Table 4.9, models descriptors used to check asymmetric volatility is Glosten Jagannathan and Ruckle (GJR-GARCH) model of crypto-currencies (CM), mineable crypto-currencies (MCM) and non-mineable crypto-currencies (NMCM).

Consequently the positively significant coefficient of γ (1) presents the presence of leverage effect, as given coefficients of CM 1.0000 (0.0000) and MCM 0.346256 (0.0000). The negative shocks are captured by $(\alpha + \gamma)$ whereas the positives shocks are captured by (α).

Since it implies that γ is greater than 0, which means that negative shocks tend to increase the volatility more than the positive shocks for overall crypto-currencies. However γ is less than 0 which indicates that positive shocks increase the volatility more than the negative shocks for mineable crypto-currencies. Though, the GARCH effect is insignificant for NMC, suggesting that the conditional volatility is not significantly influenced by past squared returns and asymmetric shocks. It implies that the volatility dynamics are not adequately captured, potentially affecting the ability to predict risk associated to it.

H3: Supply effect does influence volatility among cryptocurrencies.

The analysis of the study confirms the above hypothesis. Mineable crypto - currencies appear as high frequency assets, experiencing high volatility issues due to high and frequent speculations. Yet non-mineable are flowing on a consistent trend. Therefore, it is evident that Supply Effect does affect volatility of crypto-currencies, initially suggested by Stoffels (2017). However the study is first to incorporate supply effect to distinguish between mineable and non-minebale crypto-currencies.

4.7 Cryptocurrency as a Diversified Avenue for Investment

4.7.1 Measure of Dependence

The coefficient of correlation is a statistical measure to quantify the degree of relationship between set of independent variables. Contextually the measure provides the basis for hedging between financial assets. The coefficient of correlation serves as an indicator for investment that provides insights about the relationship between cryptocurrency market and other traditional assets. **Table 4.10**, presents Pearson Correlation, where t; represents values of t-statistics, df denotes the degree of freedom, Prob., is the p-value (significance level), corr.eff shows the sample estimates of correlation coefficients between RCM and all other variables. From the given results there is no correlation reported between RCM and other variables at 5% confidence level, however very weak correlation can be seen between RCM and, REXJP and RSMUS at 10% confidence level.

Table 4.10: Correlation Coefficients

Variables	**T**	**df**	**Corr.eff**	**Prob.**
RBBR	1.3115	1562	0.0333	0.1899
RBCA	-0.1784	1562	-0.0045	0.8584
RBGR	0.0324	1562	0.0008	0.9742
RBJP	-0.0191	1562	-0.0005	0.9848
RBKO	1.4995	1562	0.0381	0.1339
RBRU	0.2124	1562	0.0054	0.8319
RBTR	0.3849	1562	0.0098	0.7004
RBUK	0.7392	1562	0.0188	0.4599
RBUS	-0.5477	1562	-0.0139	0.584
RBVN	-0.4918	1562	-0.0125	0.623
REXBR	-1.1229	1562	-0.0286	0.2617
REXCA	-0.0079	1562	-0.0002	0.9937
REXGR	0.1871	1562	0.0048	0.8516
REXJP	-1.8123	1562	-0.0461	0.0701
REXKO	-0.0429	1562	-0.0011	0.9658
REXRU	-0.1082	1562	-0.0028	0.9139

Continued Table: 4.10 Correlation Coefficients

Variables	T	df	Corr.eff	Prob.
REXTR	0.3708	1562	0.0094	0.7108
REXUK	0.0777	1562	0.002	0.9381
REXVN	0.1619	1562	0.0041	0.8714
RSMBR	0.0704	1562	0.0018	0.9439
RSMCA	0.149	1562	0.0038	0.8816
RSMGR	0.1495	1562	0.0038	0.8812
RSMJP	1.4744	1562	0.0375	0.1406
RSMKO	-0.8459	1562	-0.0215	0.3978
RSMRU	-0.3678	1562	-0.0094	0.7131
RSMTR	-0.3272	1562	-0.0083	0.7436
RSMUK	0.1554	1562	0.004	0.8765
RSMUS	1.7299	1562	0.044	0.0838
RSMVN	-0.0064	1562	-0.0002	0.9949
RGM	-0.4608	1562	-0.0117	0.645

Table 4.10*, determines correlation between crypto-currency market and each of the traditional assets.*

4.7.2 Dependence Structure – Copula Approach

Copula approach models the dependence structure between crypto-currencies and traditional assets, which is more appropriate and flexible alternative approach than correlation analysis. It provides the modeling of the joint distribution separate from the marginal distributions for in-depth analysis of inter-dependence of crypto-currency market and other traditional assets. It captures both linear and nonlinear dependencies to capture complex relationships for volatile markets like crypto-currency market. It makes copula approach more flexible in managing tail dependence, extreme events, tail risks by providing accurate representation of the intricate dependencies between diverse asset classes.

Table 4.11 presents results of dependence structure between RCM and bonds, currency, stocks and gold. Two parameters initial and final are used to estimate copula. The final parameter (θ), maximum likelihood (LL), Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), and tail dependence (lower and upper) are reported. The technique of pseudo-maximum likelihood is applied to find copula to measure the dependence structure. The comprehensive review of copulas is provided in regard of dependence at lower and upper tail distribution. Gaussian, t-student, Gumbel, Frank, and Clayton copulas are considered yet the results of Clayton copula are not reported due to (non-finite value supplied by optim) error. The rationale supporting the dependence structure is the importance of dependence of tail distribution of two variables in the lower (left) and upper (right) quadrant of the tail distribution. Gaussian Copula disregard measuring tail distribution, T Student Copula measures tail dependence (lower left and upper right). Gumbel Copula considers upper (right) tail dependence and Clayton Copula measures lower (left) tail dependence. Moreover Frank Copula models the range of dependence (positive and negative).

However for selection of best-fitted copula AIC and BIC criteria are used. This captures the dependence structure between RCM and other assets like bonds, currency, stocks and gold, thus copula with lowest AIC is selected. Gaussian Copula is selected for RCM and RBCA, RBGR, RBKO, REXGR, REXUK, RSMBR, RSMCA, RSMUK with lowest AIC. T-Student Copula is selected for RCM and RBJP (lower and upper tail: 0.004386459), RBTR (lower and upper tail: 0.0002817 941), REXTR (lower and upper tail: 0.009316889), RSMKO (lower and upper tail: 0.0009248732), RSMUS (lower and upper tail: 0.0001392732), RSMVN (lower and upper tail: 0.007504167), based on lowest AIC. Gumbel Copula is selected for RCM and, REXJP (upper tail: 0.009613426) and REXKO (upper tail: 0.1034715) based on lowest AIC. Frank Copula is selected for RCM and RBBR, RBRU, RBUK, RBUS, RBVN, REXBR, REXCA, REXRU, REXVN, RSMGR, RSMJP, RSMRU, RSMTR and RGM based on lowest AIC.

TABLE 4.11: Copula Analysis

Variables	**Gaussian Copula (df=1)**				**t-Student Copula (df=2)**					
	θ	**LL**	**AIC**	**BIC**	θ	**LL**	**AIC**	**BIC**	**Lower**	**Upper**
RBBR	-0.01	0.16	1.68	7.03	-0.01	0.07	3.85	14.56	9E-42	9E-42
RBCA	-0.01	0.04	1.93	7.28	-0.01	-0.14	4.28	14.99	2E-62	2E-62
RBGR	0.03	0.63	0.74	6.09	0.03	0.51	2.98	13.69	3E-66	2E-63
RBJP	0.00	0.00	1.99	7.35	0.00	3.92	-3.83	6.88	4E-03	4E-03
RBKO	0.01	0.02	1.96	7.32	0.00	-0.15	4.29	15	3E-57	3E-57
RBRU	-0.04	1.17	-0.34	5.02	-0.04	0.95	2.11	12.82	5E-83	5E-83
RBTR	-0.04	1.13	-0.27	5.09	-0.04	3.35	-2.7	8.01	3E-04	3E-04
RBUK	-0.02	0.26	1.49	6.84	-0.02	0.36	3.27	13.98	5E-13	5E-13
RBUS	0	0.01	1.99	7.34	0.00	-0.11	4.22	14.93	4E-111	4E-111
RBVN	-0.01	0.15	1.69	7.05	-0.02	0.68	2.64	13.35	1E-07	1E-07
REXBR	0.02	0.28	1.44	6.79	0.02	0.1	3.81	14.52	3E-60	3E-60
REXCA	0.04	1.29	-0.58	4.78	0.04	1.15	1.71	12.42	2E-53	2E-53
REXGR	0.04	1.46	-0.92	4.43	0.04	1.32	1.37	12.08	8E-67	8E-67
REXJP	0.01	0.06	1.88	7.23	0.01	-0.11	4.22	14.93	7E-83	7E-83
REXKO	0.07	4	-6	-0.65	0.06	15.24	-26.5	-15.8	4E-02	4E-02
REXRU	0.05	2.26	-2.51	2.84	0.05	2.04	-0.08	10.63	1E-70	1E-70

Continued Table 4.11 Copula Analysis

Variables	Gaussian Copula (df=1)				t-Student Copula (df=2)					
	θ	**LL**	**AIC**	**BIC**	θ	**LL**	**AIC**	**BIC**	**Lower**	**Upper**
REXTR	0.03	0.6	0.8	6.15	0.03	6.9	-9.8	0.91	9E-03	9E-03
REXUK	0.01	0.15	1.71	7.06	0.01	0.12	3.76	14.47	8E-29	8E-29
REXVN	0.01	0.03	1.95	7.3	0.01	-0.16	4.32	15.03	3E-89	3E-89
RSMBR	0.05	1.94	-1.88	3.47	0.05	1.82	0.37	11.08	3E-59	3E-59
RSMCA	0.05	2.23	-2.47	2.89	0.05	2.17	-0.33	10.38	4E-40	4E-40
RSMGR	0.00	0.00	2.00	7.35	0.00	-0.22	4.44	15.15	2E-63	2E-63
RSMJP	-0.01	0.1	1.8	7.15	-0.01	0.00	3.99	14.7	4E-53	4E-53
RSMKO	0.01	0.12	1.76	7.12	0.01	2.69	-1.38	9.33	9E-04	9E-04
RSMRU	0.04	1.13	-0.27	5.09	5.09	1.03	1.93	12.64	7E-02	7E-02
RSMTR	0.04	1.54	-1.08	4.27	0.05	1.45	1.1	11.81	4E-46	4E-46
RSMUK	0.02	0.25	1.51	6.86	0.02	0.18	3.65	14.36	5E-58	5E-58
RSMUS	0.06	3.07	-4.14	1.21	0.06	4.47	-4.93	5.78	1E-04	1E-04
RSMVN	0.06	2.95	-3.9	1.45	0.06	8.73	-13.5	-2.75	8E-03	8E-03
RGM	0.03	0.61	0.78	6.13	0.03	0.41	3.19	13.9	3E-67	3E-67

Continued Table 4.11 Copula Analysis

Variables	**Gumbel Copula (df=1)**					**Frank Copula (df=1)**			
	θ	LL	AIC	BIC	Upper	θ	LL	AIC	BIC
RBBR	NA					-0.11	0.25	1.49	6.85
RBCA	NA					-0.01	0.00	2.00	7.35
RBGR	1.01	0.27	1.45	6.81	0.02	0.15	0.49	1.03	6.38
RBJP	NA					-0.05	0.04	1.91	7.27
RBKO	1	0.00	2	7.36	0.00	0.01	0.00	1.99	7.35
RBRU	NA					-0.25	1.39	-0.79	4.57
RBTR	NA					-0.18	0.71	0.58	5.94
RBUK	NA					-0.12	0.33	1.34	6.7
RBUS	1	0.00	2	7.36	0.00	0.06	0.08	1.84	7.19
RBVN	NA					-0.18	0.66	0.68	6.04
REXBR	1	0.00	2	7.36	0	0.12	0.31	1.38	6.73
REXCA	1.01	0.14	1.72	7.07	0.01	0.24	1.22	-0.44	4.92
REXGR	1.02	0.63	0.74	6.1	0.02	0.23	1.2	-0.39	4.96
REXJP	1.01	0.20	1.60	6.96	0.01	0.01	0.00	2.00	7.35
REXKO	1.08	15.4	-28.8	-23.45	0.1	0.36	2.53	-3.07	2.29
REXRU	1	0.00	2	7.36	0	0.38	3.24	-4.47	0.88
REXTR	1.02	0.74	0.53	5.88	0.02	0.2	0.83	0.34	5.7
REXUK	1	0.03	1.94	7.29	0.01	0.06	0.08	1.85	7.2
REXVN	1	0.00	2	7.36	0.00	0.04	0.04	1.92	7.28
RSMBR	1.02	0.62	0.77	6.12	0.02	0.29	1.8	-1.6	3.75
RSMCA	1.01	0.49	1.02	6.37	0.02	0.31	2.07	-2.13	3.22
RSMGR	NA					-0.04	0.04	1.93	7.28
RSMJP	NA					-0.11	0.27	1.47	6.82
RSMKO	1	0.01	1.97	7.33	0.00	0.06	0.06	1.87	7.23
RSMRU	1.01	0.1	1.8	7.16	0.01	0.25	1.38	-0.75	4.6
RSMTR	1.01	0.35	1.31	6.66	0.02	0.31	2.1	-2.2	3.15
RSMUK	1	0.00	2.00	7.36	0.00	0.06	0.08	1.84	7.19
RSMUS	1.03	2.95	-3.9	1.46	0.04	0.31	2	-2.01	3.35
RSMVN	1.03	1.49	-0.98	4.38	0.03	0.32	2.16	-2.32	3.03
RGM	1	0.00	2.00	7.36	0.00	0.2	0.91	0.18	5.53

Table 4.11, presents results of dependence structure between RCM and bonds, currency, stocks and gold. Two parameters initial and final are used to estimate copula. The final parameter (0), maximum likelihood (LL), Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), and tail dependence (lower and upper) are reported.

Additionally **Table 4.12**; demonstrates the marginal Normal and T-Student tail distribution selection. Therefore referring to the AIC and BIC criteria T-Student Copula Model is selected for all variables with lowest AIC reported.

Table 4.12: Selection of Tail Distribution

	Marginal Gaussian		**Marginal T-Student**		
Variables	**AIC**	**BIC**	**AIC**	**BIC**	**Selected**
RBBR	-9417.46	-9406.75	-9728.56	-9712.49	T-Student
RBCA	-7239.16	-7228.45	-7347.28	-7331.21	T-Student
RBGR	4438.912	4449.622	-2361.65	-2345.59	T-Student
RBJP	5147.816	5158.526	-2073.04	-2056.97	T-Student
RBKO	-9092.42	-9081.71	-9236.17	-9220.1	T-Student
RBRU	-9146.69	-9135.98	-10215.8	-10199.8	T-Student
RBTR	-6562.21	-6551.5	-8849.9	-8833.84	T-Student
RBUK	-6418.07	-6407.36	-6615.77	-6599.7	T-Student
RBUS	-7919.64	-7908.93	-8010.1	-7994.04	T-Student
RBVN	-11031	-11020.3	-11493.7	-11477.6	T-Student
REXBR	-9901.81	-9891.1	-10006.4	-9990.31	T-Student
REXCA	-12305.1	-12294.4	-12342.2	-12326.2	T-Student
REXGR	-12087.9	-12077.2	-12206.1	-12190.1	T-Student
REXJP	-11369.4	-11358.7	-11530.8	-11514.8	T-Student
REXKO	-136.891	-126.181	-12787.3	-12771.2	T-Student
REXRU	-9311.9	-9301.19	-9867.01	-9850.95	T-Student
REXTR	-9952.41	-9941.7	-10469.6	-10453.6	T-Student
REXUK	-11735.2	-11724.4	-12024.9	-12008.8	T-Student
REXVN	-14953.1	-14942.4	N/A	N/A	-
RSMBR	-8889.77	-8879.06	-8960.12	-8944.05	T-Student
RSMCA	-6956.64	-6945.93	-11373.7	-11357.7	T-Student
RSMGR	-9736.77	-9726.06	-9876.14	-9860.07	T-Student
RSMJP	-9304.18	-9293.47	-9608.59	-9592.52	T-Student
RSMKO	-10959.8	-10949.1	-11109.1	-11093	T-Student
RSMRU	-9712.23	-9701.52	-9925.48	-9909.41	T-Student
RSMTR	-6680.68	-6669.97	-9136.22	-9120.16	T-Student
RSMUK	-6903.2	-6892.49	-10705.6	-10689.5	T-Student
RSMUS	-10663.6	-10652.8	-10935.1	-10919.1	T-Student
RSMVN	-9750.13	-9739.42	-10037.4	-10021.3	T-Student
RGM	-8340.64	-8329.93	-9849.05	-9832.99	T-Student
RCM	16317.78	16328.49	-7047.28	-7031.21	T-Student

Table 4.12*; demonstrates the marginal Normal and T-Student tail distribution selection.*

4.7.3 Conditional Value at Risk - Expected Shortfall

Normally, risk metrics of VaR assume returns of the series to be normally distributed. Yet assets that are more volatile and the returns are certainly not normally distributed tend to have fat tailed distribution. Therefore referring to the

Table 4.13: Conditional Value at Risk – Expected Shortfall

	Probability=1%		**Probability=5%**		**Probability=10%**	
	VaR	**CoVaR**	**VaR**	**CoVaR**	**VaR**	**CoVaR**
RBBR	-2.82	-2.82	-1.7	-2.24	-1.28	-1.9
RBCA	-5.73	-5.73	-3.8	-4.74	-2.7	-4.02
RBGR	-11.1	-11.1	-2.07	-6.4	-1.05	-4.37
RBJP	-10	-10	-3.65	-6.23	-1.63	-4.13
RBKO	-3.59	-3.59	-2.22	-2.9	-1.51	-2.4
RBRU	-3.54	-3.54	-1.48	-2.47	-1.04	-1.95
RBTR	-4.11	-4.11	-2.33	-3.16	-1.56	-2.58
RBUK	-8.39	-8.39	-4.6	-6.29	-3.46	-5.25
RBUS	-4.6	-4.6	-2.89	-3.78	-2.16	-3.2
RBVN	-2.23	-2.23	-1.03	-1.62	-0.52	-1.22
REXBR	-2.71	-2.71	-1.62	-2.11	-1.62	-2.17
REXCA	-1.19	-1.19	-0.76	-0.98	-0.6	-0.84
REXGR	-1.4	-1.4	-0.78	-1.06	-0.61	-0.9
REXJP	-1.23	-1.23	-1.13	-1.19	-1	-1.12
REXKO	-1.09	-1.09	-0.79	-0.95	-0.59	-0.82
REXRU	-3.78	-3.78	-1.75	-2.71	-1.26	-2.15
REXTR	-2.86	-2.86	-1.49	-2.09	-1.06	-1.71
REXUK	-1.39	-1.39	-0.86	-1.11	-0.63	-0.94
REXVN	-0.71	-0.71	-0.26	-0.49	-0.12	-0.35
RSMBR	-3.43	-3.43	-2.33	-2.85	-1.65	-2.41
RSMCA	-2.04	-2.04	-1.14	-1.58	-0.78	-1.29
RSMGR	-2.94	-2.94	-1.77	-2.36	-1.25	-1.97
RSMJP	-3.71	-3.71	-2.08	-2.84	-1.33	-2.29
RSMKO	-2.07	-2.07	-1.27	-1.64	-0.87	-1.37
RSMRU	-2.53	-2.53	-1.62	-2.06	-1.19	-1.75
RSMTR	-3.46	-3.46	-2.12	-2.79	-1.56	-2.35
RSMUK	-2.46	-2.46	-1.31	-1.83	-0.94	-1.51
RSMUS	-2.43	-2.43	-1.35	-1.87	-0.82	-1.49
RSMVN	-3.37	-3.37	-1.63	-2.43	-1.12	-1.95
RGM	-4.9	-4.9	-1.7	-3.18	-1.08	-2.39
RCM	-7.07	-7.07	-2.69	-4.77	-1.06	-3.41

Table 4.13: Conditional Value at Risk – Expected Shortfall at 1%, 5% and 10% probability.

AIC and BIC criteria T-Student Copula Model is selected for all variables with lowest AIC reported. Selection of copula model under copula approach considers the nature of dependence between crypto-currency market and other traditional assets. Clayton and Gumbel copulas capture asymmetric dependencies, which Gaussian copula assumes symmetric dependence. Whereas, Student T copula measures dependencies in heavy tail distributions. Therefore tail dependencies guide selection of model by considering empirical fit tests like Akaike Information Criterion. Depending upon the specific dependencies, the selection of right copula enhances the accuracy of modeling the joint distribution and marginal distribution between crypto-currencies and other traditional assets. It indicates extreme shifts towards gains and losses, which normal distribution may possibly understate and thus VaR is under-stated. CoVaR (ES) is an appropriate measure for risk management rather VaR. ES refers to the conditional expectations of tail (α) considering confidence level (1- α) for a given period. In **Table 4.13**, the results summarize the expected loss under confidence interval of 1%, 5% and 10%. VaR shows Value at Risk and CoVaR shows conditional Value at Risk or Expected Shortfall (ES). In case of RCM; VaR at 1% is -7.07 which means there is 1% probability that returns of cryptocurrency market drop by 7.07%. CoVaR at 1% on the other hand is also reported as -7.07 which means in worst 1% returns the average loss does not exceed 7.07. VaR at 5% is -2.69 which means there is 5% probability that returns of cryptocurrency market drop by 2.69%. CoVaR at 5% is reported as -4.77% which means in worst 5% returns the average loss on cryptocurrency market does not exceed 4.77%. VaR at 10% is -1.06% which means there is 10% probability that returns of cryptocurrency market drop by 1.06%. CoVaR at 10% is reported as -3.41% which means in worst 10% returns the average loss on cryptocurrency market does not exceed 3.41%. The VaR and CoVaR of RCM is less than RBGR, RBJP and RBUK. Moreover at 1% probability CoVaR does not exceed VaR for each asset, yet as the probability of loss is increased CoVaR exceeds VaR as shown at 5% and 10%.

