THE INFLUENCE OF KENYA'S MONETARY POLICY AND INVESTOR BEHAVIOUR ON ITS CRYPTOCURRENCY MARKETS PERFORMANCE

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ADMISSION NO. 137343

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the proposal itself.

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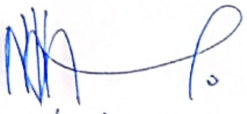
Signature: 

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Approval

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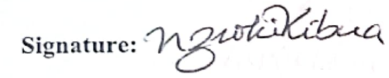
Signature: 

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DEDICATION

To my God, Lord and Savior: Jesus Christ, to my family (Rael Kimonyi “the matriarch”, Jane Kimolo, Martha Mutua, Ice Mutua, Ace Mutua, Prince Mutua and Rich Mutua), my professors (Dr. Thomas Kibua, Dr. David Mathuva & Dr. Farida Abdul), all my MDF 2020 colleagues and all those who dream and pursue their dreams.

ABSTRACT

This study investigates the relationship between Kenya's monetary policy and local investor behaviour and the performance of its price taking cryptocurrency markets. There is growing interest in cryptocurrencies mainly driven by emerging markets. These markets have non-existent or limited cryptocurrency regulation leading to many grey area transactions. Though there are increased attempts by developed nations to create and apply cryptocurrency regulations, there is little or no attempt for price taking developing nations cryptocurrency exchange markets. To ensure safe and beneficial use of cryptocurrencies, effective controls must exist that are informed by an understanding of current market dynamics within the reach of developing nations. This study investigates two major financial market dynamics (i.e monetary policy and local investor behaviour) and their associative relationship to cryptocurrency markets performance to determine if they are within reach of national monetary policies and affected by local economic conditions.

Based on the theoretical foundation of Modern Theory of Interest and Behavioural Asset Pricing Theory, high frequency data was obtained for the period of 1st January 2016 to 23rd September 2021 from various sources including 2 cryptocurrency exchange markets, the Central Bank of Kenya, and the Twitter social media platform. A Vector Autoregressive (VAR) model supported by GARCH models (gjrGARCH and DCC-GARCH) was used to analyse not only the relationship between the variables but also their volatility. The study concludes that local Cryptocurrency Markets are affected by local monetary policies and local conditions like the performance of the stock exchange, local public sentiments, and local uncertainty. Exchange Rates and Interbank Rates significantly affect cryptocurrency trade volumes. Global Sentiments have a short-term effect on cryptocurrency trade volumes, while local sentiments have long-term persistent spill-over effects. The study also concludes that local cryptocurrency investors are motivated by the potential for super normal gains rather than the fear of losing returns. This implies that the government should allow the establishment and regulation of cryptocurrency markets. Secondly, the government should establish vibrant and efficient NSE to provide hedging opportunities to cryptocurrency risks. The CBK must expand its information role to cover provision of cryptocurrency information in policy briefing while investors should incorporate local conditions in their investment models for more accurate predictive models.

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ABBREVIATIONS AND ACRONYMS

API	Application Programming Interface
CBDC	Central Bank Digital Currency
CBK	Central Bank of Kenya
CPSS	Compounded Public Sentiment Score
CTV	Cryptocurrency Trade Volumes
EMH	Efficient Market Hypothesis
FOMO	Fear Of Missing Out
FRED	Federal Reserve Economic Data
FUD	Fear, Uncertainty and Doubt
GDP	Gross Domestic Product
GPS	Geographical Positioning System
IIR	Interbank Interest Rate
LPT	Liquidity Preference Theorem
MP	Momentum Price
OMO	Open Market Operations
QTM	Quantity Theory of Money
URL	Universal Resource Locator
VADER	Valence Aware Dictionary for Sentiment Reasoning
VAR	Vector Autoregression Models
VIF	Variance Inflation Factor

DEFINITION OF TERMS

API The calls, subroutines, or software interrupts that comprise a documented interface so that an application program can use the services and functions of another application, operating system, network operating system, driver, or other lower-level software program **(Shnier, 1996)**

CBDC Central Bank Digital Currency – Digital tokens like cryptocurrency, issued by a central bank and are pegged to the value of a country's fiat currency. It is any electronic, fiat liability of a central bank that can be used to settle payments or as a store of value (Bank of England, 2018)

OMO Open Market Operations - refers to actions by the Central Bank involving purchases and sales of eligible Government securities to regulate the money supply and the credit conditions in the economy (CBK, 2023)

MP Momentum Price – measures the rate of acceleration of a security's price, usually explained by overreaction or underreaction effect where equities with high cumulative returns over the past continue to perform well in the future (Cheng, Liu, & Zhu, 2019)

VADER Valence Aware Dictionary and sEntiment Reasoner - is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains (Hutto & Gilbert)

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Ms. Martha Mutua	For your love, patience, belief, and encouragement that made me accomplish this task even with my busy and unpredictable entrepreneur's life

CHAPTER ONE: INTRODUCTION

1.1 Introduction

This study investigates the influence of Kenya's monetary policy and local investor behaviour on its unregulated cryptocurrency market represented by 2 popular cryptocurrency exchange markets. The study seeks to inform regulatory choices by the Central Bank, the Capital Markets Authority, and other financial regulators on the use of block chain-based currencies including Cryptocurrencies, Stable Coins and Digital Currencies (CBK, 2022). It seeks to answer the question of whether the current monetary policy and local investor behaviour (which can be influenced by a regulatory authority through communication and effective monetary policy signalling) have any predicting effect on local cryptocurrency exchange market's performance.

This chapter provides the background of the study, describes the study problem and objectives, and highlights the pertinent beneficiaries of the study results.

1.2 Background of the Study

1.2.1 The Relationship between Monetary Policy, Investor Behaviour & Investor Decision making.

Various studies in Kenya ((Olweny & Chiluwe, 2012) (Kamaan, 2014) and (Mutwiri & Jagongo, 2017)) and other African countries ((Brima & Brima, 2017) (Hassan, 2015)) have demonstrated that monetary policy has significant effects on private investment, inflation and economic growth. A monetary policy which controls the demand and supply of money in the economy, influences investor decision in 2 main ways: interest rate changes and investor opinion (through anticipated policy changes). A monetary policy will control interest rates which subsequently affect the cost of capital and in turn, the risk and expected returns which are core considerations in making investment decisions. On the other hand, anticipated monetary policy changes and the resulting uncertainty, affects investor opinion and sentiments. Central Banks regulates financial markets by communicating their monetary policy decisions which in turn signals the economic direction. The reaction to, or anticipation of monetary policy changes and interest rates transmissions have been identified as key drivers of financial markets performance (Kaminska, Mumtaz, & Roman, 2021). The ability of a central bank to affect the economy depends on its capacity to influence market expectations about the future

of interest rates and not merely their present level. Future market expectations are driven by investor opinions which are influenced not only by information from the financial regulators but by information from other investors. Investors influence one another through exchange of sentiments and shared historical experiences among other behaviour transmission methods like contagion, anchoring, herding, representativeness, excessive optimism, market greed, fear, uncertainty and doubt (Baddeley, 2010) (Raissi & Missaoui, 2015) and (Borgards & Czudaja, 2020).

In recent times, investor behaviour is measured by market sentiments which plays a critical role in the 2 stages of decision making: information collection and processing and the actual process of choice. (Raissi & Missaoui, 2015) demonstrates that investor sentiment is an important behavioural measure significant in determining the performance of stock returns. Further Raissi study demonstrates that investor sentiment is a combination of other indicators, including liquidity indicators of the financial market. This in turn, means that to measure investor behaviour, one must consider not only investor sentiment but also liquidity performance. A good measure of liquidity performance is momentum price which provides information about the level of investor interest (Lee & Swaminathan, 2000) and (Avramov, Cheng, & Hameed, 2016) .

1.2.1 The Growth and Challenges of Cryptocurrencies

With a global market capitalisation of over US$2.2 trillion and over 17,000 cryptocurrencies in circulation as at the end of 2021 (CoinMarketCap, 2022) & (CoinDesk Research, 2022), cryptocurrencies have continued to witness explosive growth and increasing public attention both globally, regionally and within the country. Bitcoin, which is the world's most popular cryptocurrency (based on market capitalisation (41.7%) and daily trade volumes) has seen remarkable price increases from $3,650 in June 2018 to a high of over $ 58,000 in February 2021 (with a current trading price of slightly over $37,000 as at January 2022). A similar trend has also been witnessed by other major cryptocurrencies globally including Ethereum (2nd in market capitalisation of 17%), Tether, Binance and Dogecoin among others. In Kenya, two of the leading cryptocurrency exchange markets (Paxful & LocalBitCoins), have witnessed a remarkable increase in Kenya's Bitcoin daily trading volumes from nearly zero in 2014 to over 472% in 2020 (to stand at a market capitalisation of US$45.95m). The chart below shows the growth of cryptocurrency market capitalisation since early 2017 to Feb 2023.

Figure 1 - Cryptocurrency market capitalization

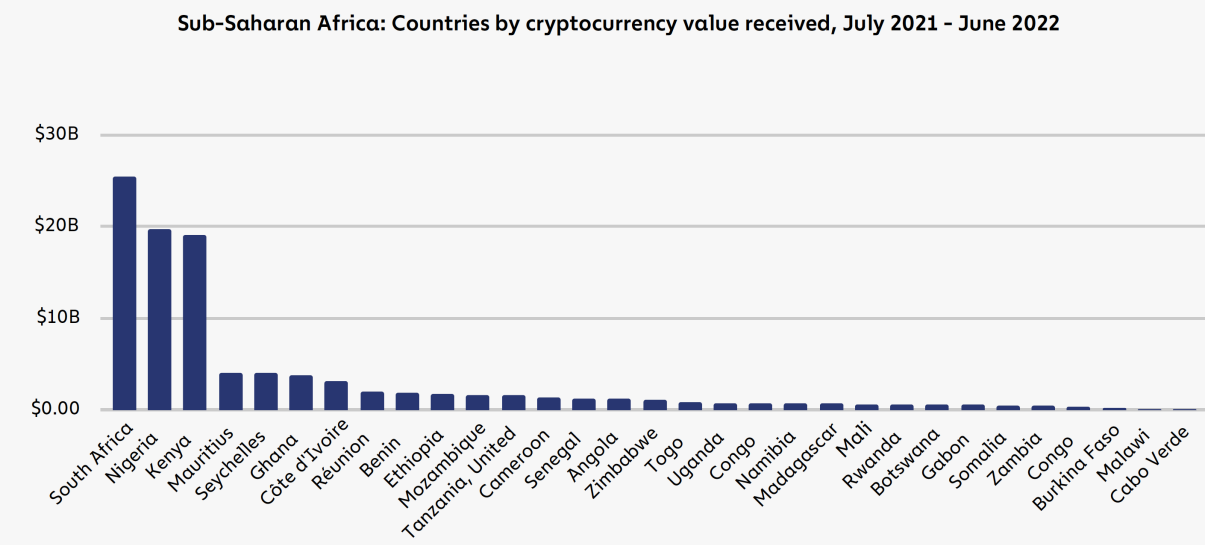
Source: CoinMarketCap (CoinMarketCap, 2023)

The interest in cryptocurrency is driven by individuals, governments, and private firms. Although more volatile in comparison to traditional financial assets, the higher returns evidenced by major cryptocurrencies at a global level, continues to outperform traditional macroeconomic assets (CoinDesk Research, 2022) and thus continue to attract growing individual and corporate investor interest.

According to (Chainalysis, 2021), of the $48 billion remitted to sub-Saharan Africa in 2019, $562 million worth of remittances were cryptocurrency based (See chart below). Additionally, their hedging potential has seen their rising usage as a counter measure to currency volatility and devaluation (Africa Growth Initiative, 2022). With this adoption, there has been a growing regulatory interest from governments across the world due to their perceived potential to negatively affect global financial stability and well-being (Bank of Russia, 2022). Governments have adopted differing strategies ranging from enhanced mainstream adoption (e.g in Elsavador and Central African Republic where cryptocurrencies are used as legal tender) to outright bans (e.g in China and other 8 countries). The lack of a single global approach to cryptocurrency regulation has led to cryptocurrency transactions in many countries remaining

in the "grey area". However, there is a growing trend towards regulatory tightening expressed in warnings and enactment of Anti-Money Laundering regulations (Bank of Russia, 2022).

Figure 2 – Sub-Saharan Africa: Countries by cryptocurrency value received, July 2021-June 2022



Source: Chainalysis (Chainalysis, 2023)

Africa is the fastest-growing cryptocurrency market among developing economies with the highest ratio of retail crypto transfers. Northern and Western Europe, East Asia, and North America, respectively, comprise the largest regional shares of cryptocurrency inflows into Africa, accounting for approximately 59 percent of the $6.7 billion sent to Africa via cryptocurrency between July 2019 and June 2020. Conversely, East Asia receives more than twice the amount of cryptocurrency outflows from Africa than Northern and Western Europe and North America, which are the second- and third-largest destinations of cryptocurrency sent from Africa (Africa Growth Initiative, 2022). Access to digital currencies provides a less costly alternative to traditional intra-regional transfer payments and international remittances systems.

Cryptocurrency markets in Kenya have remained largely unregulated and devoid of government intervention. In December 2015, the Central Bank of Kenya issued a circular advising the public against the use of cryptocurrencies, falling short of declaring their use illegal (CBK, 2015). In January 2019, the Capital Markets Authority (CMA) issued a cautionary notice warning investors against taking part in the KeniCoins Initial Coin Offering,

labelling it as unregulated and a speculative investment (CMA, 2019). These and other adverse warnings characterised the government stance in the early years of 2014 to mid 2019. However, following the recommendations of the Distributed Ledgers Technology and Artificial Intelligence Task Force (MICT, 2019), that the government should consider implementing the cryptocurrency guidelines under the G20 framework and establish Regulatory Sandboxes to facilitate controlled adoption of cryptocurrencies and other blockchain technologies in the country, the government's position has slowly shifted from outright rejection to cautious consideration (Governor: CBK, 2021).

Recognising the growth of cryptocurrency usage in Kenya, the Government through the Kenya Revenue Authority incorporated cryptocurrency earnings in the Digital Service Tax bracket ((KRA, 2021) and (KRA, 2020)). Further, and as a sign of the growing interest in cryptocurrencies, the government, through the Central Bank of Kenya recently invited comments on its Discussion Paper on Central Bank Digital Currency (CBDC) which is built on the same technology platform as many private issued Cryptocurrencies (CBK, 2022). This growing interest is also captured in the 2021 Geography of Cryptocurrency Report (Chainalysis, 2021) which ranked Kenya among top 5 countries with highest Cryptocurrency Adoption Rates measured by its Global Crypto Adoption Index which compares various parameters (on-chain cryptocurrency value, retail value and peer-to-peer (P2P) exchange trade volumes) weighed by Purchasing Power Parity (PPP) per capita. This increasing growth is further demonstrated in the Cryptocurrency markets themselves. 2 of the leading Crypto markets in Kenya: LocalBitCoins and Paxful reported weekly increasing average trade volumes of between Kshs 98m and Kshs 360m from November 2021 to January 2022 respectively (Coin Dance, 2021) and (Coin Dance, 2021). These indicators demonstrate the presence of a growing and vibrant, cryptocurrency market not only in Kenya but also in other African countries.

1.2.2 Cryptocurrencies as a unique investment asset class

Several studies have answered the question of whether cryptocurrencies are a unique investment asset class. The importance of this distinction is fundamental to this study which treats cryptocurrencies as investment assets which have unique attributes to traditional asset classes. Studies by (Holovatiuk, 2020) (Krückeberg & Scholz, 2019) (Ram, 2019) have shown that Cryptocurrencies have the key attributes of an asset class like a strong internal correlation, stable aggregation, and cost-effective access. However, they are different to traditional assets

classes because of the absence of correlation to traditional asset classes and their politico-economic profile of being decentralised. Its duo nature of being both an asset and a currency extends the differentiation further. Other studies by (Sifat, 2021) have also shown that cryptocurrencies are an independent asset class because of their unique response to global investor sentiment proxies, global risk and uncertainty. This cryptocurrency independence as an asset class necessitates a study of their behaviour in different scenarios which is a core foundation of this study.

1.3 Statement of the Problem

Cryptocurrencies have well known benefits to growing economies (Agbo & Nwadialor, 2020), however, they have the potential to cause adverse economic effects. Governments and regulatory authorities see cryptocurrencies as double edged swords with the potential to lower cross-border transaction costs, improve transaction processing efficiency, enhance financial inclusivity, promote innovation and financial sector development (Olusegun & Olaniyi, 2019) but also with significant risks of possible application in criminality (money laundering, cybercrime and terrorism financing), disintermediating banks, aggravating financial exclusion due to technical illiteracy and adverse price volatility (Dennis & Griffin, 2018). Additionally, cryptocurrencies have the potential to initiate change in public behaviour triggering a review of existing monetary policy frameworks (CBK, 2022). Without effective risk management and market regulation to guarantee social welfare improvement, financial stability, security, and transparency, cryptocurrencies will do more damage than good (Giudici, Milne, & Vinogradov, 2020) . With Kenya's increasing adoption of cryptocurrencies, the risk to the financial system has significantly increased. These risks are further exacerbated by cryptocurrency's duality (i.e as a currency and a financial asset), the lack of centralised control and their global nature (i.e their prices being determined through global demand and supply forces). The main challenge for Kenya and other countries is how to develop an effective regulatory policy to mitigate cryptocurrency risks but at the same time allow their controlled beneficial use for the benefit of the government, investors and financial institutions.

The inability of regulatory authorities to provide clear direction has led to differing responses ranging from negative advisories to cautious adoption and to serious regulatory consideration (e.g by the Central Bank of Kenya (CBK, 2022), the Capital Markets Authority and the Kenya

Revenue Authority (KRA, 2021)). This inconsistent signalling is a result of regulators inability to determine the best approach to protect Kenya's economy from adverse cryptocurrency effects while positioning the economy to take advantage of cryptocurrency's benefits. This uncertainty has hindered the sector growth. Further, this inconsistent signalling has led to missed investment opportunities and has created grey areas which allow the exploitation of potential investors by few investment agents without legal recourse.

The development of clear-cut cryptocurrency regulation in Kenya is of pertinent importance (Kamau, 2022) although it is an inherently complex process as cryptocurrencies are also a global phenomenon. Their non-centralised and global nature reduces the effectiveness of national regulatory control even when their trades are local (i.e through a cryptocurrency exchange market) and therefore subject to national regulation (Auer & Claessens, 2018). Monitory policy cannot singularly provide a comprehensive cryptocurrency regulatory tool due to the non-decentralised nature of cryptocurrencies. This calls for a combination of regulatory tools which must incorporate traditional approaches like monetary policies and non-traditional aspects like investor behaviour. This is more pertinent because cryptocurrencies are an independent asset class with unique responses to global investor sentiments, risk and uncertainty. The interrelationship between global and local parameters and how global influences affect local factors within time frames are yet to be conclusively studied.

Since cryptocurrency exchange markets are exposed to the same micro and macro-economic factors that similarly affect local financial markets (Giudici, Milne, & Vinogradov, 2020), there is a possibility of achieving local regulation. This ability to be regulated locally has led to developed nations making increased attempts to create cryptocurrency exchange markets regulations for their markets, however, there is little or no attempt by developing nations. This second form of duality (i.e cryptocurrencies being both local and global) requires regional and global collaboration in developing common regulatory approaches as well as national regulation, of which, are both lacking.

Additionally, the cost of regulation significantly affects its uptake and compliance. Any effective regulation must achieve its objectives within the minimal costs to both the regulator and the regulated. In regulating a new phenomenon, it is prudent to understand the impact of existing policies on the new phenomenon. Thus, the potential of Cryptocurrencies to affect public behaviour and trigger monetary policy action, must be investigated from the basis of

current policy that are designed to mitigate these risks in fiat currencies. This will determine whether a completely new policy is warranted, or an existing one can be enhanced to meet the regulatory challenges. To develop an effective regulation, current cryptocurrency market behaviour must be known and understood within existing financial markets that can be influenced by prevailing national and regional micro and macro-economic conditions. The lack of research in this area inhibits the development of an effective cryptocurrency regulatory framework which further reduces Kenya's ability to participate in the cryptocurrency economy leading to missed opportunities (Agbo & Nwadialor, 2020). Thus, the basis of this study is to investigate the influence of known factors (i.e monetary policy and investor behavioural factors) that affect current traditional financial markets assessing their relationship with the new cryptocurrency markets. This will shed more light on current interactions of a monetary policy and investor behaviour with cryptocurrency exchange markets which will further inform the formulation of a future regulatory framework that uses these factors as regulatory tools.

Thus, the research problem is to determine the possibility of developing new or existing regulatory tools based on monetary policy and/or investor behaviour prediction to safeguard Kenya cryptocurrency investors from systemic and market risks. A cost effective but properly functioning regulatory framework on cryptocurrencies will address systemic risk, financial stability and provide the benefits of the use of cryptocurrencies to all economic agents.

1.4 Research Objectives

1.4.1 General Objective

The general objective of the study is to investigate the associative relationship of Kenya's monetary policy and local investor behaviour on cryptocurrency market performance.