4.7.4 Delta Conditional Variance - Δ CoVaR

The interdependence of risk between RCM and other variables is estimated by applying quantile regression, **Table 4.14**;

TABLE 4.14: Delta Conditional Variance – ΔCoVaR

Variables	**50%-Quantile Regression**		**5%- Quantile Regression**			**95%- Quantile Regression**		
	VaR	**Prob.**	**VaR**	**Prob.**	**ΔCoVaR**	**VaR**	**Prob.**	**ΔoVaR**
RBBR	0.0012	0.9787	0.248	0.4108	24.70%	0.0777	0.7459	77%
RBCA	0.175	0.6123	-0.153	0.5462	-17.30%	-0.483	0.00	-47.60%
RBGR	0.0004	0.0225	-0.0004	0.3936	-0.10%	0.0034	0.00	0.30%
RBJP	0.0004	0.3766	0.001	0.0013	0.10%	0.0015	0.751	0.10%
RBKO	-0.0195	0.5061	0.2346	0.0791	25.40%	-0.1829	0.3225	-16.30%
RBRU	0.0236	0.4987	0.1242	0.0378	10.10%	0.1139	0.8436	9.00%
RBTR	-0.0778	0.00	-0.1032	0.00	-2.50%	-0.0416	0.0001	3.60%
RBUK	0.0001	0.9972	-0.1171	0.0721	-11.70%	-0.1039	0.3488	-10.40%
RBUS	-0.0137	0.7468	0.3421	0.1883	35.60%	0.2341	0.3432	24.80%
RBVN	-0.0309	0.655	0.0937	0.5411	12.50%	0.7411	0.0135	77.20%
REXBR	-0.0399	0.3946	0.1606	0.4825	20.10%	-1.3064	0.00	-126.60%
REXCA	0.0287	0.819	-0.3538	0.6081	-38.30%	0.15	0.8531	12.10%
REXGR	0.1067	0.2852	0.5176	0.2485	41.10%	1.5766	0.0033	147.00%
REXJP	0.0058	0.9342	-0.148	0.7508	-15.40%	0.0312	0.9593	2.50%
REXKO	-0.0007	0.1455	0.0017	0.0049	0.20%	-0.0057	0.00	-0.50%
REXRU	0.0676	0.0648	0.1321	0.4126	6.40%	-0.0199	0.9565	-8.70%
REXTR	-0.0831	0.3419	0.0644	0.6494	14.80%	0.2726	0.3094	35.60%

Continued Table: 4.14 Delta Conditional Variance – ΔCoVaR

Variables	**50%-Quantile Regression**		**5%- Quantile Regression**			**95%- Quantile Regression**		
	VaR	**Prob.**	**VaR**	**Prob.**	**ΔCoVaR**	**VaR**	**Prob.**	**ΔoVaR**
REXUK	-0.1047	0.4577	0.1468	0.7133	25.10%	-0.1034	0.9017	0.10%
REXVN	0.0572	0.7846	-0.4639	0.6776	-52.10%	-1.5012	0.147	-155.80%
RSMBR	0.0218	0.5315	-0.0268	0.8472	-4.90%	0.5737	0.0228	55.20%
RSMCA	0.0055	0.2566	-0.0388	0.0001	-4.40%	0.0517	0.000	4.60%
RSMGR	-0.1546	0.0044	0.331	0.2195	48.60%	-0.1472	0.5735	0.70%
RSMJP	-0.0353	0.4021	0.1872	0.2345	22.30%	-0.4691	0.0201	-43.40%
RSMKO	-0.0537	0.4626	-0.1277	0.7051	-7.40%	0.8114	0.002	86.50%
RSMRU	0.0991	0.0558	-0.0438	0.7992	-14.30%	-0.5725	0.0307	-67.20%
RSMTR	0.0046	0.321	-0.0312	0.0001	-3.60%	0.054	0.000	4.90%
RSMUK	0.0261	0.000	0.0105	0.0608	-1.60%	0.0834	0.000	5.70%
RSMUS	0.137	0.049	0.5325	0.0762	39.60%	0.2631	0.5471	12.60%
RSMVN	0.1149	0.0232	0.44	0.002	32.50%	0.1962	0.3325	8.10%
RGM	-0.0107	0.6029	0.1075	0.1174	11.83%	-0.1748	0.3589	-16.41%

*Table 4.14: Delta Conditional Variance – 50%, 5% and 95% Quantile Regression Statistical Significance: 5%*** ,Statistical Significance: 10%**

The measure is beneficial in estimating systematic relationship to determine changes in volatilities of variables over time. Higher quantile is linked to data located on the right tail, which is used to define risk interdependence between variables. Therefore, extreme shifts in the data are highly weighted particularly in times of distress under this model. Contrary to this, lower quantiles specifies position of variables on average, since model weighs data in similar manner i.e., above and below the given quantile.

The inter-dependency of volatility at lower quantile (5%-QR), median (50%-QR) and upper quantile (95%-QR) between RCM and other assets is reported. Coefficients of REXRU (0.0676) and RSMGR (-0.1546) have statistically significant impact on RCM at (50%-QR). Coefficients at (50%-QR) and (5%-QR) of RSMUK (0.0261 and 0.0105 respectively), RSMUS (0.0490 and 0.0762 respectively) and RSMVN (0.1149 and 0.4400 respectively) are statistically significant. Coefficients of RBJP (0.0010), RBKO (0.2346), RBRU (0.1242) and RBUK (-0.1171) have statistically significant impact on RCM at (5%-QR). Coefficients at (5%-QR) and (95%-QR) of REXKO (0.0017 and -0.0057 respectively), RSMCA (-0.0388 and 0.0517 respectively) and RSMTR (-0.0312 and 0.0540 respectively) find statistical significance with RCM. At (50%-QR) and (95%-QR) coefficients of RBGR (0.0004 and 0.0034 respectively) and RSMRU (0.0991 and -0.5725 respectively) are statistical significant. Moreover at (95%-QR) coefficients of RBCA (-0.4583), RBVN (0.7411), REXBR (-1.3064), REXGR (1.5766), RSMBR (0.5737), RSMJP (-0.4691) and RSMKO (0.8114) are statistically significant, and at (50%-QR), (5%-QR) and (95%-QR) only RBTR (-0.0778, -0.1032 and -0.0416 respectively) and RSMUK (0.0261, 0.0105 and 0.0834 respectively) turn out to be statistically significant. Secondly, ΔCoVaR is reported highest for RSMGR (48.6%) and lowest for REXVN (-52.1%) at 5%-QR, whereas highest for REXGR (147.0%) and lowest for REXVN (-155.8%) at 95%-QR.

H4: Cryptocurrency can be a viable alternative for investment similar to other asset classes.

The results verify the above hypothesis, showing that there is volatility interdependence between traditional assets and cryptocurrency market. The evidence of volatility transmission from financial assets to cryptocurrency market during extreme shifts is reported. Since systematic risk is one of the component of volatility transmission, and this contagion effect magnifies shocks in times of extreme movements. The financial assets like bonds, currency, stocks and gold contributes to the risk of cryptocurrency market, (Mo et al., 2022; Symss, 2023).

4.8 Vector Error Correction Model – VECM

4.8.1 Lag Selection Criteria

The selection of optimal lag length to proceed with cointegration test, the Akaike Information Criteria- AIC is used which suggested optimal lag length as 5 for all sets. It is also confirmed by trace statistics and maximum eigen statistics that at lag 5 atleast 1 cointegration equation is found in all sets, **Table 4.15**.

The VECM is applied to define long run relationships and short run dynamics between cryptocurrency market and other variables under study. It captured the short run deviations and long run equilibrium to make it suitable for forecasting and understanding the interdependencies between variables, particularly when the variables are cointegrated. VECM is utilized to estimate the static hedge ratio between cryptocurrency market and traditional assets. The cointegration modeling and short term dynamics the model provides insights into the static hedge ration over time. The approach aids in investment hedging strategies based on evolving market conditions and the changing relationship between cryptocurrency market and traditional assets.

4.8.2 Cointegration Test

Before going to VECM analysis it is important to find that whether variables are cointegrated or not. **Table 4.16**, demonstrates cointegration relationship between cryptocurrency market and each of the variables where trace statistics and maximum eigen statistics show atleast one cointegration equation between cryptocurrency market and all other asset classes.

Table 4.15: Vector Error Correction Model- VECM

	(a)				**(b)**			
	Long Term Causality ($\gamma 1$)				**Short Term Casuality**			
	Coeff.	**Std. Err**	**t-Stat**	**Prob.**	**F-stat**	**Prb.**	**Chi-sq**	**Prob.**
RGM	-0.0897	0.0131	-0.8236	0	0.0729	0.9962	0.3645	0.993
	0.0122	0.006	2.0316	0.0424	17.9043	0	89.5216	0
REXBR	-0.0856	0.0128	-6.6729	0	0.936	0.4548	4.693	0.4545
	0	0	-0.2031	0.8391	0.6119	0.6908	3.0597	0.6908
RBBR	-0.088	0.013	-6.7773	0	0.5126	0.767	2.5628	0.767
	0	0	-0.2363	0.8132	0.4081	0.8434	2.0403	0.8435
RSMBR	-0.0904	0.0131	-6.8899	0	0.4184	0.8362	2.092	0.8363
	-0.0419	0.2782	-0.1507	0.8802	0.1553	0.9785	0.7763	0.9785
REXCA	-0.0871	0.0128	-6.7812	0	1.8428	0.1015	9.2142	0.1008
	0	0	-0.3368	0.7363	0.4608	0.8056	2.3039	0.8057
RBCA	-0.0979	0.0135	-7.2255	0	2.4076	0.0347	12.0381	0.0343
	0	0	-0.1331	0.8942	0.2603	0.9347	1.3013	0.9348
RSMCA	-0.0877	0.013	-6.7473	0	0.5433	0.7435	2.7166	0.7436
	0.0024	0.0298	0.0802	0.9361	0.5577	0.7325	2.7885	0.7326
REXGR	-0.0923	0.0133	-6.9365	0	0.3867	0.8582	1.9333	0.8583
	0	0	1.1511	0.2499	1.1999	0.3068	5.9996	0.3063
RBGR	-0.0893	0.013	-6.8485	0	0.8477	0.5159	4.2385	0.5156
	0	0	-0.5841	0.5592	0.3388	0.8896	1.6939	0.8897
RSMGR	-0.0874	0.013	-6.7399	0	0.3251	0.8981	1.6254	0.8982
	-0.0448	0.0357	-1.2545	0.2099	1.0103	0.41	5.0514	0.4096
REXJP	-0.0882	0.013	-6.7932	0	1.7484	0.1205	8.742	0.1198

Continued Table: 4.16 Vector Error Correction Model- VECM

	(a) Long Term Causality ($\gamma 1$)				(b) Short Term Casuality			
	Coeff.	**Std. Err**	**t-Stat**	**Prob.**	**F-stat**	**Prb.**	**Chi-sq**	**Prob.**
	0	0	2.0459	0.0409	0.5588	0.7317	2.7939	0.7317
RBJP	-0.0736	0.0118	-6.254	0	60.1478	0	300.7389	0
	0	0	1.4797	0.1392	4.0458	0.0012	20.2291	0.0011
RSMJP	-0.0882	0.013	-6.7835	0	0.5988	0.7009	2.9941	0.7009
	-0.0977	0.0692	-1.4112	0.1584	2.0684	0.0667	10.3418	0.0661
REXKO	-0.0937	0.0134	-7.0152	0	0.0208	0.9998	0.1041	0.9998
	0	0	0.2484	0.8039	0.005	1	0.0249	1
RBKO	-0.0915	0.0133	-6.8977	0	0.5864	0.7104	2.9322	0.7104
	0	0	0.1842	0.8539	0.5867	0.7102	2.9336	0.7102
RSMKO	-0.0904	0.0131	-6.879	0	0.3341	0.8925	1.6707	0.8926
	-0.0037	0.0049	-0.7588	0.4481	1.1429	0.3355	5.7143	0.335
REXRU	-0.0872	0.013	-6.7288	0	0.4696	0.7991	2.348	0.7992
	0	0	-0.8964	0.3702	0.1912	0.966	0.956	0.966
RBRU	-0.0932	0.0133	-7.0085	0	0.0441	0.9989	0.2204	0.9989
	0	0	0.4998	0.6173	0.0678	0.9968	0.3392	0.9968
RSMRU	-0.0872	0.0129	-6.7411	0	0.0631	0.9973	0.3155	0.9973
	-0.0019	0.0061	-0.3079	0.7582	0.4656	0.8021	2.328	0.8022
REXTR	-0.0865	0.0129	-6.7074	0	0.743	0.5913	3.7148	0.5912
	0	0	-0.4305	0.6669	0.4812	0.7905	2.4061	0.7906
RBTR	-0.09	0.0132	-6.8441	0	0.4971	0.7786	2.4853	0.7787
	0	0.0001	0.7275	0.467	0.3666	0.8717	1.8329	0.8717
RSMTR	-0.0875	0.013	-6.7475	0	1.0978	0.3596	5.4889	0.3592
	-0.2175	0.3518	-0.6182	0.5366	0.4367	0.8232	2.1833	0.8232

Continued Table: 4.16 Vector Error Correction Model- VECM

	(a) Long Term Causality ($\gamma 1$)				(b) Short Term Casuality			
	Coeff.	**Std. Err**	**t-Stat**	**Prob.**	**F-stat**	**Prb.**	**Chi-sq**	**Prob.**
REXUK	-0.0857	0.0128	-6.6723	0	0.4148	0.8387	2.0739	0.8388
	0	0	0.901	0.3678	0.5309	0.753	2.6545	0.7531
RBUK	-0.0867	0.0129	-6.7302	0	1.2897	0.2656	6.4483	0.265
	0	0	-0.0272	0.9783	0.4364	0.8234	2.1818	0.8235
RSMUK	-0.0911	0.0132	-6.8924	0	0.3864	0.8584	1.9319	0.8585
	-0.0172	0.0173	-0.9928	0.3209	0.8849	0.4903	4.4245	0.4901
RBUS	-0.0987	0.0137	-7.2251	0	1.8185	0.1061	9.0923	0.1054
	0	0	-0.0355	0.9717	0.4096	0.8424	2.0478	0.8425
RSMUS	-0.0891	0.0131	-6.8232	0	0.3685	0.8704	1.8426	0.8705
	-0.0043	0.0058	-0.7503	0.4532	0.2742	0.9274	1.371	0.9275
REXVN	-0.0859	0.0128	-6.6948	0	0.1127	0.9896	0.5633	0.9896
	0	0	0.4127	0.6799	0.0852	0.9946	0.4258	0.9946
RBVN	-0.0863	0.0129	-6.7035	0	0.0967	0.9927	0.4837	0.9927
	0	0	-0.4455	0.656	0.2059	0.9601	1.0297	0.9601
RSMVN	-0.0961	0.0137	-7.0233	0	0.1066	0.9908	0.5331	0.9909
	0.0049	0.0029	1.6725	0.0946	1.0693	0.3756	5.3463	0.3751

Table 4.16 *(a) illustrates that there is long term causality coming from each of the traditional asset classes towards crypto-currency market. Table 19 (b) shows, Wald Test to find out the short term causality flowing between each of traditional assets and crypto-currency market.*

Hence the null hypothesis of no cointegration is rejected under trace as well as maximum eigen statistics at 5% level of significance. These results indicate that exchange rates, stock returns, government bonds and gold establish long run relationship with cryptocurrencies in countries where it is being traded frequently.

The coefficient of the model which is known as error correction term is denoted as $\gamma 1$. This term denotes the speed of convergence of variables towards their equilibrium. The results given **Table 4.16**(a) illustrates that there is long term causality coming from each of the traditional asset classes towards cryptocurrency market. About 8% to 9% traditional assets are adjusted in previous year's deviations from the equilibrium. However there is no long term causality found coming from cryptocurrency market to the traditional assets except cryptocurrency towards gold, REXJP and RSMVN. These sets show positive coefficient with significance at 5% and RESMVN at 10% which means any change, disequilibrium may arise. Furthermore, Wald Test is used to find out the short term causality flowing between each of traditional assets and cryptocurrency market. **Table 4.16** (b), finds there is no short term causality flowing from any of the traditional assets to the cryptocurrency market except short term causality running from cryptocurrency market to gold, short term causality running from RBCA to cryptocurrency market, short term causality running from RBJP to cryptocurrency market and vice versa, short term causality running from cryptocurrency market to RSMJP.

4.8.3 BEKK-GARCH

Table 4.17 exhibits the maximum likelihood estimation for the BEKK GARCH model. The model implies that the parameters of A(1,1) and A(2,2) turns out to be statistically significant for cryptocurrency with all traditional assets except RCM-RBRU, A(1,1) insignificant in RCM-REXVN, RCM-RBVN. The positive and statistical significance of A(1,1) indicates short term persistence in shocks on dynamic conditional correlations. However, positive value of A(1,1)+A(2,2) indicates presence of long term persistence of cryptocurrency market with traditional assets. Secondly, to measure variances and covariances between cryptocurrency market and traditional assets, positive coefficients of B(1,1) and B(2,2) indicate increase in variance in returns of crytocurrency market puts positive impact on the covariances between cryptocurrency market and traditional assets in future period. Whereas positive value of B(1,1)+B(2,2) depicts increase in covariances flows increase in covariances in future period between cryptocurrency and traditional assets. The results show statistically significance between cryptocurrency market and traditional assets except RCM-RSMTR and RCM-RGM. The movements of variances, conditional correlations and conditional covariances between cryptocurrency market and each of traditional assets can be shown in **Figures 4.6 to 4.96**.

Although Bivariate GARCH model is weaker than DCC GARCH model. Yet it is employed to faciliate the time varying hedge ratio between cryptocurrency market and traditional assets. The model accounts the dynamic volatility and correlation between the assets, providing understanding about their interdependencies over time. By joining time varying volatility and correlation, the BEKK model helps in refining hedge ratio for risk management for cryptocurrencies and traditional assets. It allows investors to adapt the hedging strategies based on changing market conditions and evolving relationships between these diverse financial assets.

4.8.4 Hedge Ratio

The hedge ratio determines the volatility of cryptocurrency relative to traditional assets. The optimal hedge ratio is 1. The ratio measures the degree of risk reduced while hedging. It means taking a position for a financial asset to compensate the risk of other financial asset. It quantifies the relationship between the size of the position and the size of the risk exposure to be hedged. The ratio above 1 for a cryptocurrency market shows rapid change in returns and inclines high risk yet typically high returns and less than 1 hedge ratio means slow change in returns, declining risk yet potentially low returns. In comparison of crytptocurrency marker and traditional assets the hedge ratio is calculated given in **Table 4.16**.

The highest hedge ratio is stated between cryptocurrency market and RSMUS as 244.4527 which indicates that cryptocurrency returns are 144.4% times less volatile than stock returns in United States and provides protection against downside risk.

Table 4.16: Hedge Ratio

Variables	VaR(ΔKt)	CoVaR(ΔCtΔKt)	Hedge Ratio
RGM	0.00028	-0.0085	-30.9873
REXBR	0.0001	-0.01298	-124.7906
RBBR	0.00014	0.01759	124.0705
RSMBR	0.0002	0.00114	5.7292
REXCA	0.00002	-0.00001	-0.5837
RBCA	0.00057	-0.00476	-8.343
RSMCA	0.00068	0.00439	6.4164
EXR	0.00003	0.00106	41.1781
RBGR	0.99839	0.03633	0.0364
RSMGR	0.00012	0.00182	15.7275
REXJP	0.00004	-0.01303	-320.1866
RBJP	1.5709	-0.02726	-0.0174
RSMJP	0.00015	0.02054	134.7619
REXKO	0.05354	-0.0111	-0.2073
RBKO	0.00017	0.02234	127.9688
RSMKO	0.00005	-0.0069	-130.5068
REXRU	0.00015	-0.00151	-9.9725
RBRU	0.00017	0.00309	18.3281
RSMRU	0.00012	-0.00448	-38.1845
REXTR	0.0001	0.00421	41.8028
RBTR	0.00088	0.01303	14.8104
RSMTR	0.00082	-0.01062	-13.0185
REXUK	0.00003	0.00048	15.031
RBUK	0.00096	0.02595	26.8933
RSMUK	0.00071	0.00466	6.5849
RBUS	0.00037	-0.01179	-31.9163
RSMUS	0.00006	0.01562	244.4527
REXVN	0	0.00037	90.326
RBVN	0.00005	-0.00394	-78.0156
RSMVN	0.00011	-0.00011	-0.9198

Table 4.18*, determines hedge ratio to report volatility of crypto-currency relative to traditional assets.*

Whereas the lowest hedge ratio is reported between cryptocurrency market and REXJP as -320.1866 which indicates that cryptocurrency market is exposed to high returns than currency exchange rate in Japan. It is worth notable that cryptocurrencies exhibit exceptional characteristics, like high volatility, sensitivity to market and liquidity issues. Therefore hedge ratio between cryptocurrencies and other traditional assets may possibly vary from asset to asset.

H5: Cryptocurrency plays dynamic role in hedging of investment.

The empirical results support the above hypothesis. There is long term unidirectional causality running from each of the given asset towards cryptocurrency market yet no causality is running from cryptocurrency market to other assets. These results show long term relationship and any change in returns of the traditional assets causes change in returns of crytpcurrencies.It proves short term and long term persistence in conditional correlations and the volatility in returns of cryptocurrencies and traditional assets are correlated and conditional to any change, findings are aligned with (Nekhili & Sultan, 2022; Karim et al., 2022; Okorie & Lin, 2020).

Chapter 5

Discussion and Conclusion

To draw the end, the preceding chapters are connected to tie up the entire study. It leaves with directions for potential research, confines and inference as of the ideas developed all through the study.

5.1 Discussion

Probability distributions express means, variances and extreme values. For instance exponential distribution; where events are rarely away from mean. However some distributions exhibit fat tails where events are certainly less away from mean, such distributions are referred as Pareto distributions. Pareto distribution defines the time variance between events as the number of events randomly occurring follows unit of time. Pareto principle states that the events occurring in a certain time are consequences of some other events. The time variance between events also follows Exponential distribution. However, Exponential distribution fails to predict clustering in the timing of such events, which indicates about some other events even closer and later disperse. Therefore to fit the time between such events by applying Pareto and Exponential distribution in order to compare the better fit distribution to model the frequency, there is Pareto II type of distribution. The analysis of the study supports that crypto-currency market exhibits extreme values which indicates fat tailed distribution. The three continuous distributions of extreme value theory i.e., Gumbel, Frechet and Weibull are compared and the study directs that the crypto-currency market follows Pareto II distribution, which is referred as Weibull distribution of the extreme value theory.

The GJR-GARCH) model, models the variance directly and does not rely on natural logarithm like other GARCH models, therefore it simplifies the modeling of forecasted volatility (Asgharian, 2016). The positively significant AR (1) reports the present day prices of crypto-currency market are based on their immediate preceding prices respectively. The negative coefficient implies that large positive values are possibly following by negative values. The significant MA (1) shows linear dependency of present day price on present day and past day error terms. It means the difference of the present price is regressed negatively on the difference of the immediate past day's price and negatively on the difference of the past day price, and negatively on the past day's residual. The ARCH (1) model which is positively significant portrays that either good or bad news comes in the market; short term volatility is being captured. Moreover, the GARCH (1) model which is positively significant directs that there is persistence in long term volatility at certain level. Resultantly the findings confirm that there is presence of leverage effect and the tendency of negative returns on future volatility of crypto-currencies and mineable crypto-currencies in particular is greater than that of their positive returns. Since it signifies that negative shocks tend to increase the volatility more than the positive shocks for overall crypto-currencies and positive shocks increase the volatility more than the negative shocks for mineable crypto-currencies particularly. There is no volatility reported in the short run as well as long run shocks for non-mineable crypto-currencies, besides discerns no leverage effect since there is not any persistence in volatility.

Furthermore, mineable crypto-currencies appear as high frequency assets, experiencing high volatility issues due to high and frequent speculations. Nevertheless non-mineable are flowing on a consistent trend. Therefore, it is evident that Supply Effect does affect volatility of crypto-currencies. Secondly, the statistically significant value of $\theta 1$ indicates presence of shock flowing from the past period and hence correlation in the present period is predicable through previous correlation. Moreover, statistically significant value of θ indicates relationship between previous and present period's correlations. Correlations of crypto-currencies are predictable since previous correlation flows to the present correlation, thus there is association between previous and present correlations of crypto-currencies. Hence to support this notion, different results are reported for crypto-currency market with other assets, correlations are associated with each other but previous correlations do not predict present period's correlations. The correlation of within crypto-currency market is predictable as previous and present correlations are time dependent. Since, it is a highly volatile market and the volatility is time dependent and correlation of crypto-currency market and other assets are associated yet not predictable.