1.4.2 Specific Objectives

The study specific objectives are to investigate:

1. The influence of the Kenya's monetary policy on the local cryptocurrency market performance
2. How investor behaviour, measured by herding and risk hedging affects Kenya's cryptocurrency market performance

3. The influence of global and local public sentiments, as a measure of investor behaviour, on Kenya's cryptocurrency market performance

1.5 Research Questions

The study will answer the following questions:

1. How does the Kenya's monetary policy affect the Kenya's cryptocurrency market trade volumes?
2. How are Kenya's cryptocurrency market trade volumes affected by investor behaviour proxy variables of market liquidity and uncertainty?
3. To what extent does local and global cryptocurrency public sentiments, as a measure of investor behaviour, affect Kenya's cryptocurrency market trade volumes?

1.6 Scope of the Study

This study analyses daily and weekly data for all the study variables for a period of 5.75 years (i.e 1st January 2016 – 23rd September 2021 a total of 69 months equivalent to 2,092 days). Cryptocurrency Trade Volumes were obtained from 2 leading Kenya Cryptocurrency trade exchanges (i.e LocalBitCoins - https://localbitcoins.com/ and Paxful - https://paxful.com/) through their Application Programming Interfaces (APIs) while Bitcoin prices were obtained from CoinDesk which is an online cryptocurrency information portal. The Central Bank of Kenya website provided current and historical interbank rates, OMO rates and Exchange Rates. A custom computer script was used to obtain daily public sentiments from geo-located tweets obtained from Twitter (www.twitter.com) social media platform and common local internet news sites. This sentiment data was analysed using the Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm for sentiment analysis and prepared for further analysis as per the model.

1.7 Significance of the Study

The main beneficiaries to this study will be policy makers and regulators although other stakeholders will also find the study useful.

1.7.1 Policymakers and regulators

This research looks at the effects of an existing monetary policy on an emerging cryptocurrency market. It seeks to generate relevant insights into the interplay of existing monetary policies with cryptocurrency economic agent activities and highlight the need to devise new approaches or strengthen existing ones. It also informs ongoing discussions on the adoption of CBDCs by the Central Bank of Kenya (CBK, 2022) and others.

1.7.2 Kenya Cryptocurrency Investors

Investors are on the constant look-out for the best investment strategy. If local investor behaviour modelled by price momentum trading and public sentiments can predict the performance of cryptocurrency markets, then it will be possible for them to tailor their investment algorithms to generate higher potential returns.

1.7.3 Academicians and researchers

This study contributes towards the general body of knowledge on cryptocurrencies and their relevance in economic development. The study results further identify potential areas of academic research pursuit especially in developing nations with lesser developed cryptocurrency and fiat currency markets.

CHAPTER TWO: LITERATURE REVIEW

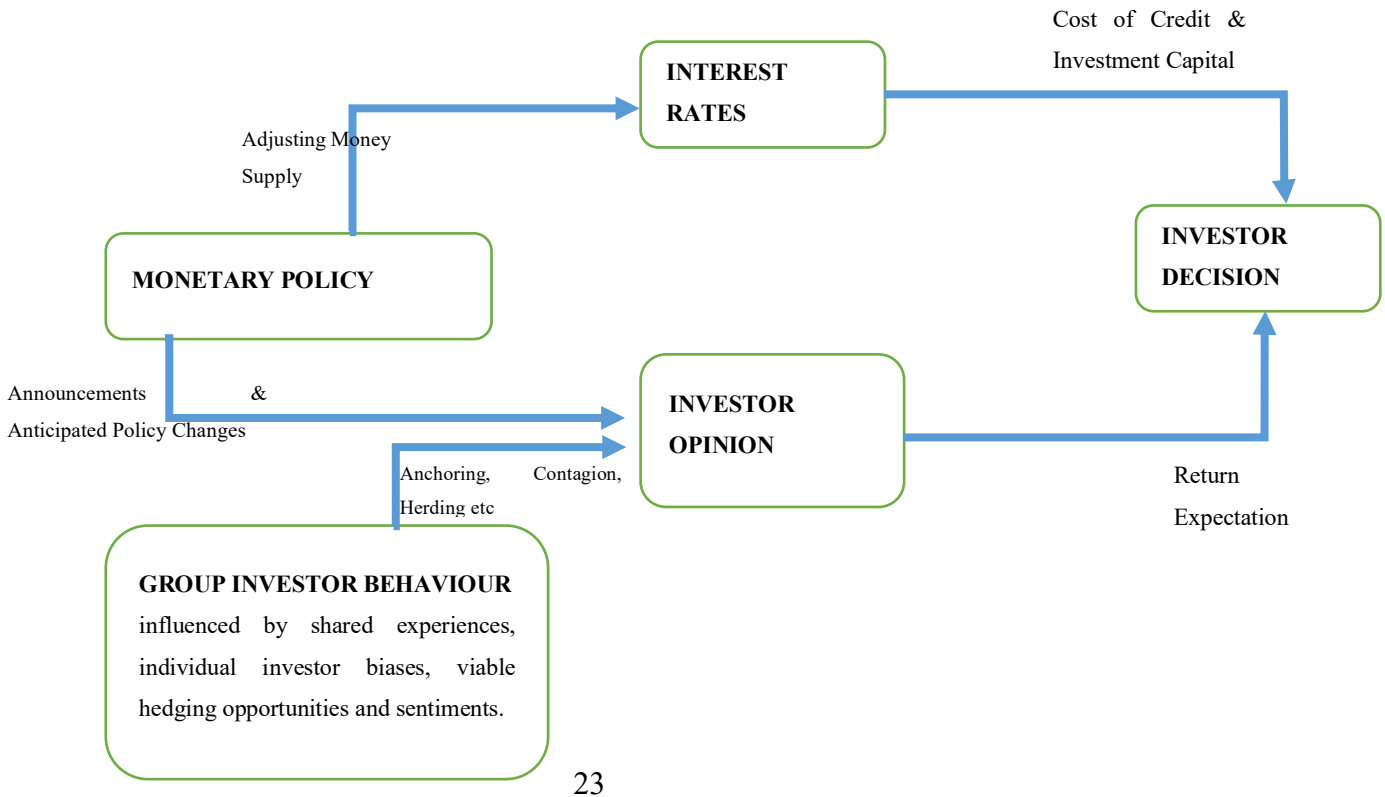
2.1 Introduction

This chapter provides an overview of the current knowledge and the theoretical and empirical foundations to which the research is based on. It also presents the research conceptual framework which maps out the expected relationships between the study variables highlighting their relevant characteristics, properties, and inter-relationships.

2.2 Theoretical Review

This study uses a multi-theoretical approach as cryptocurrencies have both assets and currency characteristics. Thus, the study looked at the role of cryptocurrencies as money and as an investment asset both of which are in the control domain of government policies (Corbet, McHugh, & Meegan, 2017) and market behaviour. In examining the monetary role of cryptocurrencies, the study investigated the effect of monetary policies on cryptocurrency performance. It studies monetary policy proxy variables that would normally affect a fiat-based currency economy. Further, the study examines cryptocurrencies as investment assets by considering investor behaviour measured by public sentiments and momentum. The chart below illustrates this logical interconnection between monetary policy, investor behaviour and investor decision which form the theoretical basis of this study.

Figure 3 - Relationship between Monetary Policy, Investor Behaviour and Investor Decision Making



In this regard therefore, the study will rely on 2 main theories: Monetary Theory and Behavioural Finance Theory which are further discussed below.

2.2.1 Modern Theory of Interest

Monetary policy is concerned with the movement of interest rates managed by controlling the supply of money which in turn drives economic activities. (Twinoburyo & Odhiambo, 2018). As shown by several research studies in Africa, interest rates, inflation rates, exchange rates and price stability controls are significant monetary policy instruments that drive both short-term and long-term growth (Fasanya, Onakoya, & Agboluaje, 2013). These policy instruments further affect income and employment levels eventually leading to an increase in aggregate demand and economic output. (Twinoburyo & Odhiambo, 2018) study on monetary policy & economic growth concluded that the relationship between monetary policy and economic growth is largely explained by, inter alia, the size of and competition within the financial sector, the monetary and exchange rate regimes, and the degree of economic openness. The theoretical foundation of this study will be the use of interest rates determined by a monetary policy which adjusts the supply and demand of money to influence investors decisions. Thus, the Modern Theory of Interest helps us to understand the expected market behaviour driven by investor cost of capital considerations.

The Modern Theory of Interest (also referred to as the Hicks IS-LM Curve (Hicks, 1937) or the Neo-Keynesian Theory of Interest) is one of main theories that are used in the study of the impact of monetary policy in an economy. It attempts to address the limitations of other related theories including the Classical Theory of Interest (Real Theory of Interest), the Neo-Classical Theory of Interest (Loanable Fund Theory of Interest) and the Keynes Theory of Liquidity Preference. The Modern Theory of Interest is a synthesis of both the classical and neoclassical Investment-Savings theories and the Keynes liquidity preference theory. It undertakes an equilibrium analysis of Investments and Savings (IS) curve and the Liquidity/Money (LM) curve to explain the joint determination of interest and real income. The IS curve is derived from the Real Theory of Interest which define an increasing relationship between savings and rate of interests and an equilibrium of declining investments with an increase in interest rate (i.e non-monetary factors). The LM curve on the other hand is derived from the Liquidity Preference and Supply of money in the money market. The evolution of IS component of the Modern Theory of Interest can be traced back to the Classical Theory of Interest where interest

is a real phenomenon determined by the equilibrium interaction of savings and investments and the Loanable Funds Theory which extended the classical theory to take into consideration hoarding, dishoarding and autonomous changes in the stock of money thus incorporating both monetary and non-monetary factors. On the other hand, the LM component is derived from the Keynes Theory of Liquidity Preference Theory which sees interest as purely a monetary phenomenon and a reward for parting with liquidity. According to this theory, the rate of interest will be determined at a point where the demand for money equals the supply of money. Therefore, the LM curve represents the equilibrium in the money market. Thus, the IS and LM curves together determine interest rates and national income in the short run when price level is fixed (Pal, 2017). A shift in the IS curve indicates a change in aggregate demand while a shift in the LM curve indicates a change in the demand or supply of money. Thus, a monetary policy will affect the LM curve. An expansionary monetary policy increases the supply of money and thus lowers the interest rate which raises investment demand.

Over the years monetary theory has evolved from initial criticisms (mostly by Keynesianism) of its perceived inability to guarantee price stability and thus drive economic growth to its modern application in targeted monetary policy strategies. The main question in monetary analysis debate is whether the quantity of money circulating in an economy is exogenous (determined by the central bank and thus the monetary policy) or endogenous (determined by the credit demand of households and firms and thus the fiscal policy) (Gaffard, 2018). Two schools of thought provide counter arguments to this question i.e the Keynesian argument and the Monetarist argument (Issing & Wieland, 2012). The Keynesian argument is drawn from the Keynesian classical thought started by John Keynes (Keynes, 1936) which advocated for the use of fiscal policy (i.e government spending and taxes) to spur economic growth with partial disregard to the quantity of money as advocated by Irvin Fisher Quantity Theory of Money (QTM). The IS-LM model attempts to merge the 2 schools of thought. With the IS curve incorporate aggregate demand analysis and the LM curve incorporating the monetary policy analysis. The monetary policy will work by adjusting the interest rates and not necessarily the demand and supply aggregates. Deposits make loans and that the amount of money in circulation is a multiple of the monetary base fixed by the central bank ((Friedman, 1968). This implies that a central bank can set and maintain an interest rate target to affect the amount of money in circulation and thus economic growth independent of demand aggregates.

The IS-LM model has been criticised for its inability to incorporate forward looking analysis on savings and investments. This has led to the evolution of the New IS-LM which incorporates forward looking aspects on saving and investment behaviour to create a more dynamic optimizing general equilibrium model (McCallum & Nelson, 1997). The reaction to, or anticipation of monetary policy changes and interest rates transmissions have been identified as key drivers of financial markets performance. In recent years, financial markets appear better able to anticipate monetary policy changes with anticipated movements of interest rates being incorporated into financial instruments valuations several months in advance (Kaminska, Mumtaz, & Roman, 2021). It is now widely accepted that the ability of a central bank to affect the economy depends on its ability to influence market expectations about the future of overnight interest rates and not merely on their present level. This is the key role of central bank communications (Blinder, Ehrmann, Fratzscher, Haan, & Jansen, 2008).

Despite the criticism of the IS-LM, interest rates are ultimately the best measure of a monetary policy performance as they have a drastic effect on consumer spending and borrowing at all levels of economic activities. Monetary policy interventions, in the form of adjusting the quantity of money in the economy, change in government expenditure, investment and saving patterns affect the interest rates. The Central Bank can use any of these monetary tools to adjust the interest rates. These rates in turn affect the cost of borrowing for investment capital which in turn influence investor decisions. Since interest rates are the best measures of a monetary policy performance, various forms of interest rates including the Interbank Interest Rate, Open Market Operations (OMO) Rates and the special interest rate in the form of Foreign Exchange Rate shall be used as variables that capture the monetary policy stance. The analysis of the effects of these interest rates to cryptocurrency market performance will then be performed. An increase in interest rates, is expected to sweep off liquidity in the money market and thus generally reduce the funds that are available for investment. This should lead to reduced financial markets activity (cryptocurrency markets included).

2.2.2 Behavioural Asset Pricing Theory

Behavioural Asset Pricing Theory is part of the theories related to behavioural finance. Behavioural Finance is the application of psychology to financial decision making and financial markets. It is the process of replacing neoclassical assumptions with behavioural counterparts (Shefrin, 2009). Traditionally, financial models have been based on the

assumptions that investors will always behave rationally and in favour of their own interests. However, recent advances in behavioural science have incorporated the interaction of cognitive and emotional factors in investor decision making. As early as 1937, John Keynes pointed out that beside the propensity to consume and save, psychology, emotion and social influence formed the basis of many economic analyses (Keynes, 1937).

Asset Pricing is central to both neoclassical and behavioural finance as both try to explain investment asset return variations. According to neoclassical asset pricing theory, the rational investor will always be able to accurately determine the current pricing of an assets based in its expected future cashflows considering risk. It is consistent with the Efficient Market Hypothesis (EMH) theory which assumes that all information has already been priced in the value of the investment asset and that rational investors will quickly drive down the value of an assets to its fundamental value if there is mispricing. However, this rationality was found to be unrealistic assumption because of market anomalies, decision making errors and biases associated with the way economic agents treat information.

The 1950's saw the emergence of improved behavioural finance theories including the Model of Bounded Rationality and Cognitive Dissonance theories (contradictory beliefs, ideas and values) followed by bias and overreaction models in 1980s and the behavioural asset pricing theory and portfolio theory in the late 1990s (Statman, 1999).The early 2000's behavioural finance evolved into more application areas including asset pricing, corporate finance, money markets and portfolio management (Veni & Kandregula, 2020). Many of the core neoclassical theories have now established their counterpart behavioural models e.g the neoclassical asset pricing has incorporated a counter premise of investors irrationality (based on beliefs and preferences) and limited arbitrage opportunities (Nanayakkara, Nimal, & Weerakoon, 2019) to create the behavioural asset pricing model. Other neoclassical theories that have incorporated behavioural finance and created revised models include Portfolio Theory (Markowitz, 1952) , Capital Asset Pricing Model (Sharpe, 1964) and the Option Pricing Theory (Black & Scholes, 1973).

Asset pricing has also evolved into Behavioural Asset Pricing by considering Investor Sentiments, Under and Overreaction, Representativeness Bias and Equity Risk Premium. Investor Sentiment which is collectively captured as market sentiment is seen as the current attitude that investors have on a particular investment asset or the financial market as a whole

revealed through buying and selling activity. It is generally caused by the crowd psychology of active investors (Raissi & Missaoui, 2015). Market under and overreaction is explained using the extent to which investors under or over-react to information in pricing securities. Overconfidence in the reliance to private signals and self-attribution allow prices to continue to overreact creating momentum. Overconfidence leads investors to overweight their private information causing prices to overreact. When public information is received, mispricing is partially corrected giving rise to under-reaction (Borgards & Czudaja, 2020). Representative bias is derived from heuristics applied by individual investors in assessing the probability of an event or situation based on superficial characteristics and similar experiences they have had rather than on the underlying probabilities. Finally, Equity Risk Premium considerations affect asset pricing based on the collective experience of each generation of investors for each asset class considering volatility. The risk premium at any point is determined by the relative volatility of the investment asset. These aspects have also been extended to capture personality, emotion and mood in financial decision making. A good example is (Baddeley, 2010) who espoused that herding and social influence is an interplay of both reason and emotion and can be heightened by contagion and information asymmetry.

Behavioural based decision making can be affected by several other factors including fear, uncertainty, shared identity of investors and opportunity for a quick win. It can also allow novices to benefit from due diligence of others e.g in Passive Index Investing by simply matching the broader market's performance and taking into consideration information asymmetry. Market psychology highlights the Fear of Missing Out (FOMO), excessive optimism, market greed, Fear, Uncertainty and Doubt (FUD) all anchored on cognitive biases (confirmation, loss aversion, endowment effect).

With this theoretical basis, investor sentiment and price momentum are selected for this study. Investor sentiment is the attitude of investors regarding a particular asset while momentum, which is a measure of the Equity-Risk Premium considerations, is the rate of acceleration of a security price or volume. Momentum is a result of direct behavioural biases which may be occasioned by trend following, anchoring, herding, representativeness, misperception of regression of the mean and market under/overreaction. Public sentiment enforces optimism, fear, uncertainty, and doubt thus affecting investors rational behaviour. On the other hand, momentum reinforces anchoring where an investor continues to follow a trend even when it

may not be rational to do so. Momentum price also measures other behavioural biases including overconfidence, regret, bounded rationality and chasing trends.

2.3 Empirical Review

This study empirical research is organised into 4 parts: Monetary policy, investor behaviour modelled by public sentiments and price momentum and other factors as an influence of investor behaviour. These 4 parts are studied with the objective of evaluating their effects on cryptocurrency exchange market trade volumes. In looking at the monetary policy, the study examines the relationship between Interbank Rates, OMO rates and Foreign Currency Exchange Rates, as monetary policy interest rates , and cryptocurrency market performance measured by Cryptocurrency Trade Volumes (CTV). The study also considers public sentiments and momentum price as a proxy measure of several behavioural aspects. Other factors that are pertinent to the study are also studied. These include Uncertainty and the NSE performance. Uncertainty affects all the other variables while the NSE Performance provides a good reference point for comparison with other financial markets movements and performance.

Investor behaviour is measured by market sentiments which play a critical role in information collection and processing and the actual process of choice. (Raissi & Missaoui, 2015) demonstrates that investor sentiment is an important behavioural measure significant in determining the performance of stock returns. Further Raissi study demonstrates that investor sentiment is a combination of other liquidity factors affecting the financial market. This in turn, means that to measure investor behaviour, one must consider not only investor sentiment but also liquidity performance. A good measure of liquidity performance is momentum price which provides information about the level of investor interest (Lee & Swaminathan, 2000) and (Avramov, Cheng, & Hameed, 2016) .

2.3.1 Monetary Policy and Cryptocurrency Market Performance

There exist conflicting research findings on the effects of monetary policy on cryptocurrencies. (Corbet, Meegan, & McHugh, 2017) and others provide compelling evidence that monetary policy decisions based on interest rates significantly impact cryptocurrency returns and that despite their nature and ideals, cryptocurrencies such as bitcoin seems subject to the same

economic factors that influence traditional fiat currencies. On the other hand, studies by (Lyocsa, Molnar, Plihal, & Siranova, 2020) & (Vidal-Tomas & Ibanez, 2018) seem to indicate that monetary policies do not influence cryptocurrency prices although this only relates to scheduled announcements and does not cover forward-looking indicators. However, although there is conflicting research, majority of the research literature indicate that monetary policy has an influence on the performance of cryptocurrency markets. This influence is easily seen in the existence of arbitrage opportunities between different cryptocurrency markets (Makarov & Schoar, 2020) and in the varying regulatory controls implemented by different countries (Jovanić , 2020).

A recent Deutsche Bundesbank sponsored study examined the relationship between Bitcoin price data and monetary policy shocks within the Euro area and the US using high-frequency data and weekly proxy VAR model analysis of bitcoin price on short-term interest rate movements during narrow windows around monetary policy announcements (Karau, 2021). This research showed that monetary announcements have sizeable effects on Bitcoin prices. It further showed that monetary policy shocks emanating from both the US and the Euro area are found to have significant and persistent effects on bitcoins valuation. However, this effect is different in the USA and in the Euro area. A disinflationary monetary tightening by the Euro system lowers Bitcoin valuations whereas a tightening by the US Federal Reserve increases Bitcoin prices. This indicate that Bitcoin is used as an inflation hedge in the Euro area while the continued use of Bitcoin in emerging markets is a cover up for the international ramifications of US monetary policy.