Since no significant correlation is reported between RCM and other assets. Therefore Copula is applied which is specified in decomposing joint probability distribution of variables which have no correlation initially. The dependence structure of cryptocurrency market and other assets (bonds, currency, stocks and gold) is defined by copula family. From comprehensive review of Gaussian, T-Student, Gumbel and Frank copula, the best fitted copula is selected on the basis of AIC criteria. Furthermore, T-Student copula is selected on the basis of AIC criteria to explain marginal behavior of assets at lower and upper tails of the distribution.

Theoretically, CoVaR of assets which are deemed safe hardly exceed VaR significantly, whereas the assets which are deemed volatile exhibit CoVaR greater than VaR significantly. However, more volatile assets may possibly exhibit more potential to get higher returns and often exhibit high CoVaR. As VaR metrics can be sufficient for stable assets over time however; assets with frequent shifts may possibly be understated by means of simple VaR risk metrics. Therefore CoVaR quantifies expected loss in extreme shifts that may occur over the cutoff specified by VaR. Moreover the quantile regression is applied to consider volatility transmission from other assets to cryptocurrency market. The results show there is volatility interdependence between traditional assets and cryptocurrency market.

Lower quantile (5%-QR) and upper quantile (95%-QR) are reported to capture maximum evidence of volatility transmission from financial assets to cryptocurrency market during extreme shifts comparative to average state median quantile (50%-QR). Since systematic risk is one of the component of volatility transmission, and this contagion effect magnifies shocks in times of extreme movements. Simultaneously, ΔCoVaR explains the assets that are "too big to fail", it quantifies that how much financial assets like bonds, currency, stocks and gold contributes to the risk of cryptocurrency market as a whole.

The role of cryptocurrency market in comparison with other traditional assets like currency exchange rates, stock returns, government bonds and gold in ten countries where cryptocurrency is being traded most frequently. The empirical results suggests that there is long term uni-directional causality running from each of the given asset towards cryptocurrency market yet no causality is running from cryptocurrency market to other assets. These results show long term relationship and any change in returns of the traditional assets cause change in returns of crytpcurrencies. However no short term causality is reported except uni-directional causality coming from cryptocurrency to gold, RBCA and RSMJP and bi-directional causality between RBJP and cryptocurrency.

Moreover, statistical significance of BEKK GARCH model proves short term and long term persistence in conditional correlations between cryptocurrency market and traditional assets except RCM-RBRU, RCM-REXVN and RCM-RBVN. The results indicate that returns of cryptocurrencies and traditional assets are correlated and conditional to any change. On the other hand change in variance in returns of cyptocurrencies (traditional assets) changes covariances between them. The positive increase in variances positively impacts the covariances between them in the future period for all combinations except RCM-RSMTR and RCM-RGM. These results show co-movements between cryptocurrencies and traditional assets. Finally the hedge ratio reports the volatility in returns of cryptocurrencies as compared to each of the traditional assets. The highest volatility is reported in cryptocurrency returns against stock market of US whereas lowest is reported against currency exchange rate of Japan.

5.2 Conclusion

The study aims to figure out exactly where crypto-currencies stand and what actually it brings to the financial systems. Apparently, the crypto-currency market exhibits extreme values and time dependent volatility prevails crypto-currency market. Consequently, the crypto-currency market is a high frequency market yet it is not efficient. Moreover, mineables crypto-currencies are more volatile than non-mineable cryptocurrencies. It is evident that Supply Effect does affect volatility of cryptocurrencies. There is no leverage effect in non-mineable crypto-currencies which concludes that there is no asymmetric volatility phenomenon present and its volatility is not negatively correlated with the returns.

Contrary to this there is presence of leverage effect in mineable crypto-currencies and concludes that there is asymmetric volatility which is negatively correlated with the returns. The increase in prices of mineable crypto-currencies is leading by decrease in its volatility and decrease in prices is leading by increase in volatility. Hence asymmetric volatility in mineable crypto-currencies tends to make it more volatile than non-mineable crypto-currencies. It supports the justification; if crypto-currency market is merely a bubble which is near to rupture, mineable crypto-currencies are more likely to fall whereas non-mineable crypto-currencies are more likely to stay and relish as a digital financial asset.

The dependence structure between cryptocurrency market and financial assets like bonds, currency, stocks and gold is clarified by using copula family. It is shown that T Student Copula measures tail dependence (lower left and upper right) of the distribution. Hence T-Student Copula defines best-fitted dependence structure between cryptocurrency market and other financial assets. Since VaR only displays the loss during extreme movements at a given probability on a given time. The results show that cryptocurrency market is volatile than rest of the assets considered.

The market is not stable therefore it exhibits greater CoVaR than VaR. The heavy tails of a distribution defines movements towards left and right extremes, which may possibly surge due to extreme variability in returns away from mean. Correspondingly such extreme movements escalate variability in risk. ΔCoVaR defines the change in VaR of financial asset conditional to extreme movements comparative to its average state. Hence T-Student Copula defines best-fitted dependence structure between cryptocurrency market and other financial assets. It concludes that highly volatile asset deemed to transmit more volatility to cryptocurrency market in extreme movements towards left and right tails of a distribution.

The study finds the long term relationship between traditional assets and cryptocurreny market, yet no short term relationship is observed as a whole. It also finds the comovements in conditional correlations and covariances, where change in returns of one asset effects covariances between them. The study concludes that cryptocurrency can be safe haven for investment, since cryptocurrency is independent of any macroeconomic changes. The change in cryptocurrency returns may not effect returns of traditional assets yet any change in traditional assets may possibly upsurge towards change in cryptocurrency market in the long term. The volatility in returns of cryptocurrencies show degree of variations over time, the more volatility means more sensitivity in change in prices which ultimately leads to more opportunities for masses interested to invest in cryptocurrencies.

5.3 Limitations of the Study

Cryptocurrencies are accessible for everyone including Islamic financial institutions and ordinary users as long as there is access to the Internet. Despite the rapid development in crypto-currency, the question of the compliance of cryptocurrencies with Shari'ah requirements remains unexplored in this study.

5.4 Directions for Future Research

The findings of the study are believed to be verified by applying other measures of volatility. It has scope to be designed on large sample to generalize the findings of the study. It may possibly be generalized by using other VaR models. The study can be tested with other parametric models of Value at risk. It has wide scope to be framed for other countries where attempts are being taken to regulate cryptocurrencies. It can also be broaden for a larger set of financial assets. Mostly researches on crypto-currencies are primilarly focused on Bitcoin, yet there are ways to replicate the exisiting studies on other set of cryptocurrencies.

5.5 Practical Implications

The study findings recommend investors to recognize crypto-currency extreme value nature, considering its fat-tailed distribution. Diversify, implement robust risk management, and remain vigilant in the highly volatile market. They should acknowledge the impact of supply effect and the factors responsible for the volatility interdependence with traditional assets, to reach a comprehensive and adaptive investment strategy.

The study recommends policy makers to recognize fat tailed and unpredictable nature of crypto-currency market. Implement dynamic regulatory frameworks, risk management protocols, and surveillance systems. Considering the impact of supply effect there is a need to collaborate with global financial institutions to address volatility interdependence, contagion effects and systematic risks, ensuring market stability and safeguard investors.

The study highlights academia to focus on advancing research on crypto-currency's fat tailed distribution, investigating time dependent correlations within the market and with other traditional assets. There is a need to study the supply effect dynamics more cohesively to explore volatility interference, contagion effects and long term causality for a comprehensive understanding of crypto-currency and financial institutions interactions.

Last but not the least, countries developing crypto-currency regulations should recognize the extreme value behavior of crypto-currency market experiencing fat tailed distribution. They should establish dynamic regulatory frameworks, surveillance systems, and risk management protocols. While considering the supply effect dynamics they need to collaborate internationally to address volatility independence, systematic risks, contagion effects and ensuring effective and adaptive regulatory measures.

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Appendix-A

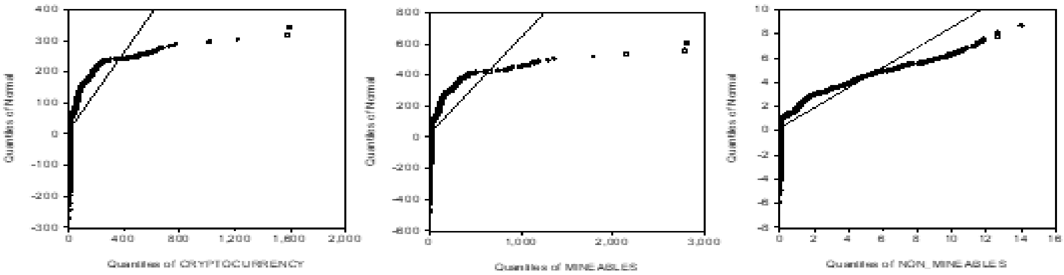


Figure. 4.5: Q-Q Plots of Crypto-currency Market, Mineable and Non-Mineable

S No.	Name of Cryptocurrency	Abbreviation	S No.	Name of Cryptocurrency	Abbreviation
1	Bitcoin	BTC	250	Mao Zedong	MAO
2	Ethereum	ETH	251	ExclusiveCoin	EXCL
3	Ripple	XRP	252	Qredit	XQR
4	Bitcoin Cash	BCH	253	Actinium	ACM
5	Litecoin	LTC	254	Teloscoin	TELOS
6	Binance Coin	BNB	255	FedoraCoin	TIPS
7	EOS	EOS	256	MIB Coin	MIB
8	Bitcoin SV	BSV	257	The ChampCoin	TCC
9	Monero	XMR	258	Lobstex	LOBS
10	Steller	XLM	259	Sphere	SPHR
11	Cardano	ADA	260	Sumokoin	SUMO
12	Tron	TRX	261	Zero	ZER
13	DASH	DASH	262	Bitcoin Incognito	XBI
14	Ethereum Classic	ETC	263	Internet of People	IOP
15	Tezos	XTZ	264	Zetacoin	ZET
16	IOTA	MIOTA	265	Zcore	ZCR
17	NEO	NEO	266	Expanse	EXP

18	ATOM	ATOM	267	EUNO	EUNO
19	NEM	NEM	268	StrongHands Masternode	SHMN
20	Ontology	ONT	269	Dynamic	DYN
21	Zcash	Zcash	270	ODUWA	OWC
22	V Systems	VSYS	271	Scorum Coins	SCR
23	DOGE	DOGE	272	SounDAC	XSD
24	VeChain	VET	273	DopeCoin	DOPE
25	Decred	DCR	274	Auxilium	AUX
26	Qtum	QTUM	275	CryptoCarbon	CCRB
27	Bitcoin Gold	BTG	276	Arionum	ARO
28	Ravencoin	RVN	277	Memetic / PepeCoin	MEME
29	Lisk	LSK	278	Ether-1	ETHO
30	Nano	NANO	279	Yocoin	YOC
31	Bitcoin Diamond	BCD	280	Commercium	CMM
32	Waves	WAVES	281	Capricoin	CPC
33	Energi	NRG	282	EtherGem	EGEM
34	ICON	ICX	283	GlobalBoost-Y	BSTY
35	THETA	THETA	284	Bitcoin Turbo Koin	BTK
36	Bytecoin	BCN	285	Unify	UNIFY

37	DigiByte	DGB	286	GoByte	GBX
38	BitShares	BTS	287	DraftCoin	DFT
39	HyperCash	HC	288	AirWire	WIRE
40	IOST	IOST	289	DeviantCoin	DEV
41	Komodo	Komodo	290	BitcoiNote	BTCN
42	MonaCoin	MONA	291	Bitcoiin	B2G
43	Siacoin	SC	292	Block-Logic	BLTG
44	Bytom	BTM	293	GravityCoin	GXX
45	Verge	XVG	294	GINcoin	GIN
46	ABBC Coin	ABBC	295	ATBCoin	ATB
47	Zilliqa	ZIL	296	BriaCoin	BRIA
48	Aeternity	AE	297	Exosis	EXO
49	Ardor	ARDR	298	Italo	XTA
50	Steem	STEEM	299	Kalkulus	KLKS
51	GXChain	GXC	300	MMOCoin	MMO
52	Metaverse ETP	ETP	301	Giant	GIC
53	Zcoin	XZC	302	BBSCoin	BBS
54	Beam	BEAM	303	GoHelpFund	HELP
55	Grin	GRIN	304	Xuez	Xuez

56	Wanchain	WAN	305	ProCurrency	PROC
57	Elastos	ELA	306	Rimbit	RBT
58	Stratis	STRAT	307	CannabisCoin	CANN
59	Project Pai	PAI	308	Gold Poker	GPKR
60	Factom	FCT	309	Bitcoin Zero	BZX
61	Electroneum	ETN	310	BitWhite	BTW
62	Horizen	ZEN	311	Octoin Coin	OCC
63	TomoChain	TOMO	312	SparksPay	SPK
64	NULS	NULS	313	Aegeus	AEG
65	Nebulas	NAS	314	MedicCoin	MEDIC
66	Newton	NEW	315	Absolute	ABS
67	ReddCoin	RDD	316	Fivebalance	FBN
68	Aion	AION	317	INDINODE	XIND
69	Ark	ARK	318	Innova	INN
70	TrueChain	TRUE	319	BitCoen	BEN
71	WaykiChain	WICC	320	Desire	DSR
72	CyberMiles	CMT	321	Quantis Network	QUAN
73	TTC	TTC	322	Mirai	MRI
74	Theta Fuel	TFUEL	323	PLATINCOIN	PLC

75	BHPCoin	BHP	324	Vitae	Vitae
76	PIVX	PIVX	325	IPChain	IPC
77	Matrix AI Network	MAN	326	GreenPower	GRN
78	Groestlcoin	GRS	327	MOAC	MOAC
79	Nxt	NXT	328	Apollo Currency	APL
80	Obyte	Obyte	329	Bitcoin Rhodium	XRC
81	PRIZM	PZM	330	SaluS	SLS
82	Nexus	NXS	331	CasinoCoin	CSC
83	Syscoin	SYS	332	Cryptonex	CNX
84	Vertcoin	VTC	333	Amoveo	VEO
85	Particl	PART	334	MicroBitcoin	MBC
86	Skycoin	SKY	335	WXCOINS	WXC
87	Einsteinium	EMC2	336	Civitas	CIV
88	Metadium	META	337	ECC	ECC
89	Divi	DIVI	338	Counterparty	XCP
90	Quantum Resistant Ledger	QRL	339	BitNewChain	BTN
91	High Performance Blockchain	HPB	340	Rubycoin	RBY
92	Clams	CLAM	341	Ondori	RSTR
93	EDC Blockchain	EDC	342	Global Cryptocurrency	GCC

94	Aeon	AEON	343	Vites	Vites
95	Namecoin	NMC	344	MintCoin	MINT
96	HYCON	HYC	345	ColossusXT	COLX
97	Lightning Bitcoin	LBTC	346	Lykke	LKK
98	ILCoin	ILC	347	Pandacoin	PND
99	Litecoin Cash	LCC	348	Global Currency Reserve	GCR
100	IRISnet	IRIS	349	Mooncoin	MOON
101	Peercoin	PPC	350	Quark	QRK
102	Wagerr	WGR	351	SafeCoin	SAFE
103	Ether Zero	ETZ	352	I/O Coin	IOC
104	VITE	VITE	353	Veil	Veil
105	VeriBlock	VBK	354	Myriad	XMY
106	Achain	ACT	355	ADAMANT Messenger	ADM
107	GoChain	Go	356	FairCoin	FAIR
108	Neblio	NEBL	357	GridCoin	GRC
109	OTOCASH	OTO	358	PetroDollar	XPD
110	Mindexcoin	MIC	359	Bitcoin Atom	BCA
111	Burst	BURST	360	HiCoin	XHI
112	ZelCash	ZEL	361	Dimecoin	DIME

113	#MetaHash	MH	362	Espers	ESP
114	Blocknet	BLOCK	363	MonetaryUnit	MUE
115	Safex Token	SFT	364	Bitcoin Interest	BCI
116	WhiteCoin	XWC	365	Golos	GOLOS
117	NavCoin	NAV	366	Bean Cash	BITB
118	FLO	FLO	367	Omni	OMNI
119	Metrix Coin	MRX	368	Swisscoin	SIC
120	Stakenet	XSN	369	NewYorkCoin	NYC
121	TERA	TERA	370	Nebula AI	NBAI
122	Dero	DERO	371	Orbitcoin	ORB
123	SmartCash	SMART	372	e-Gulden	EFL
124	XTRABYTES	XBY	373	Terracoin	TTRC
125	Viacoin	VIA	374	Uniform Fiscal Object	UFO
126	DigitalNote	XDN	375	win.win	TWINS
127	Asch	XAS	376	HEAT	HEAT
128	Pirate Chain	ARRR	377	Pinkcoin	PINK
129	Boolberry	BBR	378	Vsync	VSX
130	Loki	LOKI	379	HempCoin	THC
131	Bitcore	BTX	380	GoldMint	MNTP

132	NIX	NIX	381	StrongHands	SHND
133	Emercoin	EMC	382	Solaris	SXLR
134	Gulden	NLG	383	Manna	MANNA
135	TokenPay	TPAY	384	SHIELD	XSH
136	Spectrecoin	XSPEC	385	StarCoin	KST
137	Electra	ECA	386	DEEX	DEEX
138	BOScoin	BOS	387	Freicoin	FRC
139	Polis	POLIS	388	Auroracoin	AUR
140	Ubiq	UBQ	389	Ethersocial	ESN
141	BlackCoin	BLK	390	Halo Platform	HALO
142	Feathercoin	FTC	391	B3Coin	KB3
143	POA Network	POA	392	Motocoin	MOTO
144	LBRY Credits	LBC	393	PWR Coin	PWR
145	Primecoin	XPM	394	DubaiCoin	DBIX
146	DeepOnion	ONION	395	VeriumReserve	VRM
147	BitBay	BAY	396	Maxcoin	MAX
148	NativeCoin	N8V	397	Elite	1337
149	BridgeCoin	BCO	398	Dinastycoin	DCY
150	Nasdacoin	NSD	399	Graviocoin	GIO

151	OKCash	OK	400	ToaCoin	TOA
152	ChatCoin	CHAT	401	LoMoCoin	LMC
153	Zen Protocol	ZP	402	Trollcoin	TROLL
154	Bottos	BTO	403	Ixcoin	IXC
155	GameCredits	GAME	404	Ryo Currency	RYO
156	Shift	SHIFT	405	Lethean	LTHN
157	Peerplays	PPY	406	Magi	XMG
158	SINOVATE	SIN	407	LanaCoin	LANA
159	TurtleCoin	TRTL	408	BUZZCoin	BUZZ
160	Pascal Coin	PASC	409	KekCoin	KEK
161	VINchain	VIN	410	EverGreenCoin	EGC
162	Nimiq	NIM	411	ParallelCoin	DUO
163	HTMLCOIN	HTML	412	Bulwark	BWK
164	Diamond	DMD	413	Noir	NOR
165	Callisto Network	CLO	414	Lunes	Lunes
166	Footballcoin	XFC	415	Aced	Aced
167	Nexty	NTY	416	Advanced Internet Blocks	AIB
168	Zeepin	ZPT	417	ANON	ANON
169	GoldCoin	GLC	418	AudioCoin	ACOIN

170	Haven Protocol	XHV	419	AXE	AXE
171	X-CASH	XCASH	420	Biocoin	Biocoin
172	Observer	OBSR	421	Bitbar	Bitbar
173	Beetle Coin	BEET	422	Bitcoin Scrypt	BitScrypt
174	MIR COIN	MIR	423	Bitsend	Bitsend
175	SDChain	SDA	424	Bitstar	Bitstar
176	CrypticCoin	CRYP	425	Bitzeny	Bitzeny
177	MassGrid	MGD	426	BLOC MONEY	BLOC
178	Ulord	UT	427	BLUECOIN	BLUE
179	ZClassic	ZCL	428	CARBON	CARBON
180	BitTube	TUBE	429	CATO	CATO
181	Radium	RADS	430	CENTAURI	CENT
182	Adshares	ADS	431	CREDIT TAG CHAIN	CTC
183	VeriCoin	VRC	432	CROAT	CROAT
184	Internet Node Token	INT	433	CRYPTONITE	TONITE
185	SafeInsure	SINS	434	EDRCOIN	EDRC
186	Stealth	XST	435	Emerald Crypto	EMD
187	eXPerience Chain	XPC	436	energy coin	energy
188	Bismuth	BIS	437	ergo	ergo

189	DECENT	DCT	438	FantasyGold	FGC
190	PotCoin	POT	439	firstcoin	firstcoin
191	Phore	PHR	440	fujicoin	fujicoin
192	SelfSell	SSC	441	GCN Coin	GCN
193	BitGreen	BITG	442	Gentarium	GTM
194	PAC Global	PAC	443	Gravity	GZRO
195	Crown	CRW	444	Helium	HLM
196	RevolutionVR	RVR	445	Megacoin	MEC
197	SolarCoin	SLR	446	MediBloc	MED
198	Verasity	VRA	447	Mincoin	MNC
199	Conceal	CCX	448	Monero Classic	XMC
200	CloakCoin	CLOAK	449	Monkey Project	MONK
201	LUXCoin	LUX	450	Helleniccoin	HNC
202	Quasarcoin	QAC	451	Hush	HUSH
203	Fiii	Fiii	452	iDealCash	DEAL
204	XEL	XEL	453	Infinitecoin	IFC
205	Pigeoncoin	PGN	454	INT Chain	INT
206	BiblePay	BBP	455	Kin	KIN
207	ALQO	XLQ	456	LiteDoge	LDOGE