(Nguyen T. , Nguyen, Nguyen, & Phama, 2019) study on Asymmetric Monetary Policy effects on cryptocurrency markets further extended the research area to not only interest rates, but also to exchange rates and OMO rates. This study obtained cryptocurrency data from coimmarketcap.com and associated macroeconomic variables data from the Federal Reserve Economic Data (FRED) and the People's Bank of China for the period 1st October 2015 – 15th August 2018. The target Open Market Operations (OMO) were used to capture the Monetary Policy Rates in both countries and 4 cryptocurrencies with the largest market capitalisation were analysed to evaluate the impact of monetary policy changes on the overall cryptocurrency market. An econometric model was used with cryptocurrency returns as the dependent variable and the independent variables being both China and USA OMO rates, CNY/USD Exchange Rate, Cryptocurrency demand (as measured from Wikipedia public sentiments) and growth

rate of cryptocurrency supply (i.e the number of coins). The results generated showed that major cryptocurrencies react differently to leading economies monetary policies. For example, four of the major cryptocurrencies responded to Chinese tightening monetary policy whereas they were non responded to the USA monetary policy. This further collaborated (Karau, 2021) study findings in the Eurozone area as discussed above.

Several convergence areas exist between the above studies and the proposed study. For instance, in both studies, similar variables (Interest Rates, OMO rates and Foreign Exchange Rates) are used as indicators of monetary policy effectiveness against cryptocurrency market performance. A key area of divergence is that while the 2 studies focus on the response of cryptocurrencies to monetary policy events and shocks emanating from regulatory announcements and/or economic events, the proposed study will look at the impact of monetary policy interest rates over the study phenomenon regardless of economic events or shocks (i.e the focus is not on specific shock events but on the normal operation of a monetary policy). This is because, upon literature review, the researcher notes that the impact of monetary policy interest rates on cryptocurrency returns rather than events on cryptocurrency prices remains largely unanswered (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) . Additionally, both (Karau, 2021) and the (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) studies are based on price setting cryptocurrency markets while the proposed study will focus on a price-taking cryptocurrency market, most notably, in a developing economy. Because the study focusses on price taking markets, cryptocurrency trade volumes are more preferred as a measure of market performance than price changes. This is in addition to the fact that some researchers prefer trade volumes to price changes as a better measure of return predictability and volatility in the cryptocurrency markets (Bouri, Lau, Lucey, & Roubaud, 2019). Further, this study used additional variables i.e interbank rates, public sentiments and price momentum which are not considered in the two studies yet other studies have shown that these parameters have a significant and predictive relationship to cryptocurrency market performance.

2.3.2 Momentum Price and Cryptocurrency Market Performance

(Liu & Tsyvinski, 2020) carried out a study on the network and production drivers and predictors of cryptocurrency markets and identified that momentum and investor attention are the strongest predictor of cryptocurrency returns. The emphasis on the study was to determine the main category of factors i.e between cryptocurrency network and production factors, that

affect cryptocurrency returns. The researchers constructed a cryptocurrency market returns index which was determined to be the value of weighted returns of all coins with a capitalisation of more than USD 1m for the period 1st January 2011 – 31st December 2018. They analysed the relationship between the coin market and the main cryptocurrency specific factors proposed in the theoretical literature i.e cryptocurrency network factors, production factors, momentum, investor attention and cryptocurrency valuations. As to the cryptocurrency network effects, they realised that the coin market returns are positively and significantly exposed to cryptocurrency growth and that the prices contain information about expected network growth. Additionally, they were able to show that there is a significant time series momentum phenomenon in the cryptocurrency market. They found out that coin market returns predict cumulative future coin market returns from one week to eight weeks ahead. They also measured investor attention with Google searches and Tweeter demonstrating that high investor attention predicts high future returns over the 1 – 6 weeks horizon.

Thus, just as the previous empirical studies, (Liu & Tsyvinski, 2020) study was carried out in a price setting global market while this study is in a price taking emerging market. Secondly, the study considered the momentum and attention variables separately and not as part of a comprehensive model that could predict a local cryptocurrency market performance considering other factors. The (Liu & Tsyvinski, 2020) regression model was limited as it only considered the comparison between momentum and the attention variable as the study's focus was to investigate the network and production factors of cryptocurrencies in general. Thus, this study has a wider coverage addressing the existing conceptual gap.

2.3.3 Herding in Risk Hedging and Cryptocurrency Market Performance

(Sami & Abdallah, 2020) conducted a study on cryptocurrency markets impact on stock market returns in the Gulf countries by examining whether cryptocurrency and stock markets are substitutes or complements. If found to be substitutes, then the investors would reap diversification benefits. A complement will imply that the investors are considering cryptocurrencies as part of their investment portfolios but not necessarily for risk diversification benefits. (Sami & Abdallah, 2020) were able to extract daily cryptocurrency data obtained from cryptocurrencycharts.com for a period of 5 years (i.e 2014 – 2019) and compared this data with the main stock indices in 6 gulf countries including Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates (representing 86% of the Middle

East region stock market capitalisation). In this gulf study, they applied Least Square Regression and the Generalized Method of Moments Instrumental Variable (IV/GMM) for the analysis of various variables including Stock Market Return (Independent Variable), an openness index, inflation, GDP, Domestic Credit Index and Cryptocurrency prices as dependent variables. The results indicated that a 10% increase in the cryptocurrency market is matched with a 0.17% decrease in the stock market return. Therefore, the higher the returns in the cryptocurrency market, the lower the returns in the stock markets therefore both markets are substitutes and thus have significant diversification benefits. Similar studies by (Caferra & Vidal-Tomás, 2021) , (Bhullar & Bhatnagar, 2020), (Maitra, Rehman, Dash, & Kang, 2022), (Nkrumah-Boadu, Junior, Adam, & Asafo-Adjei, 2022) and (Jiang, Lie, Wang, & Mu, 2021) have also drawn similar results.

This study is like (Sami & Abdallah, 2020) and others in their use of stock indices and cryptocurrency price movements to determine existence of correlational relationships. The core difference is that this study focusses on price taking emerging developing nation market as opposed to a developed nation, price determining market.

2.3.4 Public sentiment and Cryptocurrency Market Performance

Several studies highlighting the predictive power of sentiment analysis obtained from social media platforms like Tweeter and Google on major cryptocurrency prices (Nie, Cheng, & Yen, 2020) (Aharon, Demir, Lau, & Zaremba, 2022) and (Kraaijeveld & De Smedt, 2020) have been conducted. (Gunay, 2019) study on predictive power of public twitter sentiment in forecasting cryptocurrency prices, which performed a daily and hourly twitter polarity analysis for 9 major cryptocurrencies, concluded that twitter sentiment can predict returns for Bitcoin, Bitcoin Cash and LiteGold cryptocurrencies, Another study by (Abraham, Higdon, Nelson, & Ibarra, 2018) on Cryptocurrency Price Prediction using Tweet Volumes and Sentiment Analysis provide similar conclusions. In this study, a collection of English hashtags (#bitcoin or #ethereum and other variants) was used to collect over 30 million tweets from the Twitter API over period of 60 consecutive days for analysis. These tweets were further subjected to sentiment analysis using the Valence Aware Dictionary for sEntiment Reasoning (VADER) analysis algorithm which classified the tweets as per their sentiment types (i.e positive, negative, or neutral) and cleaned the tweets off any noise (e.g hashtags, URLs, and emoticons). In addition, the study

obtained Google Trend data for the year 2004 which supplemented the tweet data earlier collected. Both the datasets were subjected to machine learning analysis and multiple linear regression analysis. The results demonstrated that both Google Search Trends and Tweet volumes are highly correlated to Cryptocurrency Market prices.

Both the (Abraham, Higdon, Nelson, & Ibarra, 2018) study and the this study use the Tweeter microblogging platform to obtain relevant public tweets for sentiment analysis. They also share the same data extraction techniques and the use of the VADER algorithm for public sentiment analysis. The (Abraham, Higdon, Nelson, & Ibarra, 2018) study examined the predictability of global cryptocurrency price movements using global tweet sentiments while this study will use local sentiments defined as tweet posts that originate from Kenya's GPS co-ordinates. This will filter out local investor sentiments from global sentiments. Further, the study assessed, which of the two sentiments have a higher predictability of cryptocurrency trade volumes. Thus, the study divergence areas is the use of twitter captured GPS co-ordinates to filter the origin of tweets and therefore identify local public sentiment (tweets that originate from the country i.e Kenya) which theoretically may differ from the global public sentiments.

2.4 Summary of the Literature and Research Gaps

The research addressed both contextual and conceptual gaps. In addressing the contextual gap, the study is carried out in a price taking, developing nation which is not able to singularly determine cryptocurrency prices. Current empirical research has been on developed price setting markets significantly different from developing markets vulnerable to information asymmetry and inefficient regulatory environments with little input into the pricing decisions of non-centrally regulated cryptocurrencies.

Additionally, the existing literature focusses on the effects of discrete monetary policy shocks and/or events on cryptocurrency performance rather than on the continuum of monetary policy application throughout the business cycles. i.e emphasis is placed on analysis around specific events, or shocks (Nguyen T. , Nguyen, Nguyen, & Phama, 2019)

This study addresses an existing conceptual knowledge gap of the effect of synchronized relationship between monetary policy and behavioural factors to cryptocurrency market

performance. It examines the new variables in a new light by combining them into an overall model that is unique and novel even though the variables have been separately studied in previous studies. The combination of the variables provides a wider coverage than previous studies which examined the monetary policy or behavioural aspects independently. This study takes a different approach (i.e using VAR and GARCH) to ensure more robust findings by studying all variables as endogenous while incorporating co-relationships. It is likely to shed new light in the analysis of the study parameters and predict the outcome of the dependent variable based on several aspects that can be influenced or determined by a regulatory authority.

Table 1 - Summary of Key Empirical Studies

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
1	(Karau, 2021)	To study how Bitcoin valuations respond to monetary policy shocks around monetary policy announcements.	Monetary policy shocks announcements emanating from both the US and the Euro area are found to have significant and persistent effects on Bitcoin valuations.	Focussed only on monetary policy events and shocks. The effect of monetary policy interest rates in non-shock scenario was unanswered. Focus was on leading developed markets.	Focus on price taking markets (i.e emerging economy) and investigates monetary policy effects even during non-shock periods.
2	(Nguyen T. , Nguyen, Nguyen, & Phama, 2019)	To examine the asymmetric impact of monetary policies on cryptocurrency returns during tightening versus monetary easing policy regimes.	Major cryptocurrencies react differently to leading economies monetary policies	Focussed on leading economies monitory policies investigating impact during shocks. Considered only monetary policy and failed to incorporate other important factors.	Analyse not only the monetary policy during shock times. Incorporate behavioural factors in the analysis.

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
3	(Liu & Tsyvinski, 2020)	To investigate network and production predictors of cryptocurrency market performance for all cryptocurrencies with a market capitalisation of over USD 1m.	There is a significant time series momentum phenomenon in the cryptocurrency market and that investor attention affects predicts future returns.	Limited variables as it only considered momentum and attention variables.	Investigate the variables in a new light by combining not only momentum and attention variables but also monetary policy.
4	(Abraham, Higdon, Nelson, & Ibarra, 2018)	Develop a method for predicting changes in Bitcoin & Ethereum prices using Twitter data and Google Trends Data.	Successfully predicted cryptocurrency prices using Twitter and Google Trends Data.	Focus on global price movements (beyond the control of national governments) and not on cryptocurrency markets which are within the control of national governments.	Extract local sentiments from Geo-tagged Tweets and use them to predict local cryptocurrency markets performance.

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
5	(Nie, Cheng, & Yen, 2020)	To assess the impact of US investor sentiment on a cryptocurrency market using trade volumes.	The change rate of the trading volume of Bitcoin and Ethereum are affected by the US sentiment index.	Used a monthly sentiment index which required the averaging of monthly returns to facilitate comparison.	Uses more accurate analysis using daily sentiment scores.
6	(Corbet, Meegan, & McHugh, 2017)	Investigate the effects of international monetary policy changes on bitcoin prices.	Monetary policy decisions based on interest rates taken by the Federal Open Market Committee (FOMC) in the United States significantly impact upon bitcoin returns and that bitcoin seems to be subject to the same economic factors as traditional fiat currencies and it is not entirely	Focussed on the arrival of "news" in the form of FOMC monetary policy announcements. The study did not consider behavioural aspects which are known to affect investor decision.	Incorporate not only monetary policy interest rates but also investor behaviour aspects.

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
			unaffected by government policies.		
7	(Lyocsa, Molnar, Plihal, & Siranova, 2020)	Study whether news and sentiment about bitcoin regulation, hacking of bitcoin exchanges and scheduled macroeconomic news announcement affect bitcoin volatility.	Bitcoin prices react similarly to various types of news especially regulation and positive investor sentiment. It also found out that bitcoin volatility is not influences by most scheduled US macroeconomic news announcements.	Did not incorporate other sources of uncertainties including global economic uncertainties and adhoc monetary policy announcements.	Incorporate the World Uncertainty Index (WUI) as a moderating variable to access the general effects of uncertainty which includes economic, monetary, and political uncertainty.
8	(French, 2021)	Investigated the differential impact of new Twitter-based Market Uncertainty Index (TMU) and variables for Bitcoin before and during the COVID-19 pandemic.	TMU is a leading indicator of Bitcoin returns only during the pandemic but its effect on bitcoin volatility during the COVID-19 pandemic is significant.	Used only sentiment-based uncertainty indices which are based on twitter posts. Developing nations contribution on social media is significantly lower than for developed nations.	Used the World Uncertainty Index which incorporates other forms of uncertainties.

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
9	(Caporale & Plastun, 2020)	Examined if there exists a momentum effect after one-day abnormal returns in the cryptocurrency market.	Prices tend to move in the direction of the abnormal returns till the end of the day when it occurs, which implies the existence of a momentum effect which give rise to exploitable profit opportunities.	Considered only days with abnormal negative or positive returns. An analysis covering all trading days would bring more comprehensive results.	Incorporate 7 days momentum trade moving average analysis.
10	(Kraaijeveld & De Smedt, 2020)	Study to what extent public twitter sentiment can be used to predict price returns for 9 largest cryptocurrencies.	Twitter sentiments had predictive power for the returns of some cryptocurrencies including bitcoin, bitcoin cash and Litecoin.	The study was focussed on price prediction which works for major global economies (price setting economies) and not for developing or emerging economies which are price taking.	Considered not only global twitter sentiments but also local public sentiments obtained from geo-tagged tweets and mapped to Kenya.

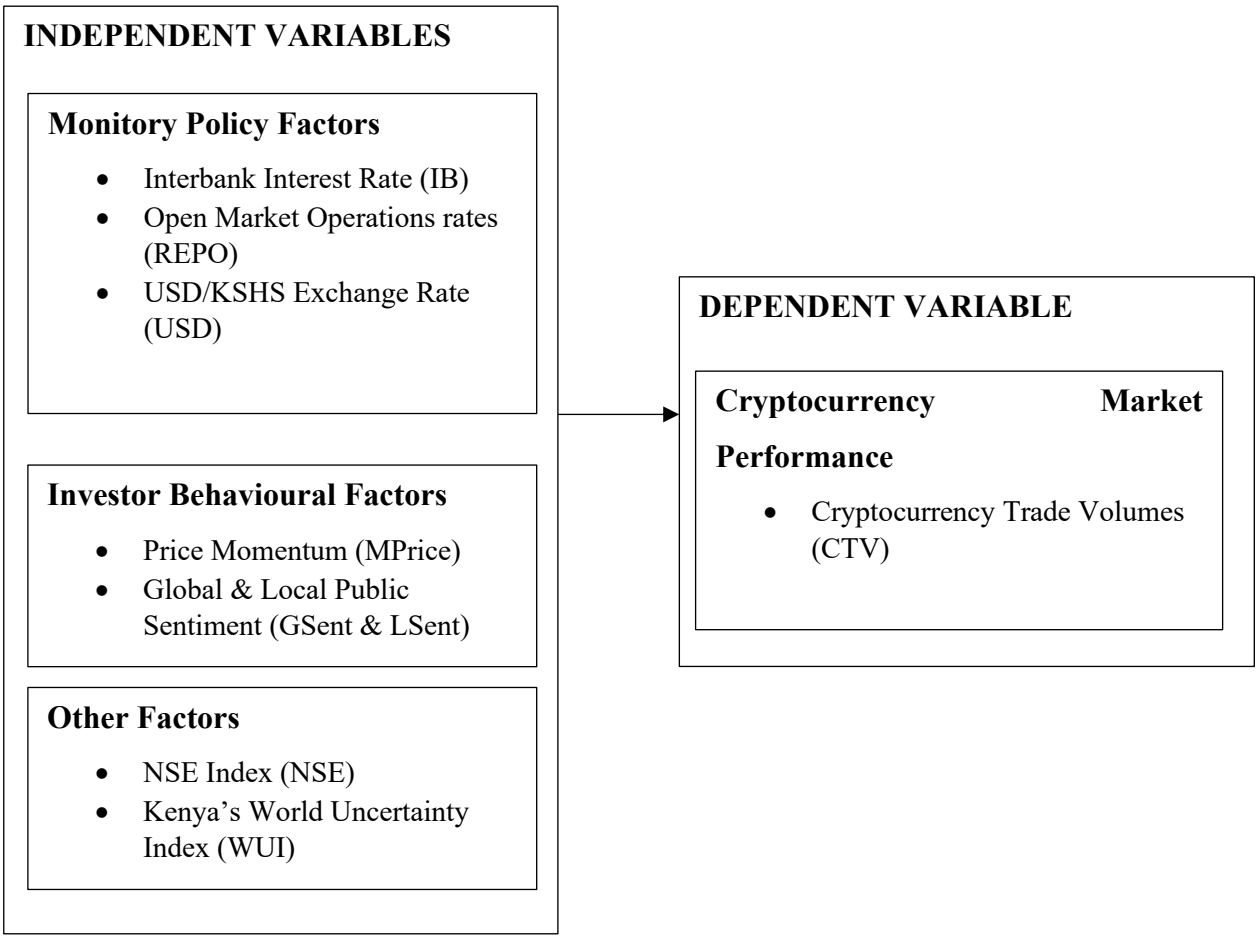
No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
11	(Sami & Abdallah, 2020)	Examine whether cryptocurrency market activities impact stock market returns in the Gulf region.	The cryptocurrency & stock markets are substitutes. A higher return in the cryptocurrency market is matched with a corresponding lower return in the stock market.	The cryptocurrency market analysis considered global price movements even when the study was targeting gulf countries.	All variables are local.
12	(Kumah, Odei-Mensah, & Amanamah, 2022)	Investigate the co-movement between cryptocurrencies and African stock returns to uncover the degree of their association and global portfolio diversification benefits.	High degree of co-movement and that stock markets in Africa are highly exposed to cryptocurrency market disruptions from the medium term.	Did not consider local cryptocurrency market specific factors.	Compare the performance of a local stock exchange market to local cryptocurrency exchange markets.

No.	Ref	Purpose	Findings	Research gaps (areas of further research)	How the Proposed Study Addressed Gap
13	(Nguyen, Schinckus, Nguyen, & Tran, 2022)	Investigated the effects of global and domestic uncertainty on the dynamics of portfolio investments in 21 economies from 2001 – 2016.	An increase in World Uncertainty Index (WUI) has a significant effect on portfolios net inflows.	The study applied to stock market portfolios and not cryptocurrency markets.	Compared WUI with Cryptocurrency Markets Performance.

2.5 Conceptual Framework

The study examined the effect of various independent variables as related to monetary policy effectiveness and investor behaviour dynamics to the dependent variable of Cryptocurrency Daily Trade Volumes (CTVs) for 2 leading Cryptocurrency Exchange Markets in Kenya. The independent variables are divided into monitory policy and investor behavioural variables (i.e price momentum, hedging opportunities measured by the NSE Index, public sentiments, and uncertainty) as illustrated in the conceptual framework below.

Figure 4 - Conceptual Framework Diagram



2.5.1 Operationalization of the Variables

Cryptocurrency Market Performance was measured using Cryptocurrency Trade Volumes (CTV) as applied by (Brauneis, Mestel, Riordan, & Theissen, 2021) and (Guler, 2021). CTV is a measure of the number of cryptocurrency coins traded at a particular price within a day in the 2 exchange markets (Paxful & LocalBitCoins). To ensure series stationarity the log differencing of CTV was used:

$$\mathrm{CTV} = \mathrm{CTV_t} - \mathrm{CTV_{t-1}}$$
$$\ln\mathrm{CTV} = \ln(CTV)$$

The independent variables are divided into 2 main groups i.e the Monetary Policy Factors and the Behavioural Factors. The Monetary Policy Factors are measured by the daily Interbank Interest Rate (IB), Repurchase Agreement Rate (REPO) and USD/KSH Foreign Exchange Rate (USD) as obtained from the Central Bank of Kenya website. Like CTVs the log differencing of the rates was used as below:

$$\mathrm{USD} = \mathrm{USD_t} - \mathrm{USD_{t-1}}\,,\ \mathrm{IB} = \mathrm{IB_t} - \mathrm{IB_{t-1}}$$
$$\ln\mathrm{USD} = \ln(USD)\,,\ \ln\mathrm{IB} = \ln(IB)$$

The REPO rate is used as a Liquidity Indicator. The net of REPO (REPO – Reverse REPO) is used to measure excess market liquidity. If the CBK undertakes a Repurchase Agreement (REPO) then ∂REPO will be measured as the difference between the REPO Rate and the Reverse REPO Rate. If ∂REPO > 0 then the CBK will be mopping out excess liquidity indicating that the Market has excess liquidity. On the other hand, if the CBK undertake a Reverse Repurchase Agreement (Reverse REPO) and ∂REPO < 0, then this would be a measure of low market liquidity and that the CBK would like to increase liquidity. It is expected that because of this netting, the REPO time series will be stationary.