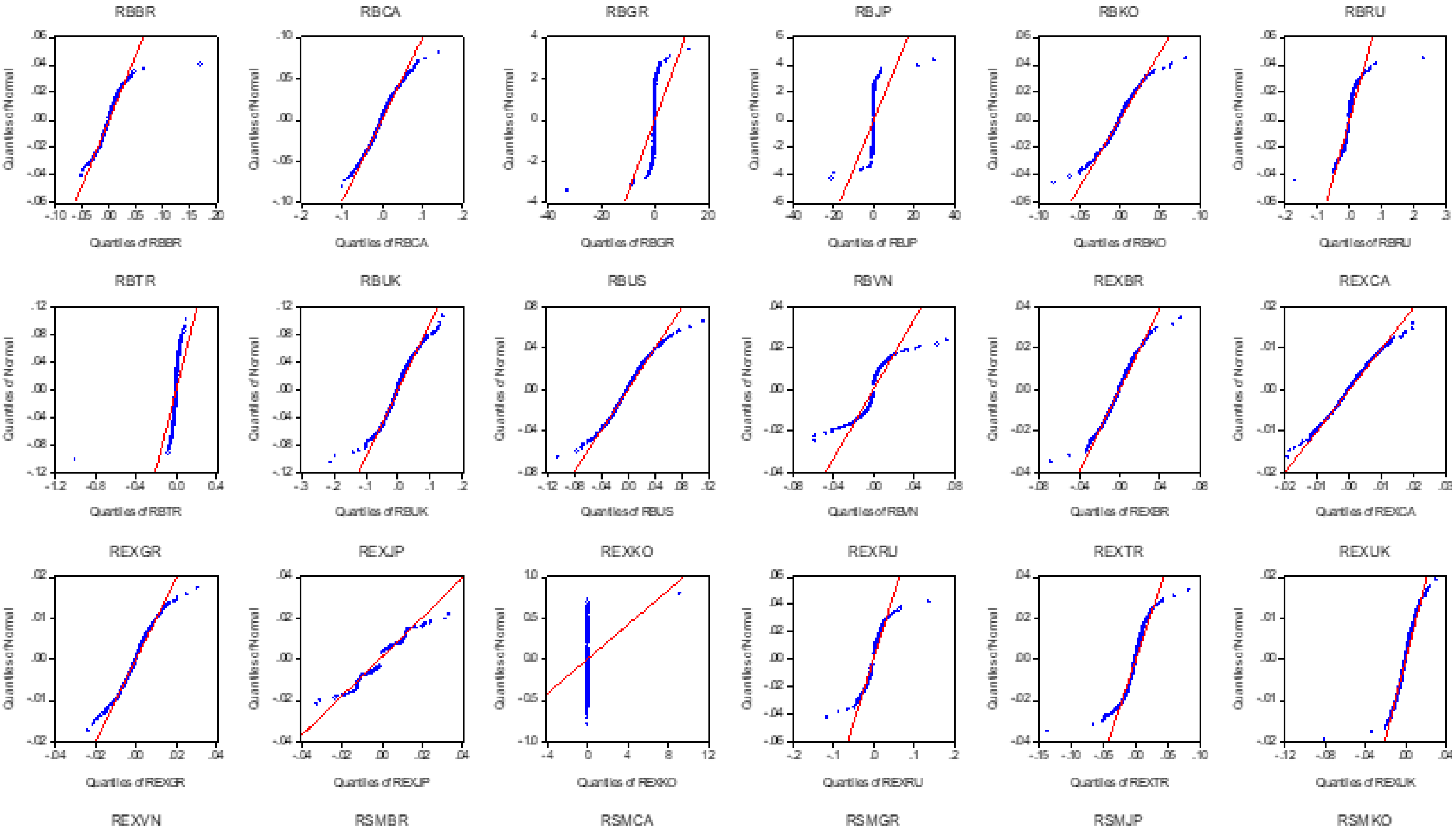
208	Semux	SEM	457	ZumCoin	ZUM
209	Novacoin	NVC	458	Zennies	ZENI
210	Graft	GRFT	459	Zeitcoin	ZEIT
211	Vipstar Coin	VIPS	460	XGOX	XGOX
212	Rapids	RPD	461	WIZBL	WBL
213	Curecoin	Cure	462	WAX	WAXP
214	Bitcoin Private	BTCP	463	VULCANO	VULC
215	NuBits	USNBT	464	VoteCoin	VOT
216	Cashbery Coin	CBC	465	Vision Industry Token	VIT
217	Shard	Shard	466	Vexanium	VEX
218	Swap	XWP	467	Unobtanium	UNO
219	NoLimitCoin	NLC2	468	Universe	UNI
220	42-coin	42	469	Unify	UNIFY
221	MinexCoin	MNX	470	Ultimate Secure Cash	USC
222	ION	ION	471	Trumpcoin	Trump
223	WebDollar	WEBD	472	TrezarCoin	TZC
224	Bitcoin Plus	XBC	473	Synergy	SNRG
225	SIBCoin	SIB	474	Streamit Coin	STREAM
226	Experience Points	XP	475	Startcoin	START

227	Pirl	Pirl	476	SnodeCoin	SND
228	BitcoinZ	BTCZ	477	SmileyCoin	SMLY
229	MktCoin	MLM	478	Sentient Coin	SEN
230	Flash	Flash	479	Scala	XLA
231	Happycoin	HPC	480	RSK Smart Bitcoin	RBTC
232	Trittium	TRTT	481	Repme	RPM
233	ESBC	ESBC	482	ProxyNode	PRX
234	DNotes	NOTE	483	PoSW Coin	POSW
235	eBoost	EBST	484	Photon	PHO
236	SophiaTX	SPHTX	485	Phoenixcoin	PXC
237	Stipend	SPD	486	Pesetacoin	PTC
238	SnowGem	XSG	487	PENG	PENG
239	Birake	BIR	488	PeepCoin	PCN
240	Rise	Rise	489	Pascal	PASC
241	uPlexa	UPX	490	Own	CHX
242	Denarius	D	491	NKN	NKN
243	Utrum	OOT	492	Niobio Cash	NBR
244	Karbo	KRB	493	Netko	NETKO
245	Masari	MSR	494	Neutron	NTRN

246	PAL Network	PAL	495	Bolivarcoin	Boli
247	Nerva	XNV	496	Denarius	DEN
248	BitCash	BITC	497	Steem Dollars	SteemD
249	GlobalToken	GLT	498	ToaCoin	TCoin

Regulations of Crypto-Currency Market Around the World

Banned		**Regulated**			
Absolute Ban	Implicit Ban	Application of Tax Laws	Anti-Money Laundering & Anti-Terrorism Financing Laws	Both	**Developing Hub**
Algeria	Bahrain	Argentina	Cayman Islands	Australia	Malta
Bolivia	Bangladesh	Austria	Costa Rica	Canada	Singapore
Egypt	China	Bulgaria	Czech Republic	Denmark	Switzerland
Iraq	Colombia	Finland	Estonia	Japan	
Morocco	Dominican RP	Iceland	Gibraltar	Switzerland	
Nepal	Indonesia	Israel	Hong Kong		
Pakistan	Iran	Italy	Isle of Man		
United Arab	Kuwait	Norway	Jersey		
	Lesotho	Poland	Latvia		
	Lithuania	Romania	Liechtenstein		
	Macau	Russia	Luxembourg		
	Oman	Slovakia	Singapore		
	Qatar	South Africa			
	Saudi Arabia	Spain			
	Taiwan	Sweden			
		United Kingdom			
		United States			


RBBR
Quantiles of RBBR
RBCA
Quantiles of RBCA
RBGR
Quantiles of RBGR
RBJP
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RBKO
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Quantiles of RBTR
RBUK
Quantiles of RBUK
RBUS
Quantiles of RBUS
RBVN
Quantiles of RBVN
REXBR
Quantiles of REXBR
REXCA
Quantiles of REXCA
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Quantiles of REXJP
REXKO
Quantiles of REXKO
REXRU
Quantiles of REXRU
REXTR
Quantiles of REXTR
REXUK
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REXVN
RSMBR
RSMCA
RSMGR
RSMJP
RSMKO

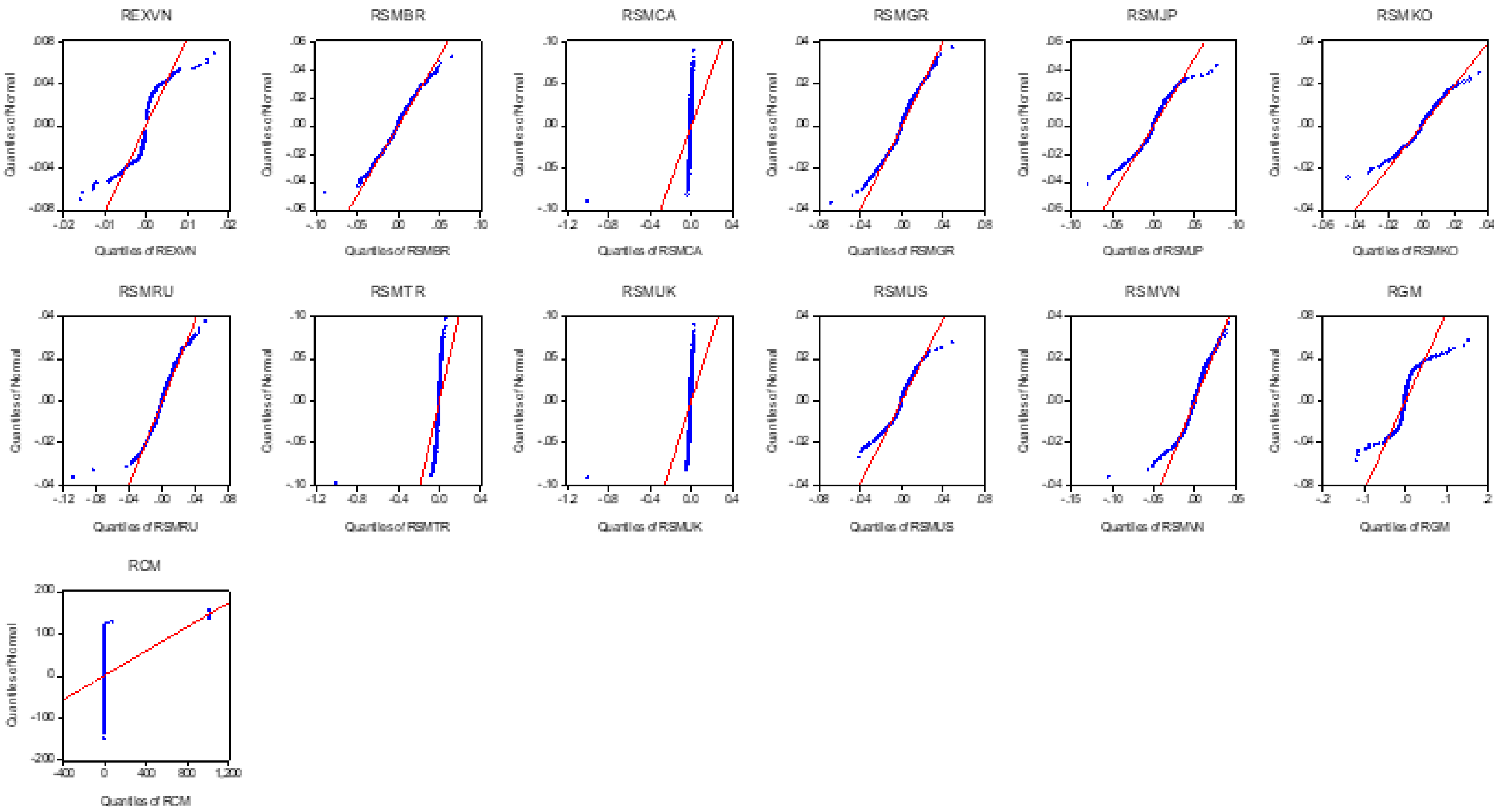

Figure. 4.4: Quantile- Quantile Plot

Table. 4.15: Lag Selection and Cointegration

Variables	**Lag**		**Trace Stat**	**C.Value 0.05**	**Prob.**	**Max-Eig**	**C.Value 0.05**	**Prob.**
RCM	-		-	-	-	-	-	-
RGM	5	None *	55.208	15.495	0	50.446	14.265	0
		At most 1 *	4.762	3.841	0.0291	4.762	3.841	0.0291
REXBR	5	None *	46.371	15.495	0	44.243	14.265	0
		At most 1	2.127	3.841	0.1447	2.127	3.841	0.1447
RBBR	5	None *	45.877	15.495	0	45.628	14.265	0
		At most 1	0.249	3.841	0.6178	0.249	3.841	0.6178
RSMBR	5	None *	47.124	15.495	0	47.122	14.265	0
		At most 1	0.002	3.841	0.9591	0.002	3.841	0.9591
REXCA	5	None *	49.595	15.495	0	46.118	14.265	0
		At most 1	3.477	3.841	0.0622	3.477	3.841	0.0622
RBCA	5	None *	54.937	15.495	0	51.757	14.265	0
		At most 1	3.18	3.841	0.0746	3.18	3.841	0.0746
RSMCA	5	None *	50.562	15.495	0	45.204	14.265	0
		At most 1 *	5.358	3.841	0.0206	5.358	3.841	0.0206
REXGR	5	None *	50.873	15.495	0	49.086	14.265	0
		At most 1	1.787	3.841	0.1813	1.787	3.841	0.1813
RBGR	5	None *	48.813	15.495	0	46.835	14.265	0
		At most 1	1.978	3.841	0.1596	1.978	3.841	0.1596
RSMGR	5	None *	51.106	15.495	0	46.381	14.265	0
		At most 1 *	4.725	3.841	0.0297	4.725	3.841	0.0297
REXJP	5	None *	52.897	15.495	0	48.899	14.265	0
		At most 1 *	3.998	3.841	0.0456	3.998	3.841	0.0456

Continued Table: 4.15 Lag Selection and Cointegration

Variables		**Lag**	**Trace Stat**	**C.Value 0.05**	**Prob.**	**Max-Eig**	**C.Value 0.05**	**Prob.**
RBJP	5	None *	47.956	15.495	0	43.69	14.265	0
		At most 1 *	4.266	3.841	0.0389	4.266	3.841	0.0389
RSMJP	5	None *	52.027	15.495	0	48.741	14.265	0
		At most 1	3.286	3.841	0.0699	3.286	3.841	0.0699
REXKO	5	None *	51.563	15.495	0	48.887	14.265	0
		At most 1	2.676	3.841	0.1019	2.676	3.841	0.1019
RBKO	5	None *	49.305	15.495	0	47.313	14.265	0
		At most 1	1.992	3.841	0.1581	1.992	3.841	0.1581
RSMKO	5	None *	51.684	15.495	0	47.463	14.265	0
		At most 1 *	4.221	3.841	0.0399	4.221	3.841	0.0399
REXRU	5	None *	49.832	15.495	0	45.788	14.265	0
		At most 1 *	4.044	3.841	0.0443	4.044	3.841	0.0443
RBRU	5	None *	51.41	15.495	0	48.996	14.265	0
		At most 1	2.414	3.841	0.1202	2.414	3.841	0.1202
RSMRU	5	None *	45.333	15.495	0	45.288	14.265	0
		At most 1	0.045	3.841	0.8324	0.045	3.841	0.8324
REXTR	5	None *	45.675	15.495	0	44.859	14.265	0
		At most 1	0.816	3.841	0.3663	0.816	3.841	0.3663

Continued Table: 4.15 Lag Selection and Cointegration

Variables		**Lag**	**Trace Stat**	**C.Value 0.05**	**Prob.**	**Max-Eig**	**C.Value 0.05**	**Prob.**
RBTR	5	None *	47.826	15.495	0	46.951	14.265	0
		At most 1	0.875	3.841	0.3495	0.875	3.841	0.3495
RSMTR	5	None *	51.361	15.495	0	48.086	14.265	0
		At most 1	3.274	3.841	0.0704	3.274	3.841	0.0704
REXUK	5	None *	45.873	15.495	0	45.309	14.265	0
		At most 1	0.563	3.841	0.4529	0.563	3.841	0.4529
RBUK	5	None *	46.671	15.495	0	44.992	14.265	0
		At most 1	1.679	3.841	0.195	1.679	3.841	0.195
RSMUK	5	None *	53.101	15.495	0	47.878	14.265	0
		At most 1 *	5.223	3.841	0.0223	5.223	3.841	0.0223
RBUS	5	None *	55.232	15.495	0	51.8	14.265	0
		At most 1	3.433	3.841	0.0639	3.433	3.841	0.0639
RSMUS	5	None *	47.049	15.495	0	46.456	14.265	0
		At most 1	0.592	3.841	0.4415	0.592	3.841	0.4415
REXVN	5	None *	45.121	15.495	0	44.686	14.265	0
		At most 1	0.435	3.841	0.5094	0.435	3.841	0.5094
RBVN	5	None *	46.829	15.495	0	44.986	14.265	0
		At most 1	1.843	3.841	0.1745	1.843	3.841	0.1745
RSMVN	5	None *	53.796	15.495	0	52.279	14.265	0
		At most 1	1.516	3.841	0.2182	1.516	3.841	0.2182

Table, *demonstrates co-integration relationship between crypto-currency market and each of the variables.*

Table 4.17: BEKK GARCH Analysis

	RCM-REXBR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00234	0.00024	9.73666	0.0000
Con.(REXBR)	-9.90E-05	0.00019	-0.51061	0.6096
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	2.34E-07	5.84E-07	0.4001	0.6891
M(1,2)	-1.31E-06	1.67E-06	-0.78336	0.4334
M(2,2)	2.06E-05	1.14E-05	1.80356	0.0713
A1(1,1)	-9.23E-06	2.62E-06	-3.52459	0.0004
A1(2,2)	0.84018	0.15868	5.29483	0.0000
B1(1,1)	1.00147	0.00012	8350.09	0.0000
B1(2,2)	0.96097	0.00964	99.7358	0.0000
Log Likelihood		8592.11		
	RCM-RBBR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.0023	0.00024	9.65655	0.0000
Con. (RBBR)	-0.0006	0.00021	-2.85322	0.0043
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	3.06E-07	6.01E-07	0.50917	0.6106
M(1,2)	-6.36E-07	4.73E-06	-0.13438	0.8931
M(2,2)	0.00012	5.24E-05	2.3278	0.0199
A1(1,1)	9.39E-06	2.59E-06	3.62132	0.0003
A1(2,2)	1.13999	0.21904	5.20439	0.0000
B1(1,1)	1.00145	0.00012	8620.99	0.0000
B1(2,2)	0.89771	0.02463	36.4436	0.0000
Log Likelihood		8443.18		

Continued Table: 4.17 BEKK GARCH Analysis

		RCM-RSMBR		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00253	0.00024	10.4041	0
Con.(RSMBR)	0.00058	0.00028	2.04144	0.0412
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	9.32E-08	5.03E-07	0.18522	0.8531
M(1,2)	-1.04E-06	2.51E-06	-0.41373	0.6791
M(2,2)	6.36E-05	3.34E-05	1.90004	0.0574
A1(1,1)	-8.81E-06	2.45E-06	-3.58913	0.0003
A1(2,2)	0.78304	0.15352	5.10063	0
B1(1,1)	1.00151	0.00012	8435.8	0
B1(2,2)	0.95428	0.01326	71.9812	0
Log Likelihood		8053.87		
		RCM-REXCA		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002582	0.000249	10.3675	0
Con.(REXCA)	-0.00022	9.41E-05	-2.29645	0.0217
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-4.40E-08	4.61E-07	-0.09531	0.9241
M(1,2)	-4.64E-08	3.53E-07	-0.13131	0.8955
M(2,2)	1.20E-06	1.19E-06	1.002573	0.3161
A1(1,1)	-8.49E-06	2.46E-06	-3.4497	0.0006
A1(2,2)	0.601906	0.116726	5.156551	0
B1(1,1)	1.001522	0.000123	8117.906	0
B1(2,2)	0.978357	0.006352	154.027	0
Log Likelihood		9743.518		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RBCA			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002498	0.000242	10.3006	0
Con. (RBCA)	-0.00086	0.000415	-2.06338	0.0391
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	7.86E-08	5.38E-07	0.146158	0.8838
M(1,2)	-3.43E-07	1.93E-06	-0.1772	0.8594
M(2,2)	1.48E-05	1.74E-05	0.848618	0.3961
A1(1,1)	9.35E-06	2.48E-06	3.773721	0.0002
A1(2,2)	0.715282	0.133513	5.357378	0
B1(1,1)	1.001492	0.000122	8237.472	0
B1(2,2)	0.976312	0.005906	165.3167	0
Log Likelihood		7338.244		
	RCM-RSMCA			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.958938	4.546857	0.210901	0.833
Con.(RSMCA)	0.000136	0.001857	0.072978	0.9418
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	25.71032	13.98571	1.838327	0.066
M(1,2)	8.45E-05	0.026637	0.003173	0.9975
M(2,2)	6.92E-06	2.33E-06	2.974914	0.0029
A1(1,1)	-0.00016	3.72E-05	-4.21108	0
A1(1,2)	0.008321	0.15514	0.053636	0.9572
A1(2,2)	-0.00033	4.30E-05	-7.63233	0
B1(1,1)	0.865175	0.072301	11.96625	0
B1(1,2)	0.929519	3.596769	0.258432	0.7961
B1(2,2)	0.979281	0.007093	138.0543	0
Log Likelihood		-142.779		

Continued Table: 4.17 BEKK GARCH Analysis

		RCM-REXGR		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00237	0.00024	9.79848	0
Con.(REXGR)	-8.39E-05	9.18E-05	-0.91434	0.3605
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-2.47E-08	5.12E-07	-0.04821	0.9615
M(1,2)	-8.12E-08	3.70E-07	-0.21934	0.8264
M(2,2)	8.65E-07	8.53E-07	1.01472	0.3102
A1(1,1)	9.52E-06	2.48E-06	3.8294	0.0001
A1(2,2)	0.62687	0.12433	5.04188	0
B1(1,1)	1.00151	0.00012	8235.91	0
B1(2,2)	0.97981	0.00533	183.739	0
Log Likelihood		9721.98		
		RCM-RBGR		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00215	0.00022	9.75534	0
Con. (RBGR)	-0.0031	0.00093	-3.35043	0.0008
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	5.41E-07	8.30E-07	0.65123	0.5149
M(1,2)	-3.39E-05	2.59E-05	-1.30748	0.191
M(2,2)	0.00117	0.00046	2.52936	0.0114
A1(1,1)	-1.14E-05	2.64E-06	-4.32105	0
A1(2,2)	2.11678	0.37809	5.5986	0
B1(1,1)	1.00142	0.00011	8905.81	0
B1(2,2)	0.84282	0.01014	83.1203	0
Log Likelihood		5139.31		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-REXGR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.0024	0.00024	10.2262	0
Con. (RSMGR)	0.00077	0.00019	4.10017	0
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	4.69E-07	6.21E-07	0.75491	0.4503
M(1,2)	-5.50E-07	1.10E-06	-0.50119	0.6162
M(2,2)	-3.77E-07	3.75E-06	-0.10043	0.92
A1(1,1)	8.31E-06	2.81E-06	2.95623	0.0031
A1(2,2)	0.80635	0.14965	5.38818	0
B1(1,1)	1.00144	0.00012	8439.18	0
B1(2,2)	0.97179	0.00548	177.444	0
Log Likelihood		8593.88		
	RCM-RBGR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.001991	0.000211	9.433028	0
Con. (REXJP)	-0.00012	0.000109	-1.08094	0.2797
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	1.40E-06	1.35E-06	1.042285	0.2973
M(1,2)	3.38E-06	6.20E-06	0.545568	0.5854
M(2,2)	4.73E-05	2.22E-05	2.130252	0.0332
A1(1,1)	1.22E-05	3.20E-06	3.810627	0.0001
A1(2,2)	1.822232	0.389189	4.682131	0
B1(1,1)	1.001404	0.00011	9137.014	0
B1(2,2)	0.866996	0.018779	46.16829	0
Log Likelihood		9458.905		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RBJP			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002032	0.000218	9.338795	0
Con. (RBJP)	-0.00275	0.000905	-3.04006	0.0024
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	1.23E-06	1.08E-06	1.136424	0.2558
M(1,2)	2.90E-05	5.14E-05	0.56501	0.5721
M(2,2)	0.002672	0.000999	2.674734	0.0075
A1(1,1)	1.14E-05	3.08E-06	3.692452	0.0002
A1(2,2)	2.599417	0.476333	5.457141	0
B1(1,1)	1.00127	0.000115	8698.99	0
B1(2,2)	0.747105	0.012074	61.87755	0
Log Likelihood		4854.357		
	RCM-RSMJP			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00239	0.000232	10.30966	0
Con. (RSMJP)	0.000877	0.000201	4.368162	0
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	8.41E-07	8.64E-07	0.973066	0.3305
M(1,2)	-1.51E-06	5.27E-06	-0.2873	0.7739
M(2,2)	6.03E-05	2.94E-05	2.051908	0.0402
A1(1,1)	9.85E-06	2.98E-06	3.29947	0.001
A1(2,2)	1.380336	0.261645	5.275614	0
B1(1,1)	1.001385	0.000115	8695.334	0
B1(2,2)	0.911567	0.014088	64.70645	0
Log Likelihood		8465.567		

Continued Table: 4.17 BEKK GARCH Analysis

		RCM-REXKO		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	-0.0001	0.00024	-0.73518	0.4622
Con. (REXKO)	1.58E+00	1.28E-06	12.3096	0
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	0.10533	0.0587	1.79455	0.0727
M(1,2)	0.00186	0.00112	1.66262	0.0964
M(2,2)	-1.79E-05	8.08E-06	-2.21219	0.027
A1(1,1)	0.02866	0.00812	3.53044	0.0004
A1(2,2)	-0.79788	0.23337	-3.41899	0.0006
B1(1,1)	1.00092	6.36E-05	15733	0
B1(2,2)	1.00139	0.00013	8001.03	0
Log Likelihood		13936.5		
		RCM-RBKO		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00239	0.00024	9.82275	0
Con. (RBKO)	-0.0004	0.00024	-1.89006	0.0587
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	1.79E-08	5.08E-07	0.03517	0.9719
M(1,2)	1.06E-06	1.19E-06	0.88881	0.3741
M(2,2)	8.43E-06	6.26E-06	1.34672	0.1781
A1(1,1)	-9.34E-06	2.47E-06	-3.77699	0.0002
A1(2,2)	0.65916	0.11583	5.69092	0
B1(1,1)	1.00148	0.00012	8238.06	0
B1(2,2)	0.97478	0.00598	163.058	0
Log Likelihood		8249.52		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RBKO			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
	RCM-RSMKO			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00255	0.00024	10.5988	0
Con. (RSMKO)	0.00046	0.00014	3.28134	0.001
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	2.37E-07	5.44E-07	0.43653	0.6625
M(1,2)	-1.33E-06	1.53E-06	-0.8691	0.3848
M(2,2)	2.10E-05	1.18E-05	1.78811	0.0738
A1(1,1)	-8.97E-06	2.47E-06	-3.62857	0.0003
A1(2,2)	0.74224	0.14695	5.05086	0
B1(1,1)	1.00144	0.00012	8375.27	0
B1(2,2)	0.94751	0.01638	57.8436	0
Log Likelihood		9155.33		
	RCM-REXRU			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002644	0.000252	10.47861	0
Con.(REXRU)	-0.00027	0.000167	-1.64096	0.1008
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-1.40E-07	4.04E-07	-0.34637	0.7291
M(1,2)	6.33E-07	8.27E-07	0.764711	0.4444
M(2,2)	7.00E-06	3.20E-06	2.187184	0.0287
A1(1,1)	8.12E-06	2.26E-06	3.589227	0.0003
A1(2,2)	0.700878	0.117123	5.984107	0
B1(1,1)	1.001548	0.000126	7918.097	0
B1(2,2)	0.965602	0.006748	143.0989	0
Log Likelihood		8671.534		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RBRU			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.001876	0.000174	10.78409	0
Con. (RBRU)	-7.23E-05	0.000145	-0.50046	0.6168
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	0.01867	3.079193	0.006063	0.9952
M(1,2)	-0.00819	1.351684	-0.00606	0.9952
M(2,2)	0.000505	0.083678	0.006033	0.9952
A1(1,1)	-0.00033	0.02735	-0.01216	0.9903
A1(2,2)	65.49637	5399.084	0.012131	0.9903
B1(1,1)	1.00109	8.80E-05	11381.99	0
B1(2,2)	0.972904	0.003751	259.3832	0
Log Likelihood		8789.363		
	RCM-RSMRU			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002525	0.000244	10.33298	0
Con.(RSMRU)	0.000483	0.000198	2.440494	0.0147
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	6.98E-08	4.58E-07	0.152366	0.8789
M(1,2)	9.44E-07	2.53E-06	0.372876	0.7092
M(2,2)	5.07E-05	2.24E-05	2.266541	0.0234
A1(1,1)	-8.15E-06	2.43E-06	-3.36009	0.0008
A1(2,2)	0.852615	0.157886	5.400202	0
B1(1,1)	1.001518	0.000121	8282.191	0
B1(2,2)	0.932961	0.017739	52.59381	0
Log Likelihood		8570.978		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-REXTR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00251	0.00024	10.4352	0
Con. (REXTR)	-0.0003	0.00016	-2.13255	0.033
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	4.37E-07	6.18E-07	0.70744	0.4793
M(1,2)	6.89E-07	3.56E-06	0.19376	0.8464
M(2,2)	6.35E-05	2.68E-05	2.36636	0.018
A1(1,1)	8.97E-06	2.69E-06	3.33608	0.0008
A1(2,2)	1.27173	0.23672	5.37241	0
B1(1,1)	1.00139	0.00012	8486.89	0
B1(2,2)	0.8832	0.02263	39.0206	0
Log Likelihood		8883.4		
	RCM-RBTR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00282	0.00028	10.2147	0
Con. (RBTR)	0.00011	0.00028	0.38637	0.6992
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-1.12E-08	2.73E-07	-0.04092	0.9674
M(1,2)	4.51E-07	3.24E-08	13.9345	0
M(2,2)	-6.08E-06	1.04E-10	-58391	0
A1(1,1)	-4.56E-06	2.13E-06	-2.1357	0.0327
A1(2,2)	-0.02216	0.00291	-7.6265	0
B1(1,1)	1.00153	0.00013	7892.16	0
B1(2,2)	1.00375	6.30E-05	15924.7	0
Log Likelihood		8011.64		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RSMTR			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00223	0.00022	10.1489	0
Con. (RSMTR)	0.00043	0.00027	1.5799	0.1141
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	2.03E-06	1.59E-06	1.27475	0.2024
M(1,2)	0.00019	0.00705	0.02708	0.9784
M(2,2)	0.00364	0.05549	0.06566	0.9477
A1(1,1)	-1.00E-05	3.54E-06	-2.83634	0.0046
A1(2,2)	-0.00017	7.89836	-2.15E-05	1
B1(1,1)	1.00137	0.00011	9228.52	0
B1(2,2)	-0.1719	43.2145	-0.00398	0.9968
Log Likelihood		8140.95		
	RCM-REXUK			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002293	0.000238	9.647259	0
Con. (REXUK)	-6.81E-05	9.79E-05	-0.69535	0.4868
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-9.89E-08	4.93E-07	-0.20073	0.8409
M(1,2)	-2.31E-07	3.77E-07	-0.61235	0.5403
M(2,2)	1.03E-06	9.10E-07	1.128683	0.259
A1(1,1)	-9.64E-06	2.41E-06	-3.99706	0.0001
A1(2,2)	0.607778	0.117744	5.161837	0
B1(1,1)	1.001537	0.000119	8416.266	0
B1(2,2)	0.979585	0.004638	211.2218	0
Log Likelihood		9630.458		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RBUK			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002484	0.00024	10.33466	0
Con. (RBUK)	-0.00094	0.000515	-1.82601	0.0678
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	3.40E-08	5.60E-07	0.060718	0.9516
M(1,2)	-5.12E-07	1.94E-06	-0.26421	0.7916
M(2,2)	3.41E-05	2.38E-05	1.434146	0.1515
A1(1,1)	-1.00E-05	2.49E-06	-4.02592	0.0001
A1(2,2)	0.654022	0.120639	5.42134	0
B1(1,1)	1.00149	0.000119	8394.832	0
B1(2,2)	0.97952	0.004629	211.5982	0
Log Likelihood		6966.372		
	RCM-RSMUK			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.003066	0.000277	11.06248	0
Con.(RSMUK)	0.000159	0.000163	0.977869	0.3281
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-4.59E-07	2.59E-07	-1.77561	0.0758
M(1,2)	-5.06E-08	2.26E-08	-2.23524	0.0254
M(2,2)	-9.80E-07	6.37E-07	-1.53918	0.1238
A1(1,1)	-6.26E-06	1.53E-06	-4.09486	0
A1(2,2)	0.012453	0.001372	9.074351	0
B1(1,1)	1.001702	0.000146	6855.919	0
B1(2,2)	1.001779	0.001203	832.5755	0
Log Likelihood		8930.516		

Continued Table: 4.17 BEKK GARCH Analysis

		RCM-REXVN		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00669	0.00048	13.9462	0
Con.(REXVN)	2.17E-09	6.62E-06	0.00033	0.9997
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	0.00061	0.00106	0.57229	0.5671
M(1,2)	-5.40E-10	2.42E-07	-0.00223	0.9982
M(2,2)	1.19E-12	1.05E-12	1.12715	0.2597
A1(1,1)	6.89E-07	5.86E-05	0.01177	0.9906
A1(2,2)	1.83187	0.22581	8.11249	0
B1(1,1)	0.87642	0.22935	3.82136	0.0001
B1(2,2)	0.74371	0.00815	91.2102	0
Log Likelihood		11962.9		
		RCM-RBVN		
		Mean Equation		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00671	0.00047	14.1527	0
Con. (RBVN)	-2.28E-09	2.07E-05	-0.00011	0.9999
		Covariance Specifications		
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	0.00033	0.00035	0.94095	0.3467
M(1,2)	1.47E-11	1.29E-06	1.14E-05	1
M(2,2)	2.17E-13	3.00E-13	0.7244	0.4688
A1(1,1)	3.05E-06	9.06E-05	0.03362	0.9732
A1(2,2)	1.39974	0.20273	6.90445	0
B1(1,1)	0.9469	0.05631	16.8146	0
B1(2,2)	0.80995	0.0045	180.087	0
Log Likelihood		9969.84		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RSMVN			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.0027	0.00025	11.0196	0
Con.(RSMVN)	0.00083	0.00018	4.56098	0
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	2.09E-07	4.88E-07	0.42766	0.6689
M(1,2)	6.05E-07	2.81E-06	0.21536	0.8295
M(2,2)	4.68E-05	1.89E-05	2.48074	0.0131
A1(1,1)	-8.21E-06	2.56E-06	-3.20635	0.0013
A1(2,2)	1.06426	0.18483	5.75813	0
B1(1,1)	1.00144	0.00012	8363.33	0
B1(2,2)	0.90961	0.0174	52.2781	0
Log Likelihood		8663.54		
	RCM-RBUS			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.00248	0.000246	10.10117	0
Con. (RBUS)	-0.0002	0.000353	-0.57698	0.564
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	-5.81E-08	4.61E-07	-0.12592	0.8998
M(1,2)	9.80E-07	1.23E-06	0.799592	0.4239
M(2,2)	1.04E-05	1.05E-05	0.996768	0.3189
A1(1,1)	8.79E-06	2.37E-06	3.705828	0.0002
A1(2,2)	0.537285	0.10796	4.976726	0
B1(1,1)	1.001523	0.000128	7841.964	0
B1(2,2)	0.983511	0.00494	199.111	0
Log Likelihood		7635.333		

Continued Table: 4.17 BEKK GARCH Analysis

	RCM-RSMUS			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002412	0.000236	10.23933	0
Con. (RSMUS)	0.00071	0.000125	5.684077	0
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	4.08E-07	6.53E-07	0.624194	0.5325
M(1,2)	5.62E-07	2.40E-06	0.234101	0.8149
M(2,2)	1.92E-05	8.41E-06	2.285062	0.0223
A1(1,1)	-9.54E-06	2.64E-06	-3.61176	0.0003
A1(2,2)	1.33286	0.228856	5.824018	0
B1(1,1)	1.001456	0.000115	8693.384	0
B1(2,2)	0.91018	0.014264	63.80978	0
Log Likelihood		9171.604		
	RCM-RGM			
	Mean Equation			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
Con. (RCM)	0.002077	0.000218	9.516471	0
Con. (RGM)	-0.00011	0.00019	-0.56079	0.5749
	Covariance Specifications			
	Coeff.	**Std. Err**	**Z-Stat**	**Prob.**
M(1,1)	1.24E-06	1.23E-06	1.001219	0.3167
M(1,2)	-3.60E-06	5.62E-05	-0.06408	0.9489
M(2,2)	0.001381	0.000513	2.690369	0.0071
A1(1,1)	-1.25E-05	3.06E-06	-4.07737	0
A1(2,2)	2.159624	0.429764	5.025143	0
B1(1,1)	1.001437	0.000107	9381.931	0
B1(2,2)	0.127022	0.139253	0.912172	0.3617
Log Likelihood		8535.88		

Note: Table 4.17, exhibits the maximum likelihood estimation for the BEKK GARCH model.

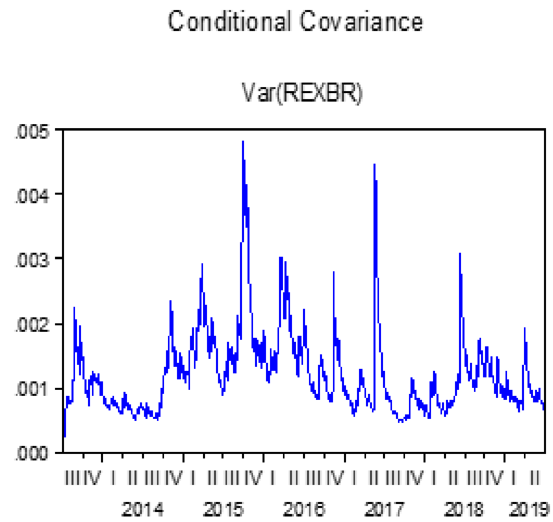

Figure. 4.6: Graphical Representation of Variance of REXBR from 2013-2019

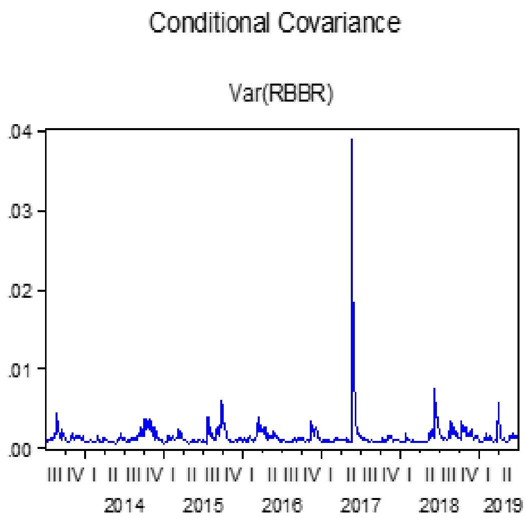

Figure. 4.7: Graphical Representation of Variance of REXBR from 2013-2019

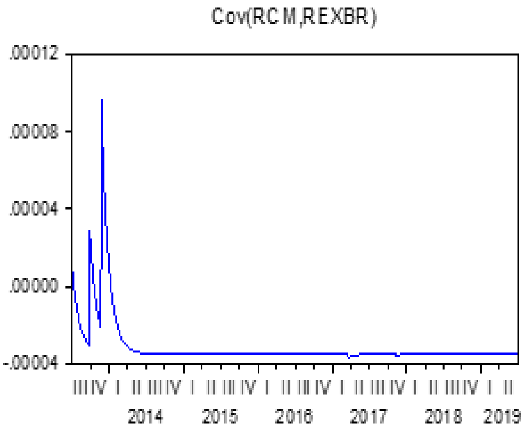

Figure. 4.8: Graphical Representation of Covariance Between RCM and REXBR from 2013-2019

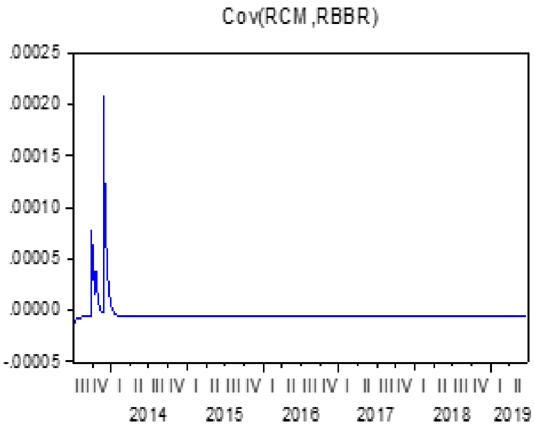

Figure. 4.9: Graphical Representation of Covariance Between RCM and RBBR from 2013-2019

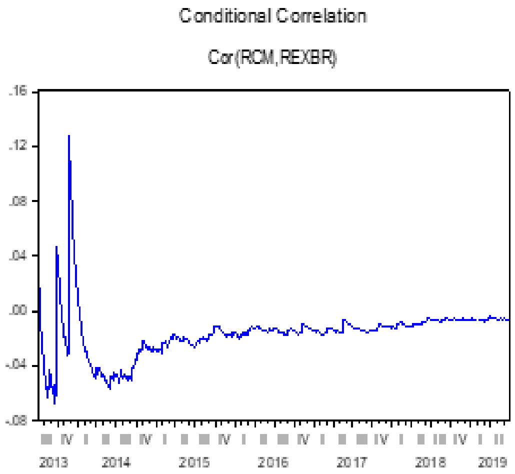

Figure. 4.10: Graphical Representation of Correlation Between RCM and REXBR from 2013-2019

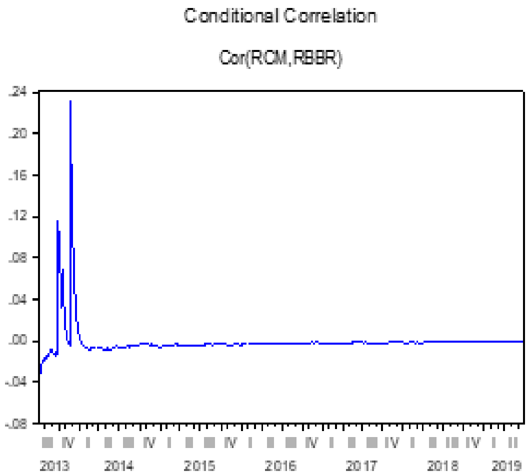

Figure. 4.11: Graphical Representation of Correlation Between RCM and RBBR from 2013-2019

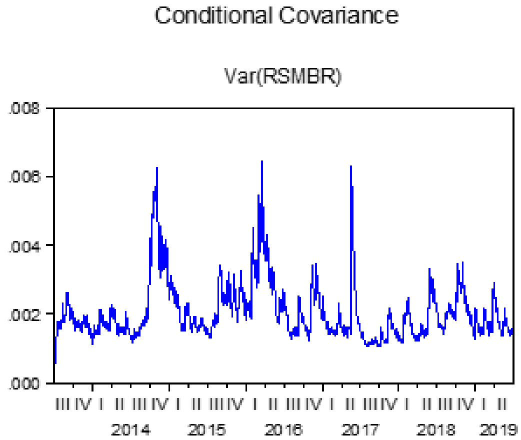

Figure. 4.12: Graphical Representation of Variance of RSMBR from 2013-2019

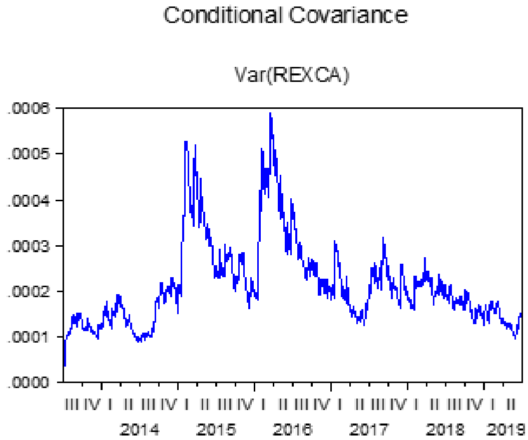

Figure. 4.13: Graphical Representation of Variance of REXCA from 2013-2019

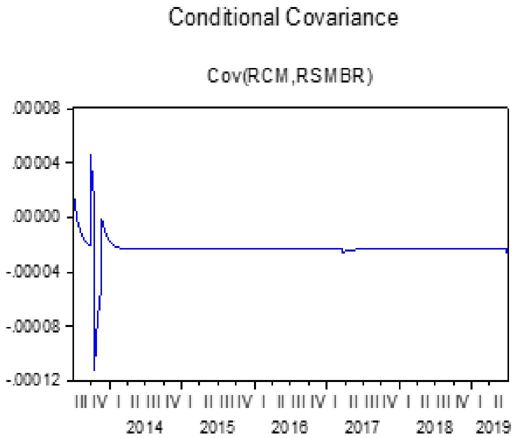

Figure. 4.14: Graphical Representation of Covariance Between RCM and RSMBR from 2013-2019

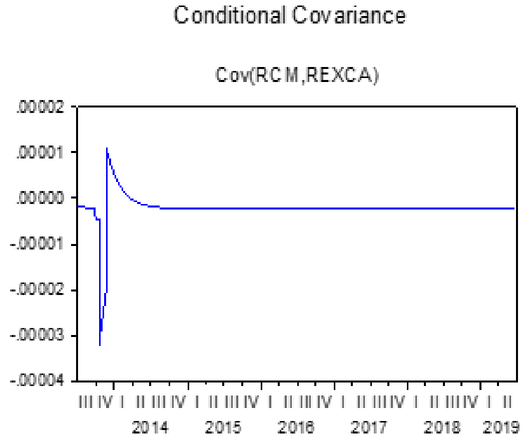

Figure. 4.15: Graphical Representation of Covariance Between RCM and REXCA from 2013-2019

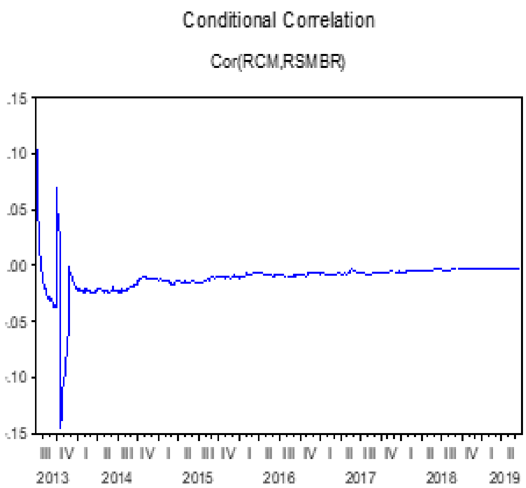

Figure. 4.16: Graphical Representation of Correlation Between RCM and RSMBR from 2013-2019

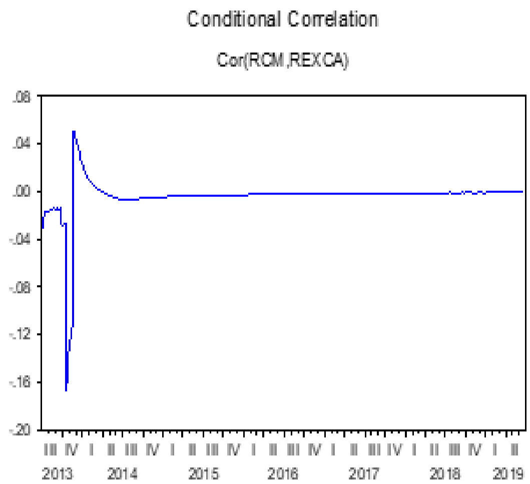

Figure. 4.17: Graphical Representation of Correlation Between RCM and REXCA from 2013-2019