The behavioural factors are measured by Price Momentum, the NSE Index performance, Public Sentiment Scores and Uncertainty. Price Momentum measures the rate at which the pricing of a cryptocurrency asset is changing (both in magnitude and speed). It is an oscillating indicator useful in identifying overbought (momentum and/or price is rising) and oversold (momentum increasing on the downside indicating increased pressure to sell) market conditions. It is a

measure of overall market sentiment that can support buying and selling with and against market trends. It is the basis of momentum trading which describes a herding behaviour. Secondly, to examine investor behaviour on risk, the study compares CTVs to the Nairobi Stock Exchange (NSE) Index, identifying hedging opportunities and assessing whether investors are taking advantage of these opportunities by shifting their investments between cryptocurrencies and publicly traded shares. Thirdly, the study looked at global and local public sentiments and assessed their effects on CTVs. Public Sentiments obtained from the Twitter Social Media platform were subjected to sentiment analysis and categorised into 3: Positive, Negative or Neutral similarly to (Abraham, Higdon, Nelson, & Ibarra, 2018) analysis. If the sentiment is positive, then a bullish investor is encouraged to invest more, if negative, then the investor can sell, while, if neutral the investor is not compelled to take any action. Further, the public sentiment shall be divided into 2: global and local sentiment and the effect of each type of assessment on the model shall be determined and the most influential of the 2 types of sentiments used to draw research conclusions. Finally, Kenya's World Uncertainty Indicator (WUI) was used to model uncertainty on investor behaviour. The WUI is a measure that tracks uncertainty across the globe by text mining the country reports of the Economic Intelligence Unit maintained by the IMF (Ahir, Bloom, & Furceri, 2022).

A 7-day moving average (as recommended by (Liu & Tsyvinski, 2020)) of BitCoin Prices (BTC) was used to compute the Momentum Price (MPrice). Different weights were assigned with larger weights assigned to the most recent BTC:

$$\text{MPrice} = \frac{\lambda_0 BTC_t + \lambda_1 BTC_{t-1} + \lambda_2 BTC_{t-2} + \lambda_3 BTC_{t-3} + \lambda_4 BTC_{t-4} + \lambda_5 BTC_{t-5} + \lambda_6 BTC_{t-6}}{7}$$

Such that

$\sum_{i=0}^{6} \lambda_i = 1 \; and \; \lambda_{i+1} < \lambda_i$

Therefore

$$\text{MPrice} = \text{MPrice}_t - \text{MPrice}_{t-1}$$

$$\text{lnMprice} = \ln(Mprice)$$

This moving average is used to compute the daily change in MP (∂MP) an indicator of positive or negative return expectations. If ∂MP > 0, then the Cryptocurrency Market Investor has an expectation of positive returns. On the other hand, if ∂MP < 0, then the Cryptocurrency Market Investor has an expectation of negative returns.

The Nairobi Securities Exchange 25 Share Index (NSE-25) which is a market capitalisation-weighted index of the top 25 companies listed in the Nairobi Securities Exchange provided a measure of investor risk aversion strategies when compared to CTV. If a reduction in CTV corresponds to an increase in NSE index and vice versa, then it meant that cryptocurrency investors are hedging cryptocurrencies with the stock exchange and vice versa.

$$\mathrm{NSE} = \mathrm{NSE_t} - \mathrm{NSE_{t-1}}$$
$$\ln\mathrm{NSE} = \ln(NSE)$$

The Compounded Public Sentiment Score (CPSS) obtained from the Global Public Sentiment Score (GSent) and the Local Public Sentiment Score (LSent) was derived from Twitter sentiment score computations. It was expected that the Local Public Sentiment score (LSent) is a subset of the Global Public Sentiment score (GSent) and that GSent will have a stronger influence on CTV than LSent. Both Gsent and Lsent were differenced to address stationarity.

$$\mathrm{GSent} = \mathrm{GSent_t} - \mathrm{GSent_{t-1}}, \mathrm{LSent} = \mathrm{LSent_t} - \mathrm{LSent_{t-1}}$$
$$\ln\mathrm{GSent} = \ln(\mathrm{GSent}), \ln\mathrm{LSent} = \ln(\mathrm{LSent})$$

Uncertainty was measured using the World Uncertainty Index (WUI). The mean of the WUI scores for Kenya for the entire study period have been computed for each month and published in the World Uncertainty Index website. Any month with a WUI score greater than the mean of the scores is considered to have a higher-than-normal level of uncertainty. If the WUI is equal or lesser than the mean of all the indices in Kenya, the month is considered as having normal level of certainty.

The table below gives a summary of the indicators and measures of the study variables.

Table 2 - Variable definitions (operationalization)

Variable	Indicator	Measurement	Literature source
Dependent Variable			
Cryptocurrency Market Performance	Change in Cryptocurrency Trade Volumes (CTVs)	= Daily BitCoin Cryptocurrency Trade Volumes	(Brauneis, Mestel, Riordan, & Theissen, 2021) & (Guler, 2021)
Independent Variables			
Monetary Policy Factors	Interbank Interest Rate (IB)	=Daily Interbank Interest Rates (IB)	(Nguyen T. , Nguyen, Nguyen, Pham, & Nguyen, 2022)
	USD/KSHS Exchange Rates (USD)	= Daily KSHS to USD Exchange Rate (USD)	(Cheong, 2019)
	Open Market Operations REPO rates (REPO)	= Daily Repo & Reverse Repo Market Rates (REPO)	(Nguyen T. , Nguyen, Nguyen, & Phama, 2019)
Behavioural Factors	Momentum Price(MPrice)	= P_t – P_{t-1} where P_t = BitCoin Momentum Price at day t and P_{t-1} is BitCoin Momentum Price at day t-1	(Liu & Tsyvinski, 2020)

Variable	Indicator	Measurement	Literature source
	NSE Index (NSE)	NSE Index = NSE 25 Share Index Movement	(Sami & Abdallah, 2020) and (Kumah, Odei-Mensah, & Amanamah, 2022)
	Global & Local Public Sentiment (GSent & LSent)	GSent or LSent > 0: Overall sentiment is positive. GSent or LSent = 0: Overall sentiment is neutral GSent or LSent < 0: Overall sentiment is negative	(Abraham, Higdon, Nelson, & Ibarra, 2018)
	World Uncertainty Index for Kenya (WUI)	=Monthly World Uncertainty Index (WUI)	(Ahir, Bloom, & Furceri, 2022)

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter gives an overview of the research methodology, the research design and associated data collection, analysis, and model validation procedures in addition to relevant ethical considerations.

3.2 Research Philosophy

A research philosophy is a belief about the way in which data about a phenomenon should be gathered, analysed, and used (Creswell, 2009). The study utilises ontological approach because the reality being focussed on is measurable and exists in the real world. The dependent variable of Cryptocurrency Trade Volume is objectively measurable in addition to all the independent variables. These variables exist independent of individual consciousness.

The study's adopted research philosophy is that of positivism through the ontological lens. Positivism believes that reality is stable and can be observed and described from an objective viewpoint without interfering with the phenomena being studied. Positivism further states that reality is real and apprehensible, where the collection and analysis of data facilitates the testing of hypotheses and theories. It is based on real facts, objectivity, neutrality, and measurable results (Saunders, Lewis, & Thornhill, 2012). This research philosophy is the most appropriate for the study because the study parameters are observable and are quantitatively measurable.

The study lends itself to a deductive strategy, which enhances the independence of the researcher in examining the study phenomenon. The researcher is external to the data collection process and maintains independence in a value free manner (Saunders, Lewis, & Thornhill, 2012). The deductive reasoning methods that are independent of the researcher and are statistically repeatable are employed to ensure objectivity in the study's field of reality. The inter-relationships and associations between the Cryptocurrency Trade Volumes and the independent variables can be explained using existing theories (interest rates and behavioural finance theories), therefore it was possible to develop research questions that were tested through analysis and generate findings in support of the theories.

3.3 Research Design

A research design provides the overall strategy and analytical approach to thoroughly investigate the study phenomenon. It constitutes the blueprint for the collection, measurement, and interpretation of research data (Creswell, 2009). This study is correlational with an emphasis on the discovery of any relationship between the study parameters. It seeks to establish the existence of statistically significant relationships between various parameters. It clearly defines what is to be measured and seeks to obtain complete and accurate information on the phenomenon by reducing the effects of bias and unreliability.

The study employs quantitative research methods where the relationship among variables is examined. The study not only looks at the relationship between the various study variables themselves but also with the dependent variable.

3.4 Population

Large data sets to facilitate more accurate generalisations (Saunders, Lewis, & Thornhill, 2007) were used. The study collected daily time series data from 1st January 2016 to 23rd September 2021 (5.75 years or 59 months) for all the data sets. A total of 41,657,075 global tweets, in English language, containing the word Bitcoin or its variant were obtained from the Twitter API for the said period. This dataset is compared to other similar sets contained in public domain (e.g Kaggle (Kaggle, 2023)) for accuracy. This forms the total population of relevant tweets. Duplicates and null tweets were removed before analysis. Geo-tagged Kenyan tweets were also extracted.

Additional monetary policy and investor behaviour data was collected accordingly. The total population size for all the study variables representing the number of days from 1 January 2016 to 23rd September 2021 is as summarised in Table 3.