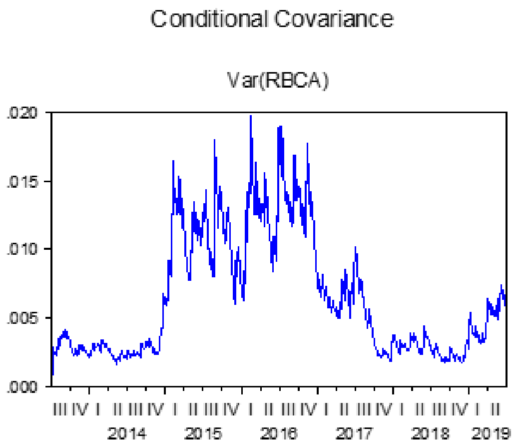

Figure. 4.18: Graphical Representation of Variance of RBCA from 2013-2019

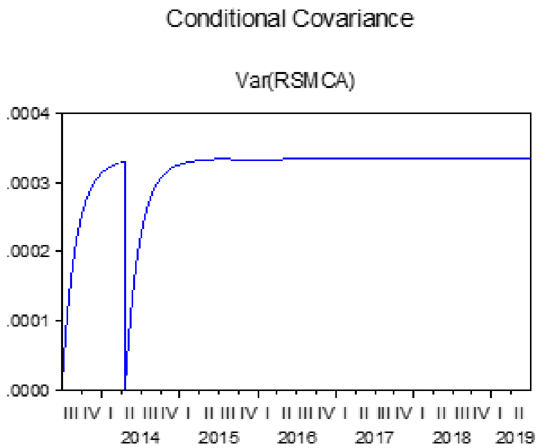

Figure. 4.19: Graphical Representation of Variance of RSMCA from 2013-2019

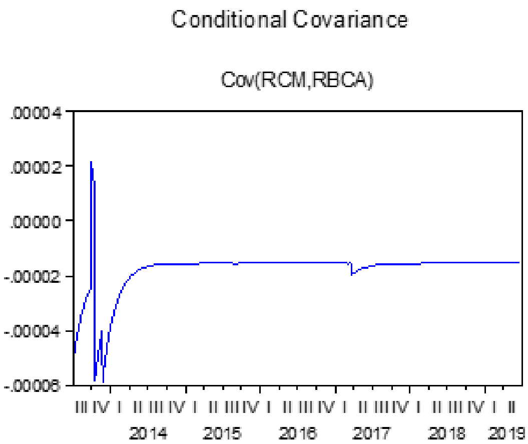

Figure. 4.20: Graphical Representation of Covariance Between RCM and RBCA from 2013-2019

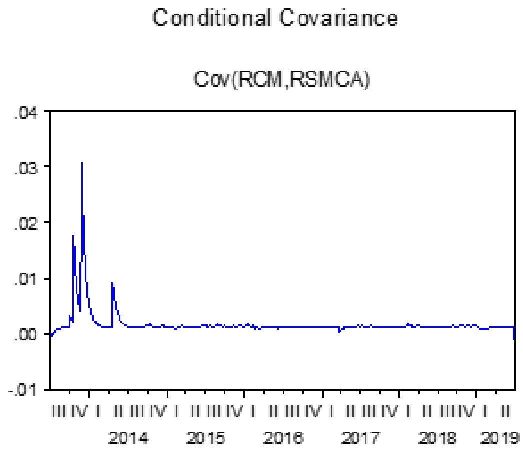

Figure. 4.21: Graphical Representation of Covariance Between RCM and RSMCA from 2013-2019

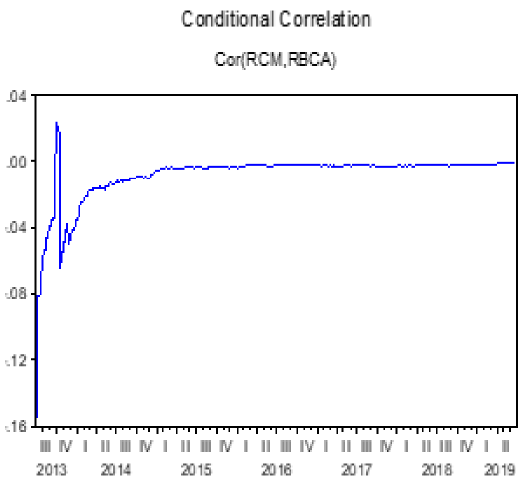

Figure. 4.22: Graphical Representation of Correlation Between RCM and RBCA from 2013-2019

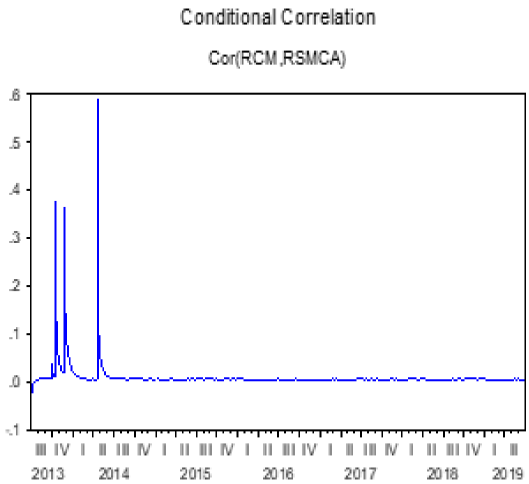

Figure. 4.23: Graphical Representation of Correlation Between RCM and RSMCA from 2013-2019

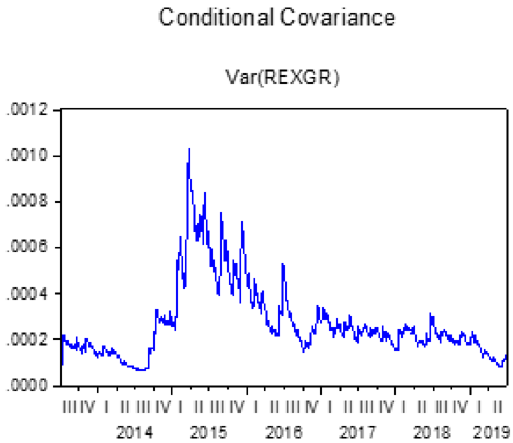

Figure. 4.24: Graphical Representation of Variance of REXGR from 2013-2019

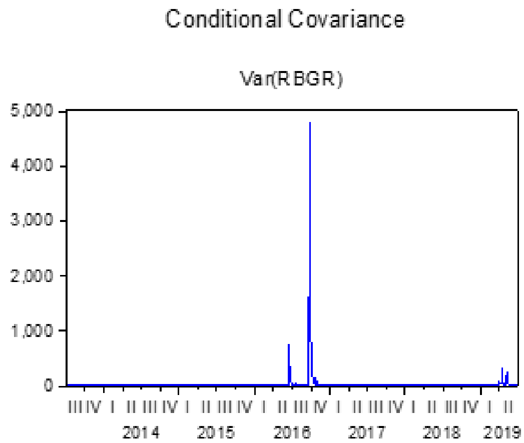

Figure. 4.25: Graphical Representation of Variance of RBGR from 2013-2019

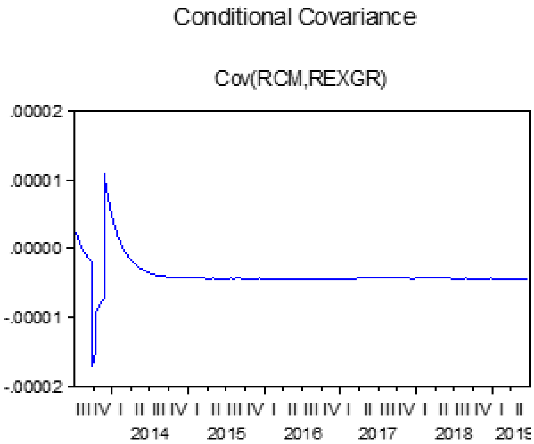

Figure. 4.26: Graphical Representation of Covariance Between RCM and REXGR from 2013-2019

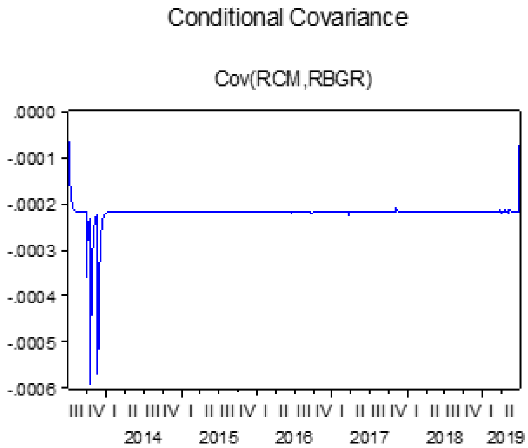

Figure. 4.27: Graphical Representation of Covariance Between RCM and RBGR from 2013-2019

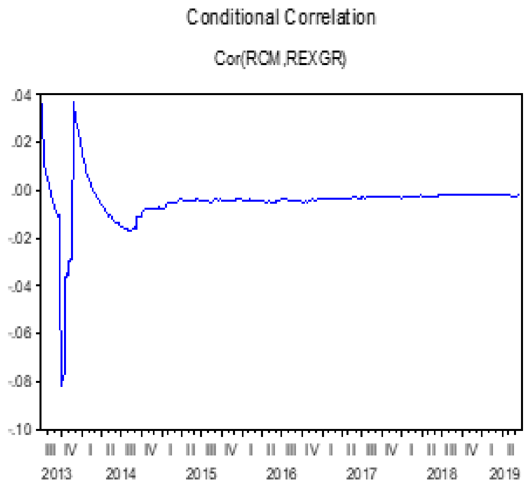

Figure. 4.28: Graphical Representation of Correlation Between RCM and REXGR from 2013-2019

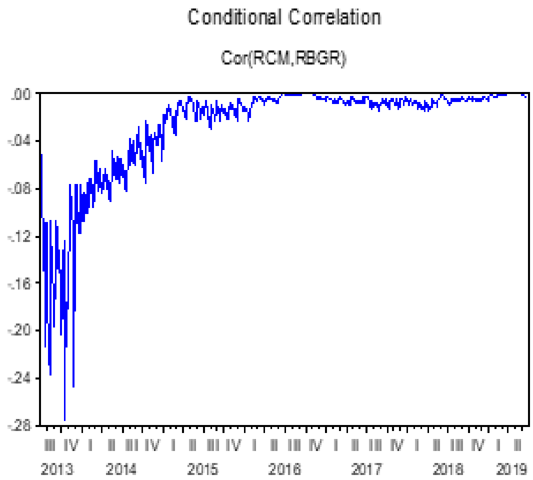

Figure. 4.29: Graphical Representation of Correlation Between RCM and RBGR from 2013-2019

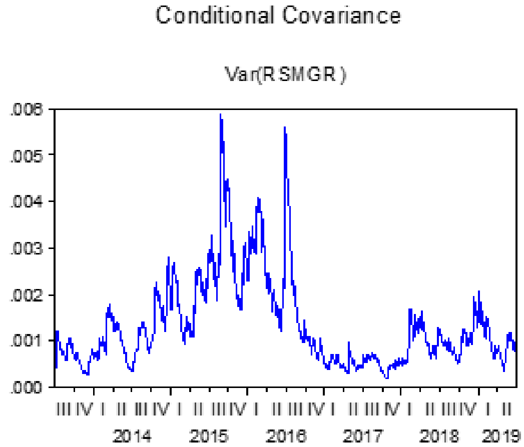

Figure. 4.30: Graphical Representation of Variance of RSMGR from 2013-2019

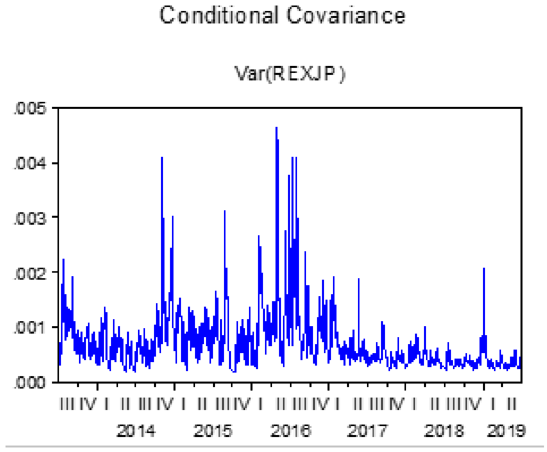

Figure. 4.31: Graphical Representation of Variance of REXJP from 2013-2019

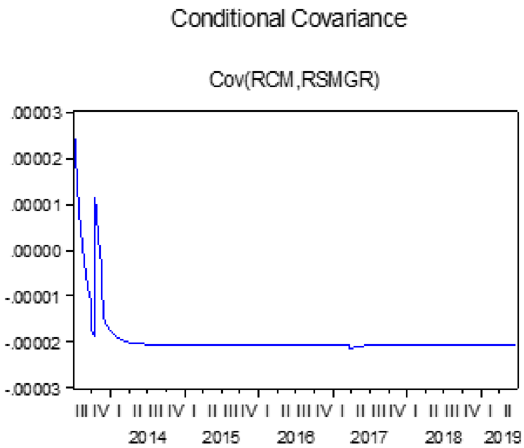

Figure. 4.32: Graphical Representation of Covariance Between RCM and RSMGR from 2013-2019

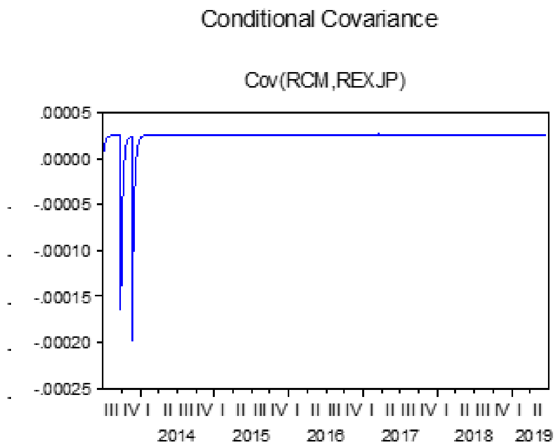

Figure. 4.33: Graphical Representation of Covariance Between RCM and REXJP from 2013-2019

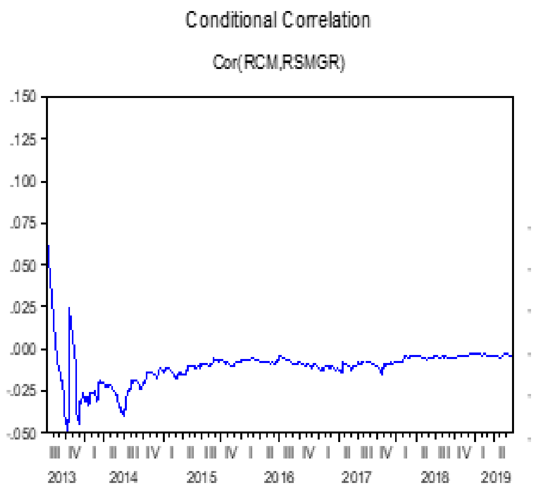

Figure. 4.34: Graphical Representation of Correlation Between RCM and RSMGR from 2013-2019

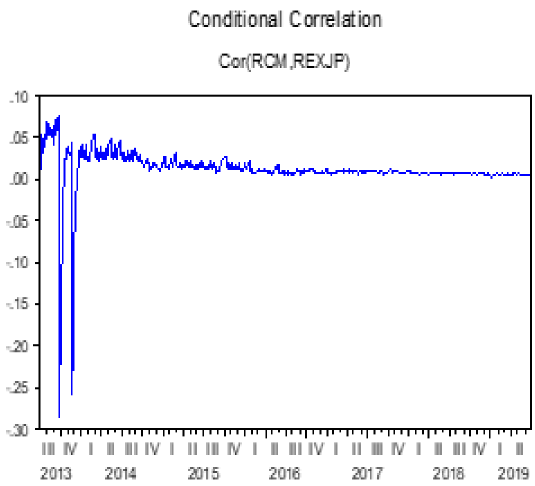

Figure. 4.35: Graphical Representation of Correlation Between RCM and REXJP from 2013-2019

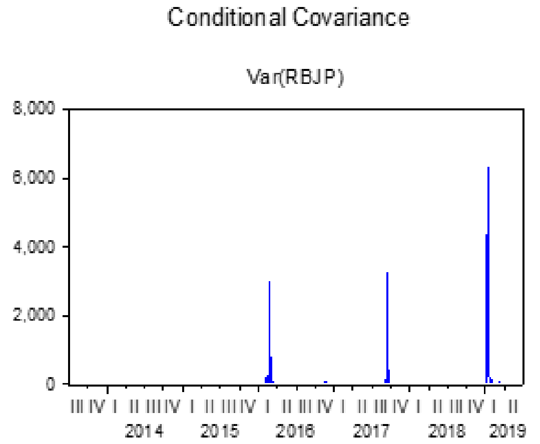

Figure. 4.36: Graphical Representation of Variance of RBJP from 2013-2019

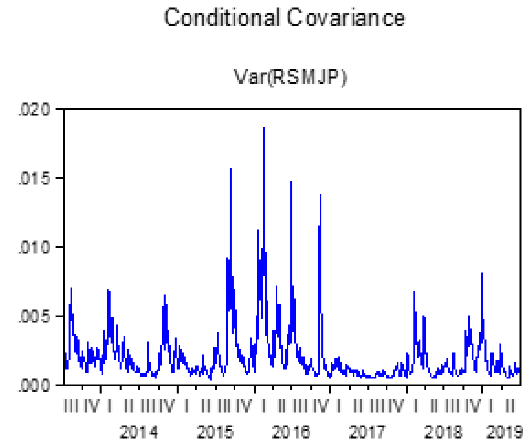

Figure. 4.37: Graphical Representation of Variance of RSMJP from 2013-2019

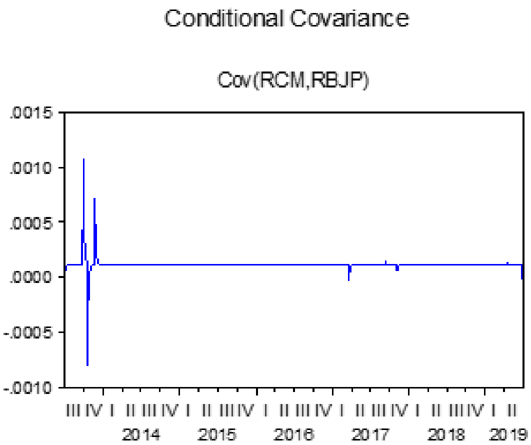

Figure. 4.38: Graphical Representation of Covariance Between RCM and RBJP from 2013-2019

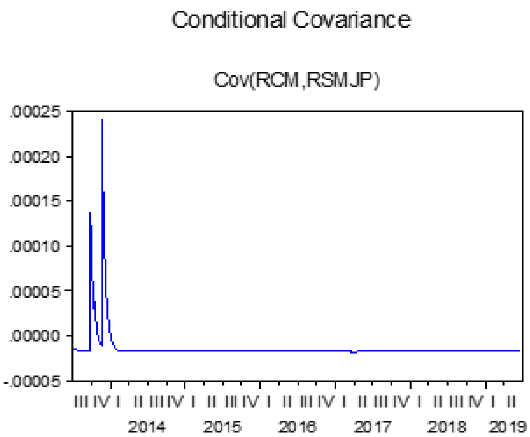

Figure. 4.39: Graphical Representation of Covariance Between RCM and RSMJP from 2013-2019

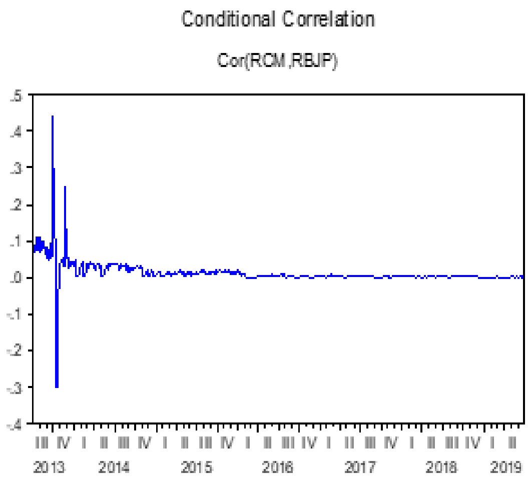

Figure. 4.40: Graphical Representation of Correlation Between RCM and RBJP from 2013-2019

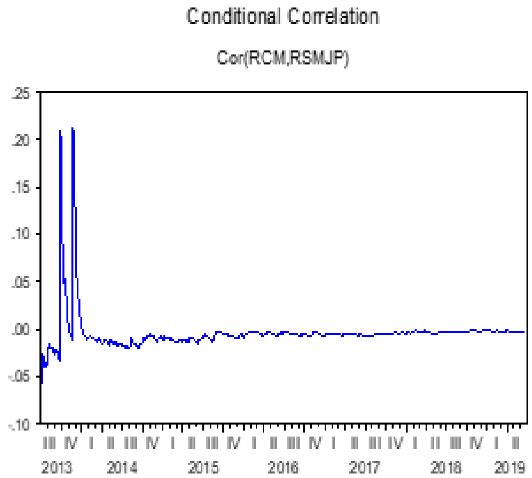

Figure. 4.41: Graphical Representation of Correlation Between RCM and RSMJP from 2013-2019

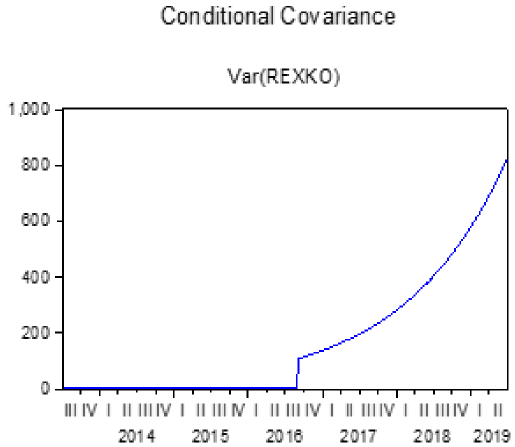

Figure. 4.42: Graphical Representation of Variance of REXKO from 2013-2019

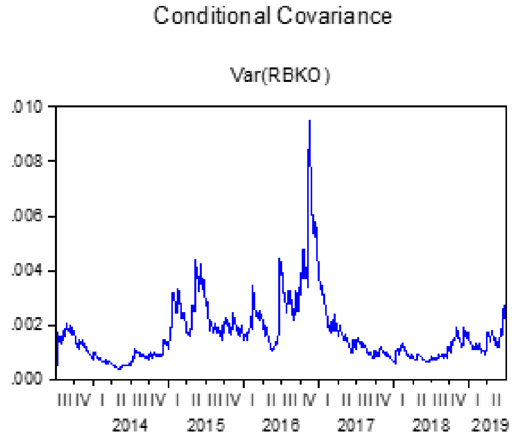

Figure. 4.43: Graphical Representation of Variance of RBKO from 2013-2019

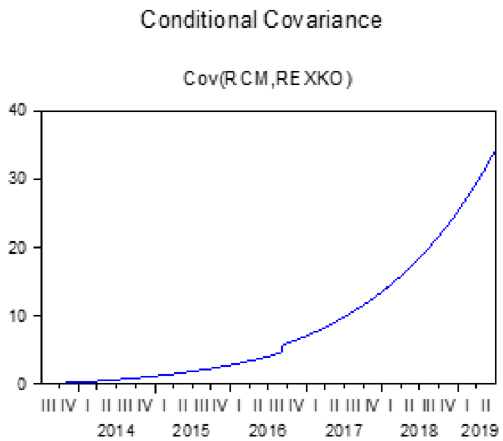

Figure. 4.44: Graphical Representation of Covariance Between RCM and REXKO from 2013-2019

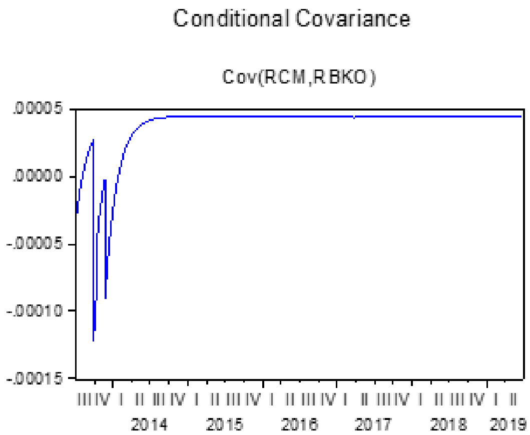

Figure. 4.45: Graphical Representation of Covariance Between RCM and RBKO from 2013-2019

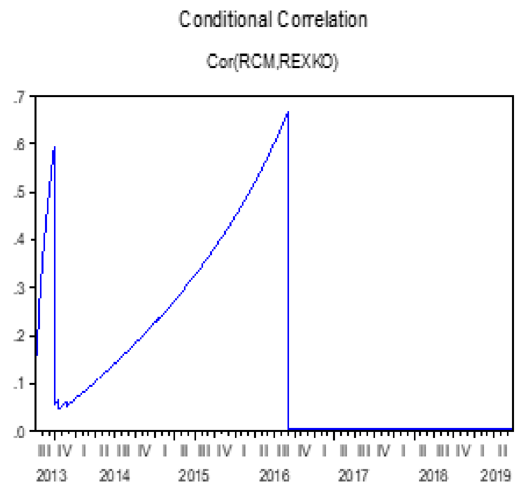

Figure. 4.46: Graphical Representation of Correlation Between RCM and REXKO from 2013-2019

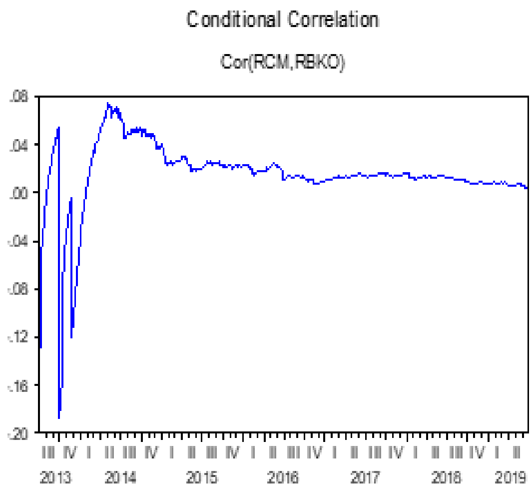

Figure. 4.47: Graphical Representation of Correlation Between RCM and RBKO from 2013-2019

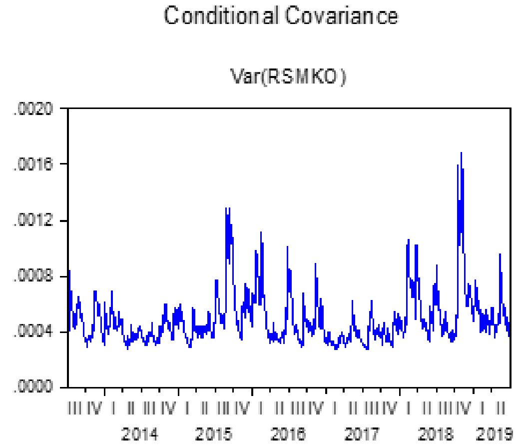

Figure. 4.48: Graphical Representation of Variance of RSMKO from 2013-2019

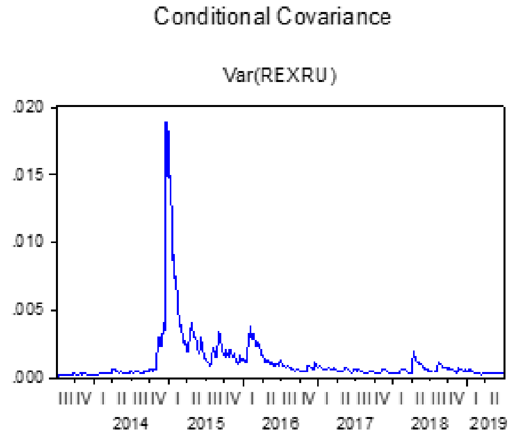

Figure. 4.49: Graphical Representation of Variance of REXRU from 2013-2019

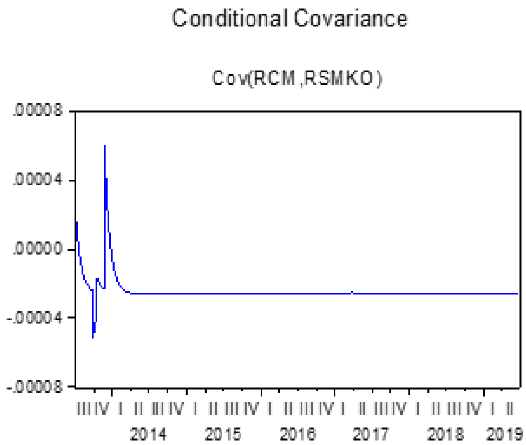

Figure. 4.50: Graphical Representation of Covariance Between RCM and RSMKO from 2013-2019

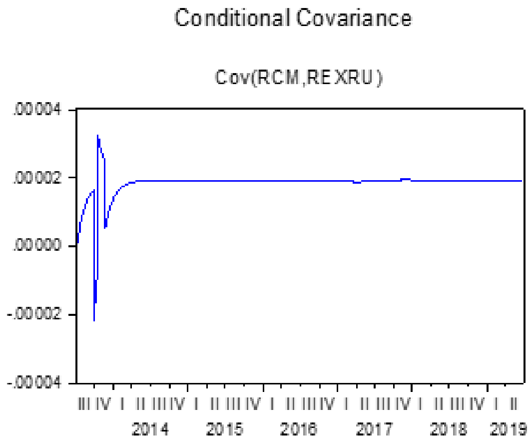

Figure. 4.51: Graphical Representation of Covariance Between RCM and REXRU from 2013-2019

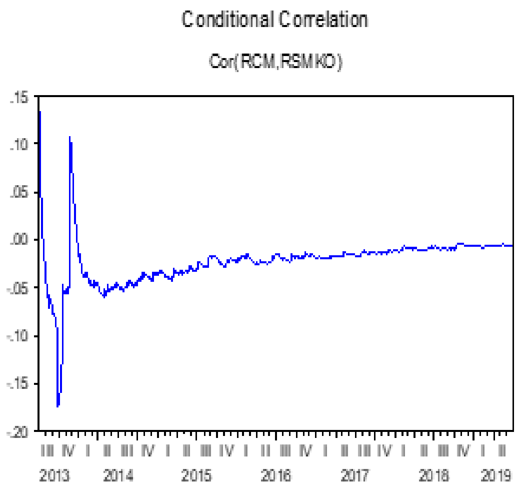

Figure. 4.52: Graphical Representation of Correlation Between RCM and RSMKO from 2013-2019

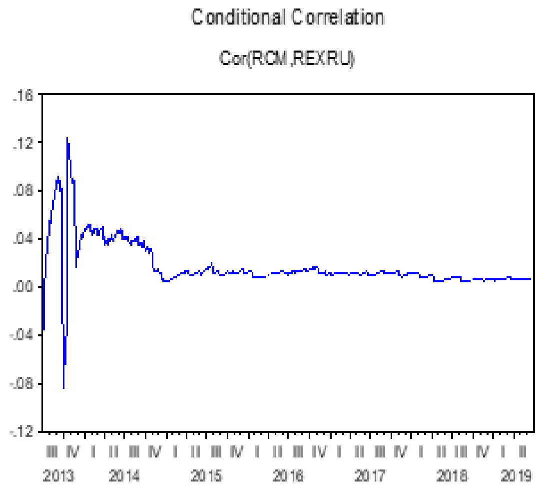

Figure. 4.53: Graphical Representation of Correlation Between RCM and REXRU from 2013-2019

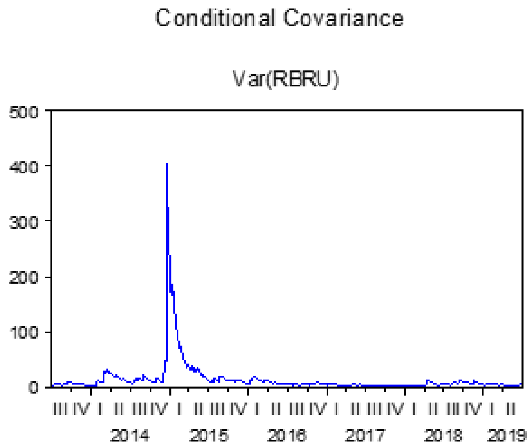

Figure. 4.54: Graphical Representation of Variance of RBRU from 2013-2019

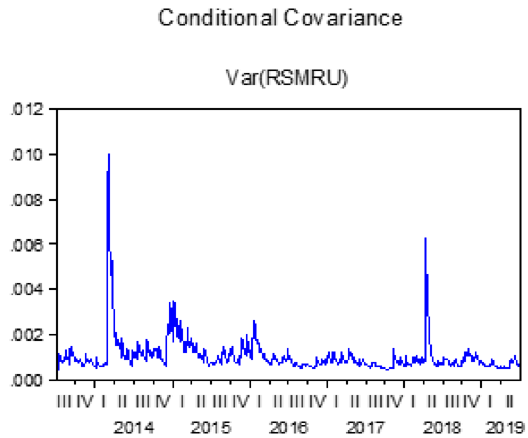

Figure. 4.55: Graphical Representation of Variance of RSMRU from 2013-2019

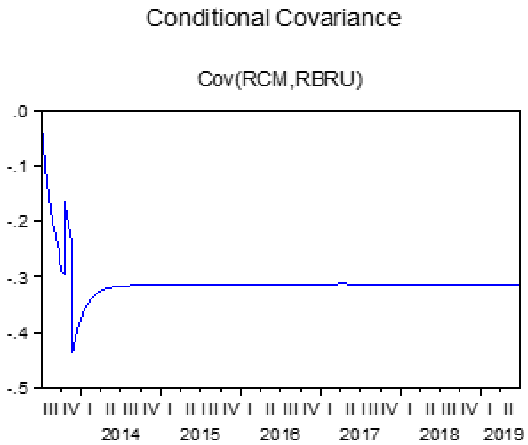

Figure. 4.56: Graphical Representation of Covariance Between RCM and RBRU from 2013-2019

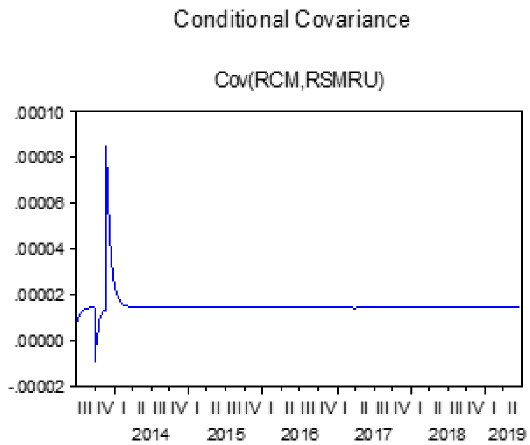

Figure. 4.57: Graphical Representation of Covariance Between RCM and RSMRU from 2013-2019

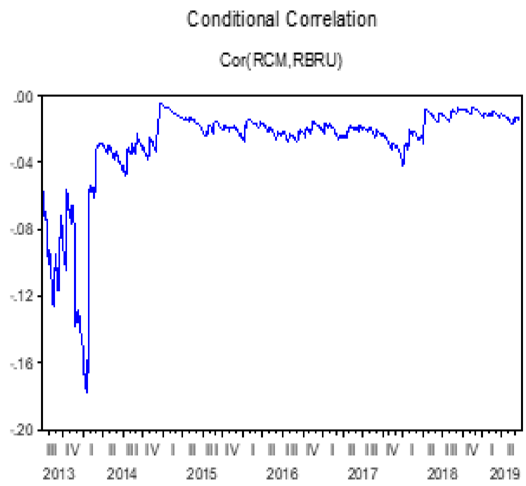

Figure. 4.58: Graphical Representation of Correlation Between RCM and RBRU from 2013-2019

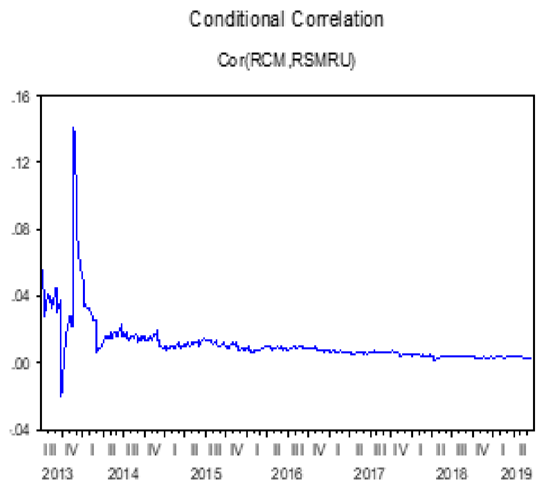

Figure. 4.59: Graphical Representation of Correlatio Between RCM and RSMRU from 2013-2019

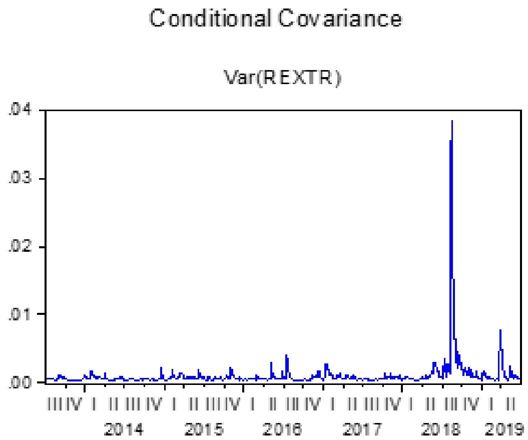

Figure. 4.60: Graphical Representation of Variance of REXTR from 2013-2019

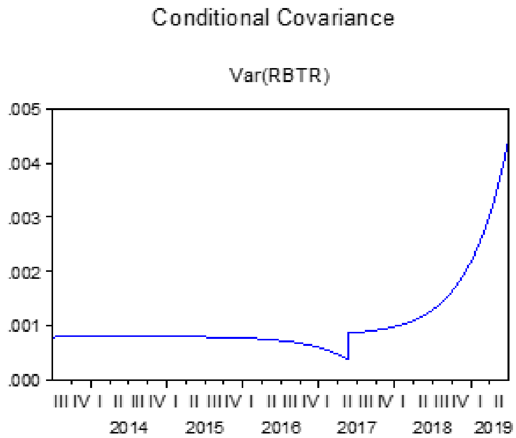

Figure. 4.61: Graphical Representation of Variance of RBTR from 2013-2019

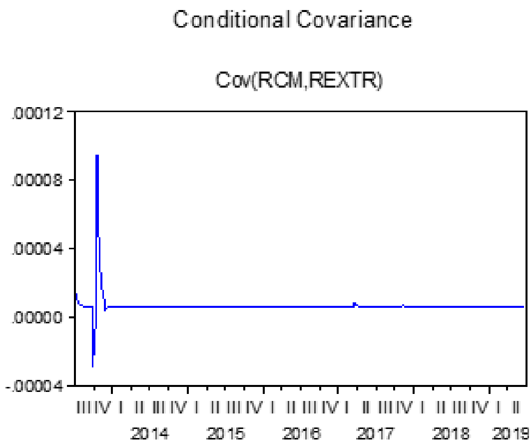

Figure. 4.62: Graphical Representation of Covariance Between RCM and REXTR from 2013-2019

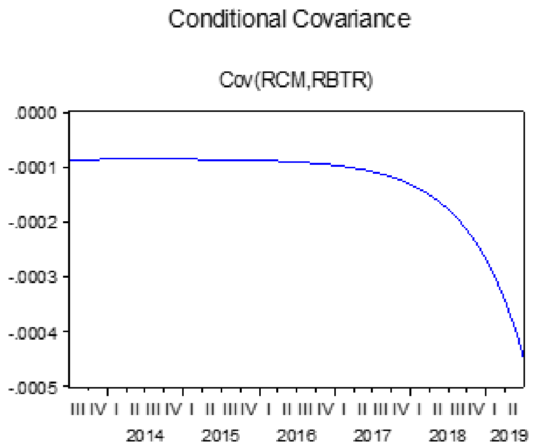

Figure. 4.63: Graphical Representation of Covariance Between RCM and RBTR from 2013-2019

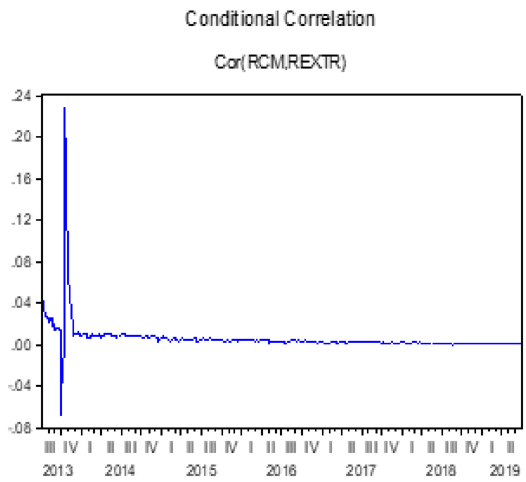

Figure. 4.64: Graphical Representation of Correlation Between RCM and REXTR from 2013-2019

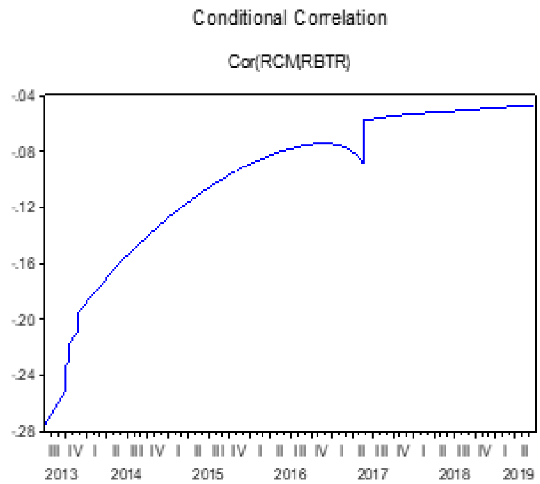

Figure. 4.65: Graphical Representation of Correlation Between RCM and RBTR from 2013-2019

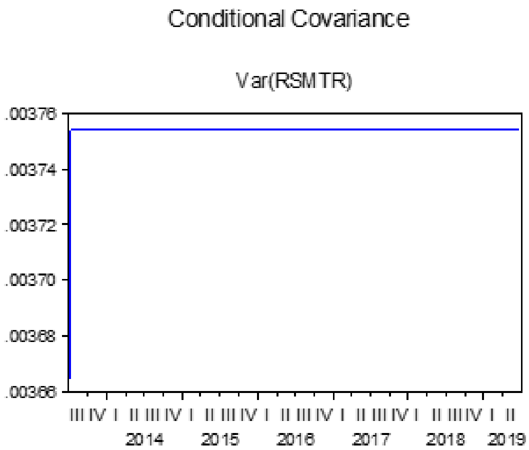

Figure. 4.66: Graphical Representation of Variance of RSMTR from 2013-2019

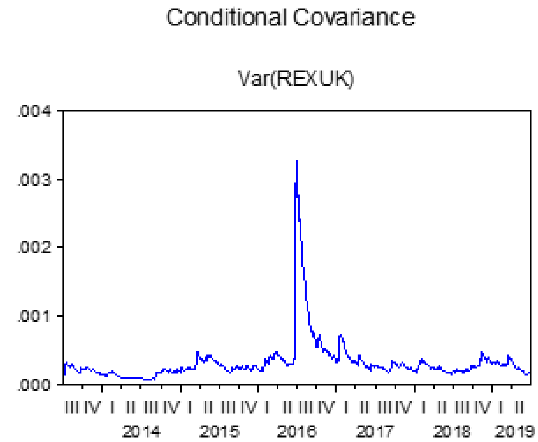

Figure. 4.67: Graphical Representation of Variance of REXUK from 2013-2019

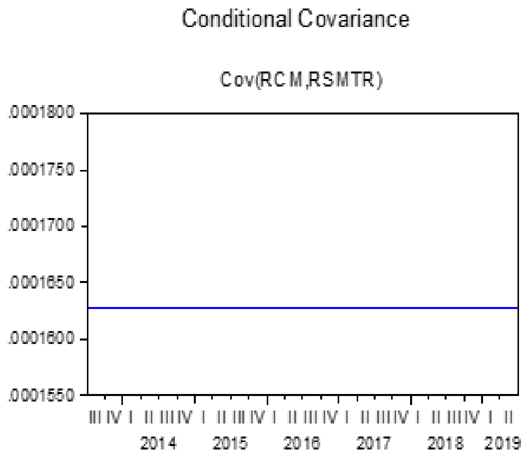

Figure. 4.68: Graphical Representation of Covariance Between RCM and RSMTR from 2013-2019

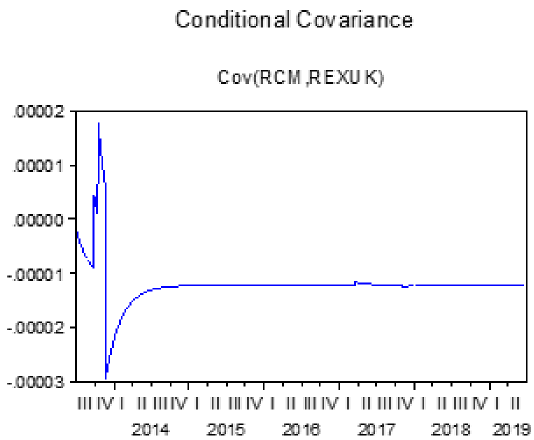

Figure. 4.69: Graphical Representation of Covariance Between RCM and REXUK from 2013-2019

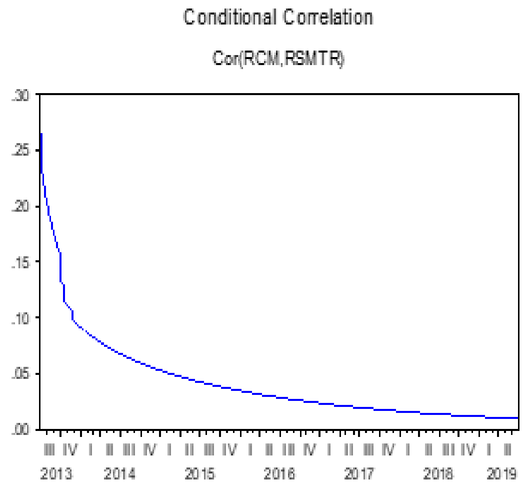

Figure. 4.70: Graphical Representation of Correlation Between RCM and RSMTR from 2013-2019

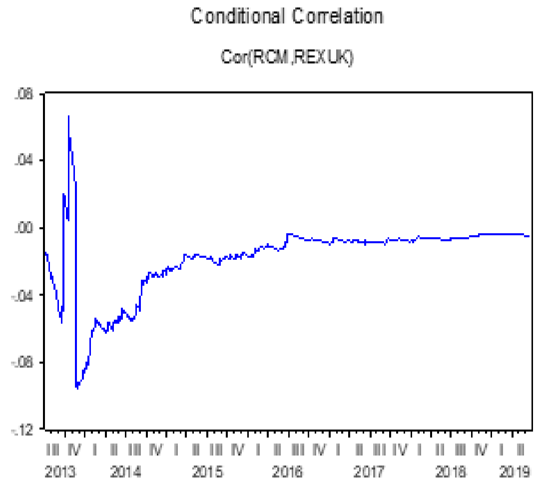

Figure. 4.71: Graphical Representation of Correlatio Between RCM and REXUK from 2013-2019

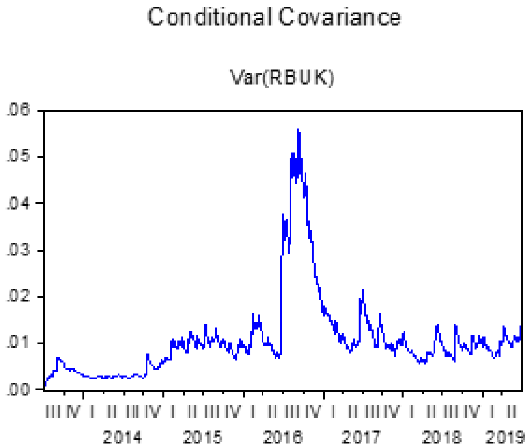

Figure. 4.72: Graphical Representation of Variance of RBUK from 2013-2019

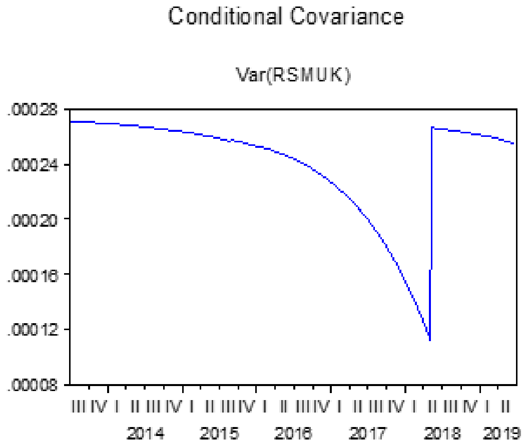

Figure. 4.73: Graphical Representation of Variance of RSMUK from 2013-2019

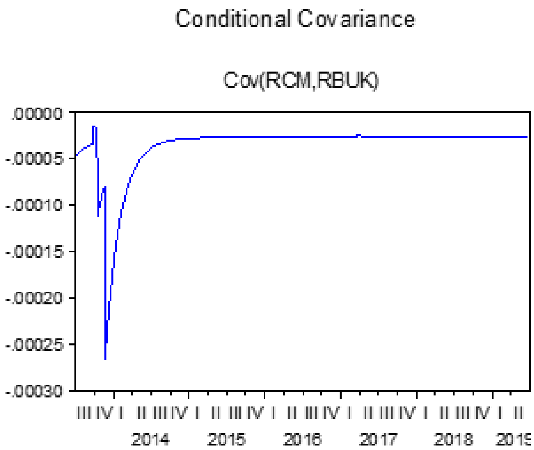

Figure. 4.74: Graphical Representation of Covariance Between RCM and RBUK from 2013-2019

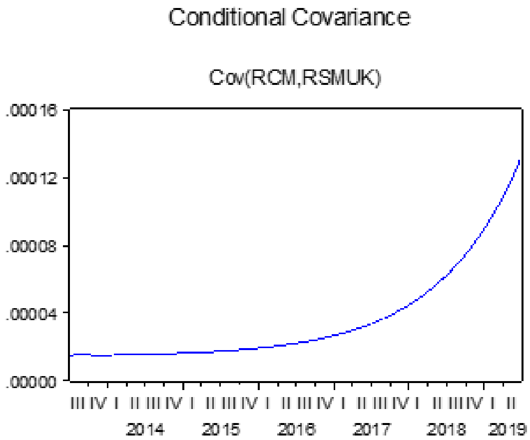

Figure. 4.75: Graphical Representation of Covariance Between RCM and RSMUK from 2013-2019

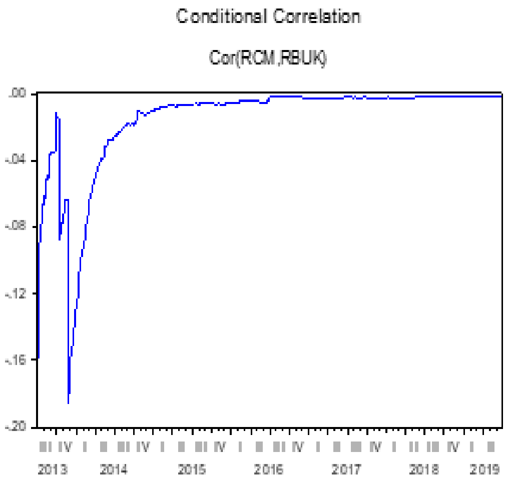

Figure. 4.76: Graphical Representation of Correlation Between RCM and RBUK from 2013-2019

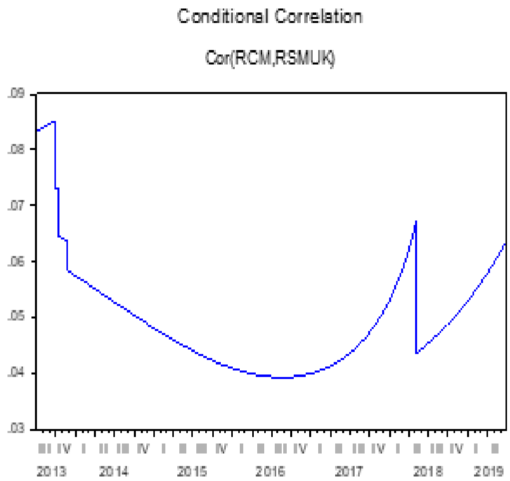

Figure. 4.77: Graphical Representation of Correlation Between RCM and RSMUK from 2013-2019

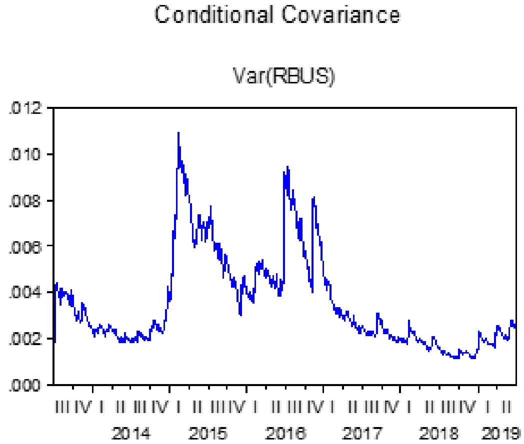

Figure. 4.78: Graphical Representation of Variance of RBUS from 2013-2019

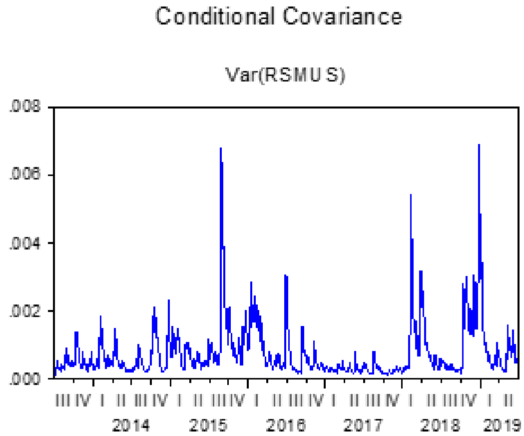

Figure. 4.79: Graphical Representation of Variance of RSMUS from 2013-2019

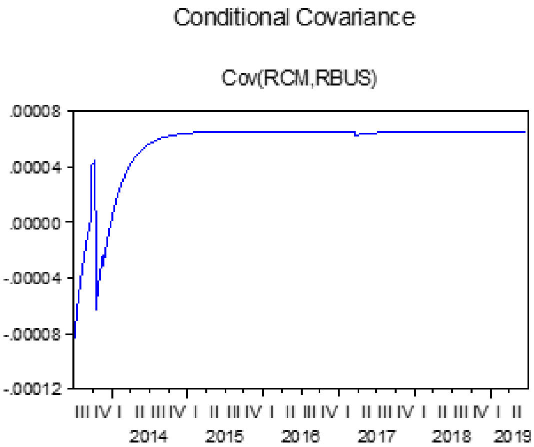

Figure. 4.80: Graphical Representation of Covariance Between RCM and RBUS from 2013-2019

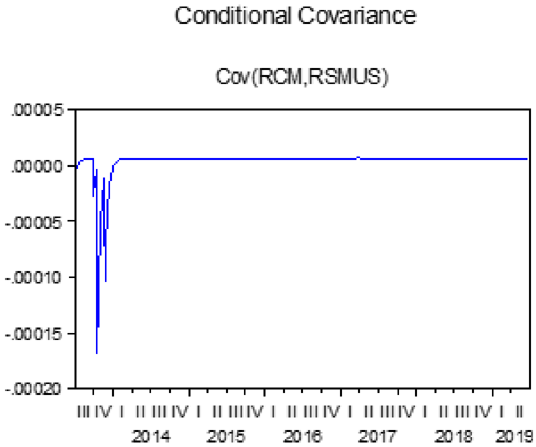

Figure. 4.81: Graphical Representation of Covariance Between RCM and RSMUS from 2013-2019

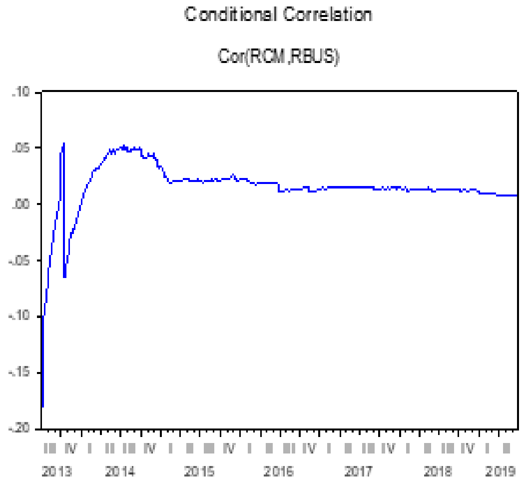

Figure. 4.82: Graphical Representation of Correlation Between RCM and RBUS from 2013-2019

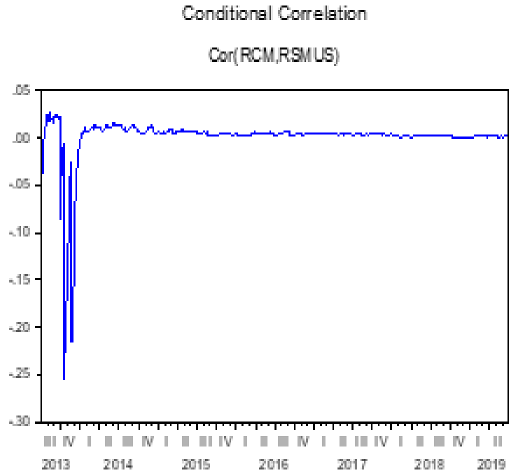

Figure. 4.83: Graphical Representation of Correlation Between RCM and RSMUS from 2013-2019

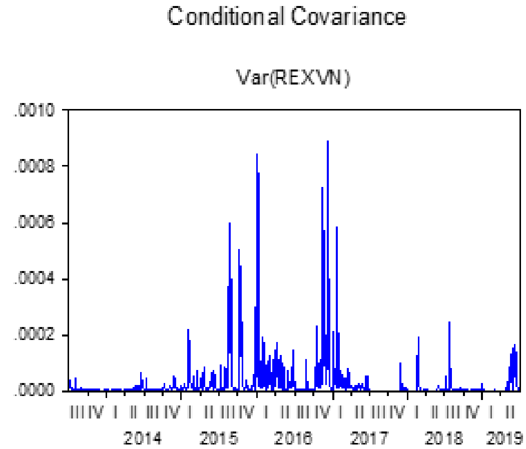

Figure. 4.84: Graphical Representation of Variance of REXVN from 2013-2019

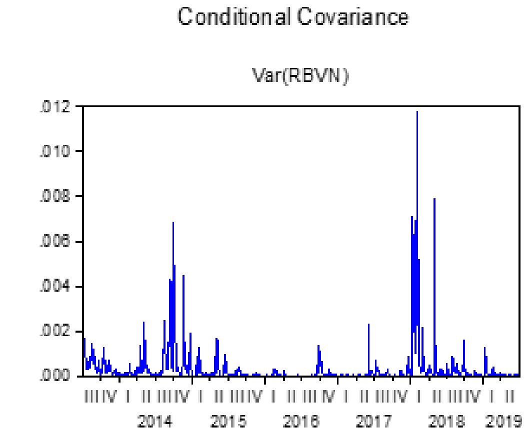

Figure. 4.85: Graphical Representation of Variance of RBVN from 2013-2019

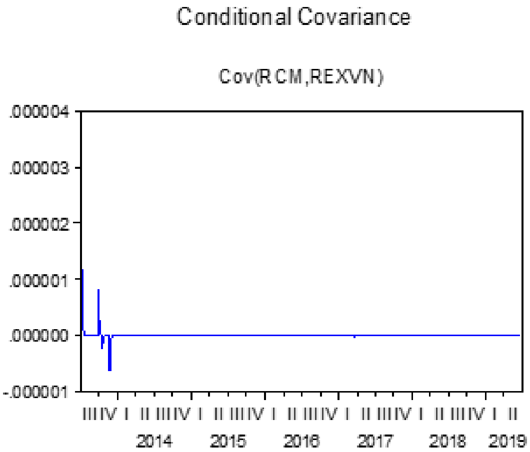

Figure. 4.86: Graphical Representation of Covariance Between RCM and REXVN from 2013-2019

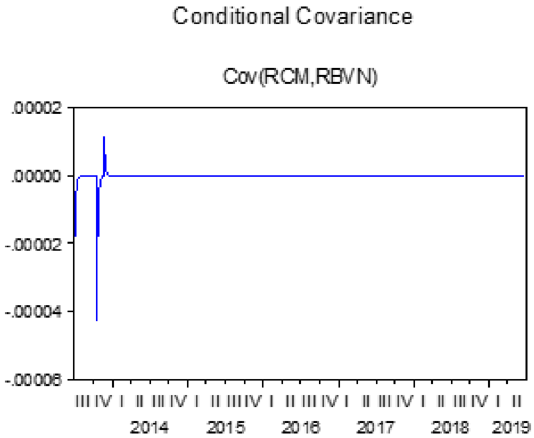

Figure. 4.87: Graphical Representation of Covariance Between RCM and RBVN from 2013-2019

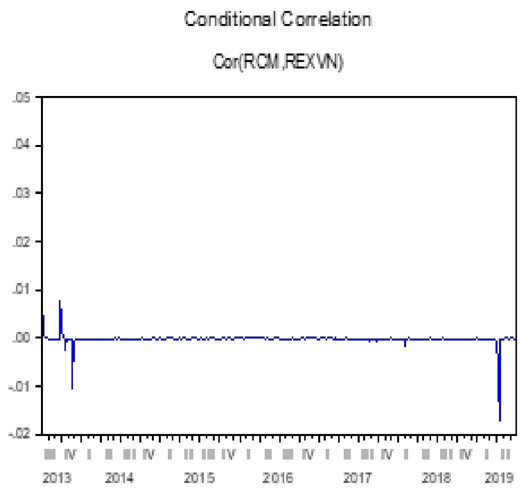

Figure. 4.88: Graphical Representation of Correlation Between RCM and REXVN from 2013-2019

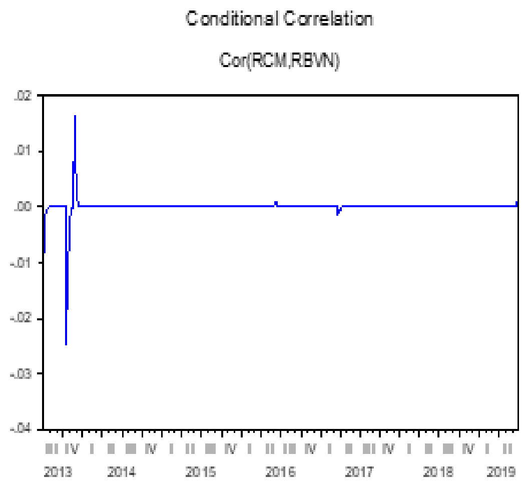

Figure. 4.89: Graphical Representation of Correlation Between RCM and RBVN from 2013-2019

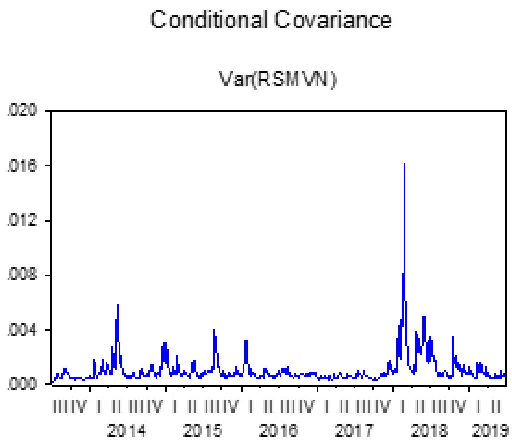

Figure. 4.90: Graphical Representation of Variance of RSMVN from 2013-2019

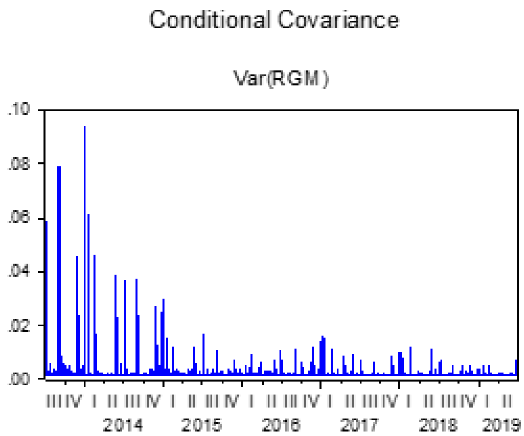

Figure. 4.91: Graphical Representation of Variance of RGM from 2013-2019

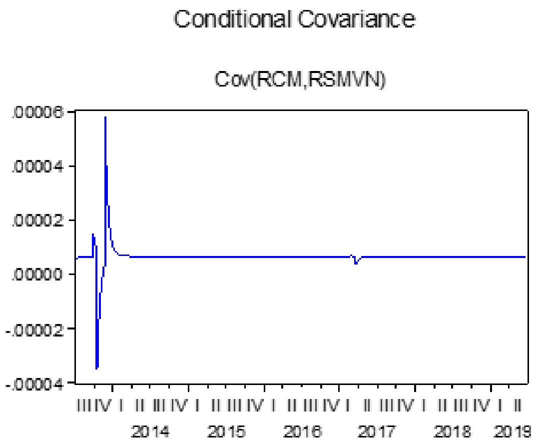

Figure. 4.92: Graphical Representation of Covariance Between RCM and RSMVN from 2013-2019

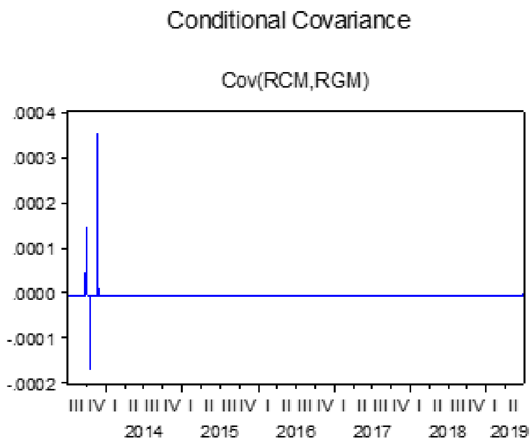

Figure. 4.93: Graphical Representation of Covariance Between RCM and RGM from 2013-2019

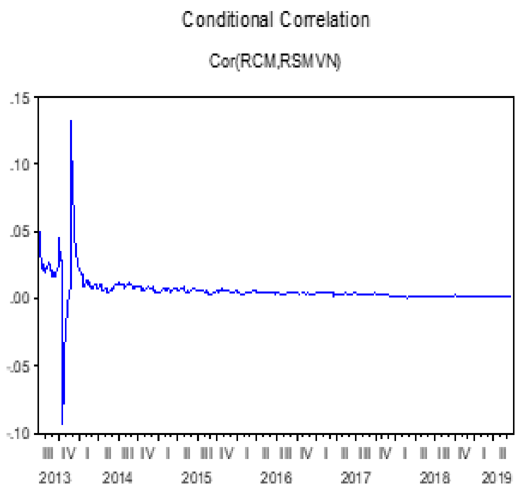

Figure. 4.94: Graphical Representation of Correlation Between RCM and RSMVN from 2013-2019

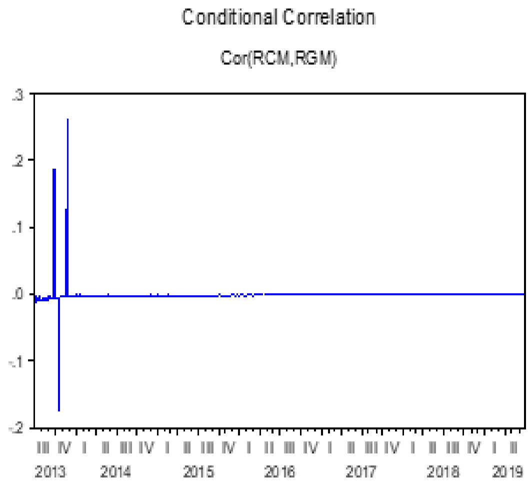

Figure. 4.95: Graphical Representation of Correlation Between RCM and RGM from 2013-2019

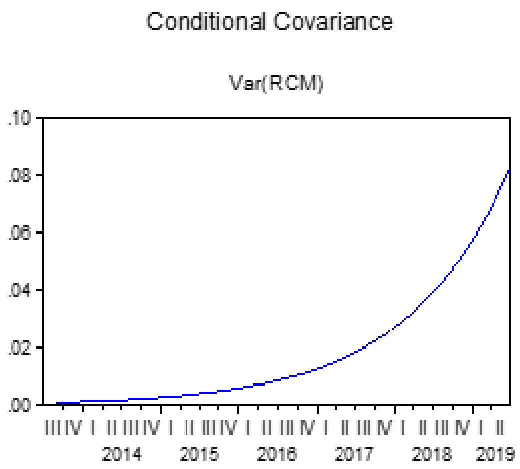

Figure. 4.96: Graphical Representation of Variance of RCM from 2013-2019