Table 3 -Data population sizes

Variables	Data Source	Data Collection Method	Population Size (1st Jan 2016 – 23rd Sept 2021)
Daily (7-day week) Global Cryptocurrency Prices	Cryptocompare.com API BitCoin Prices	API	2,092
Daily (7-day week) Cryptocurrency Trade Volumes in USD	LocalBitCoins & Paxful API See link to archived CTV Data (Kimolo N. , 2023)	API	2,092
Daily (5-day week) Interbank Interest Rates Daily (5-day week) REPO rates Daily (5-day week) Foreign Exchange Rates	Central Bank of Kenya	Central Bank of Kenya Website	1,433
Daily (5-day week) NSE 25 Share Index Values	NSE	NSE Website	1,433
Compounded Global and Local Public Sentiment Score (Geo-tagged)	Twitter/Kaggle See link to Google Collab Script ((Kimolo & Machua, 2022)	Twitter API & Kaggle	41,657,075 global tweets containing "BITCOIN". Tweets geo-tagged for Kenya

To obtain uniformity between Monetary Policy data (i.e Interbank Rates, Repo and Reverse Repo data and Foreign Exchange Rate) published on 5-day trading weeks basis (i.e excluding weekends and public holidays) and BitCoin Trade Volumes, Price (which is used to compute the Momentum Price) and Public Sentiments data which is available on 7 days trading weeks, weekends were removed from the data set generalising the data set into a 5 day trading week. Because of this, 658 days were deducted from the 2092 days to a population size of 1,434 records. In addition, a further 127 days were deducted from the sample size as Paxful began trading on the 7th of May 2016 and not on the 1st of January 2016. The total population was

thus 1,307 daily transactions. Of the 1,307 transactions, 1,175 (90% of the population size) were found to have all the required daily fields and thus deemed complete. The non-complete data points were removed to prevent underestimation of true correlations as did (Martens & Poon, 2001) and (Das & Kannadhasan, 2018). These 1,172 records had global sentiment scores but not all of them had the local sentiment score, thus in order to have a dataset with both global and local sentiment scores, further records were remove creating a uniform time series 969 records (74% of all transactions).

According to literature review, the use of secondary data in cryptocurrency research is widely used. Some relevant studies using only secondary data include (Brauneis, Mestel, Riordan, & Theissen, 2021), (Guler, 2021), (Corbet, Meegan, & McHugh, 2017), (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) and (Liu & Tsyvinski, 2020). This is because, all cryptocurrency transactions are recorded in a transparent block chain with visibility by all participants. These transactions are permanently recorded and unalterable. Although on one hand, cryptocurrency transactions are completely transparent and trackable, they are also entirely anonymous in the sense that the participant's identity is not revealed (As it is represented in the form of a cryptographic hash). The study has a singular perspective on describing current situations and explaining the causal relationship between variables, thus it is objective in nature. This makes it a good candidate for quantitative analysis.

3.5 Data Collection Methods

The study makes use of secondary data only. Data related to cryptocurrency performance is usually published transparently in block chain registers that operationalise the cryptocurrency platform. This data is further aggregated by several cryptocurrency platforms from which it can be accessed publicly through various channels including Application Programming Interfaces (APIs). An API is a software interface that allows two applications to interact with each other without any user intervention. It facilitates the automatic extraction of data on a real-time basis from computerised system. This study made use of APIs to access data from LocalBitCoin and Paxful Cryptocurrency Exchange Markets. Data related to Tweeter was obtained through the Twitter API which provides real time access to tweet posts for academic and research purposes through its Developer API. Data related to local monetary variables and

the NSE Index was obtained directly from their respective authoritative sources i.e Central Bank of Kenya (CBK) and the NSE website.

3.6 Data Analysis and Presentation

The relationship between the study variables was estimated using two types of models: Vector Autoregressive (VAR) model and the Generalised Autoregressive Conditional Heteroscedasticity (GARCH). Financial time series data is expected to have heteroskedasticity as the series variance changes over time. This makes it difficult to use the standard regression models which require constant variance. Literature has modelled stylized facts of financial time series to include the presence of fat tails, volatility clustering, asymmetry-symmetry response to news/innovations/errors, non-stationarity, auto correlation and auto-regression with stochastic volatility (He, 2020) (Thapar, 2006) (Malmsten & Teräsvirta, 2004). Because of this, the study relied on various statistical tests to detect and correct autocorrelation and heteroskedasticity. In considering these facts, time series analysis provided the best model for the study.

3.6.1 Empirical Model

The relationship between the study variables was studied using 2 time series analysis models i.e Vector Autoregressive and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to achieve the study objectives. These models are discussed below.

Vector Autoregressive (VAR) Model

VAR models are used for Multivariate Time Series with each variable being a linear function of past lags of itself and past lags of other variables. As expected, the study variables were heteroskedastic and had non-constant variance because of the stylized properties of financial time series (He, 2020) (Thapar, 2006) (Malmsten & Teräsvirta, 2004). The study will fit the VAR(9) in differences model as opposed to the VAR in levels to address stationarity model as defined below:

$$Y_{it} = \{CTV_{1t},\ USD_{2t}, IB_{3t,} REPO_{4t}, MPrice_{5t}, NSE_{6t}\ , GSent_{7t}, LSent_{8t}\ , WUI_{9t}\}$$

Y_{it}denotes an N x 1 vector time series with T observations. Thus, considering 2 variables i.e CTV_{1t} and USD_{2t}

$$Y_{1t} = CTV_{1t} = \beta_{01} + \beta_{11,1}\, Y_{1t-1} + \beta_{12,1}\, Y_{2t-1} + \beta_{11,2}\, Y_{1t-2} + \beta_{12,2}\, Y_{2t-2} + \varepsilon_{1t}$$
$$Y_{2t} = USD_{2t} = \beta_{02} + \beta_{21,1}\, Y_{1t-1} + \beta_{22,1}\, Y_{2t-1} + \beta_{21,2}\, Y_{1t-2} + \beta_{22,2}\, Y_{2t-2} + \varepsilon_{1t}$$

$$Y_{9t} = WUI_{9t} = \beta_{09} + \beta_{91,1}\, Y_{1t-1} + \beta_{92,1}\, Y_{2t-1} + \beta_{91,2}\, Y_{1t-2} + \beta_{92,2}\, Y_{2t-2} + \varepsilon_{1t}$$
$$Y_t = c + A_1\, Y_{t-1} + A_2\, Y_{t-2} + \cdots \ldots \ldots \ldots + A_P\, Y_{t-p} + \varepsilon_t$$

Where A_i are (n x n) coefficients to be estimated and ε_t are n x 1 unobservable zero-mean white noise. All the Y_{1t} variables are defined as follows:

$Y_{1t} = CTV_{1t}$: Cryptocurrency Trade Volumes

$Y_{2t} = USD_{2t}$: Kenya Shillings to 1 USD Exchange Rate

$Y_{3t} = IB_{3t}$: Interbank Rate

$Y_{4t} = REPO_{4t}$: Net REPO rate as an OMO Liquidity Indicator

$Y_{5t} = MPrice_{5t}$: Momentum Price as an indicator of anticipated returns

$Y_{6t} = NSE_{6t}$: Nairobi Stock Exchange Index as an hedging alternative

$Y_{7t} = GSent_{7t}$: Global Public Sentiment

$Y_{8t} = LSent_{8t}$: Local Public Sentiment

$Y_{9t} = WUI_{9t}$: World Uncertainty Indicator for Kenya

To select the optimum number of lags, the study used the Akaike Information Criterion (AIC) and the Schwarz-Bayesian (BIC) criterion. The best lag is the one with the lowest information criterion. To determine whether one variable is useful in forecasting another, the study performed Granger & Instantaneous Causality tests accompanied by Impact Response Function (IRF) analysis. In IRF analysis, the response of one variable to a sudden but temporary change in another variable is analysed to assess the significance of the relationship between the variables.

Univariate & Multivariate GARCH model

Due to expected heteroskedasticity, the study modelled volatility instead of removing it. While the VAR model handles heteroskedasticity by removing it (i.e through differencing), GARCH

models the volatility using various distributions (i.e normal, student t-distribution, skewed student t-distribution etc). It makes conditional volatility assumptions other than constant volatility assumption. The study identifies the best GARCH model by comparing the information criterion. Low order GARCH models will be preferred to high order GARCH models.

Both univariate (focussing on CTVs volatility) and multivariate (focussing on joint volatility between CTV and the independent variables) were performed. For the univariate GARCH model, the variance in CTVs (σ_t^2) was given as follows

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where $\alpha_0 \geq 0, \alpha_j \geq 0$ for all $j = 1\ to\ p, \alpha_j \geq 0, \beta_j \geq 0$ for all $j = 1\ to\ q$, $\sum_{j=1}^{p} \alpha_j + \sum_{j=1}^{q} \beta_j < 1$ and ε_t^2 is the squared error term.

Applying these formulae on the univariate variable CTV in the standard model GARCH (1,1), proposed by (Bollerslev, 1990), we obtain the following.

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

ε_t is normally distributed with a zero mean, while the conditional variance σ_t^2 is a function of the mean volatility level ω (estimated weighted average of the long-term average), the news from previous period ε_{t-1}^2, and the variance σ_{t-1}^2 in the last period. The sum of $\sum(\alpha + \beta)$ measures the persistence of volatility for a given shock. α is the ARCH component that estimates the relation to the conditional volatility observed in the previous period, while β (GARCH component) is the estimated forecasted variance from the last period. Further restrictions are placed on the model such that both α and β are between 0 and 1 and $\alpha + \beta < 1$. Thus, the parameter α_j denotes shocks to CTV returns due to short-run persistence (i.e the ARCH effect) and β_j denotes shocks to CTV returns due to a long-run persistence (GARCH effects).

If CTV variance in the current period is high, then the forecasted volatility the following day will be high unless the mean of the volatility shifts considerably. The magnitude of α and β

determine the short-term dynamics of the forecasted volatility series. A large value of β indicates persistence (i.e., shocks of the conditional variance will take long to die out), while a large value of α indicates that the volatility reacts quite fast to market movements.

The GJR-GARCH model, proposed by (Glosten, Jagannathan, & Runkle, 1993) was used in addition to the standard GARCH because of its ability to provide more information on news.

$$CTV_t\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2$$

The term $\varepsilon_{t-1}^2 d_{t-1}$ defines the asymmetric component where the parameter $d_t = 1$ if $\varepsilon_t < 0$ (bad news) and dt = 0 otherwise. Thus, good news (positive errors) have an impact on, α and bad news (negative errors) has an impact of $\alpha + \gamma$. The impact of news on volatility is asymmetric if γ is significantly different from zero. The persistence of volatility is measured as $\alpha + 0.5\,\gamma + \beta$.

Multivariate Dynamic Conditional Correlation GARCH (DCC-GARCH) model was used to extend the volatility analysis to other n independent variables. DCC-GARCH is known to perform better than other multivariate models (Acatrinei, Gorun, & Marcu, 2013) (Gabauer, 2020) (Orskaug, 2009). Several studies have used this model to study financial series volatilities and spill overs (Smales,2021; Wei,2008) (Smales, 2021) (Wei, 2008). It calculates the correlation between 2 variables as a function of their past volatility and the correlations among the variables themselves. It allows a correlation matrix to be dependent on time. The DCC GARCH model uses the recent past information to estimate the present correlation between series. It will be used to model the short-run and lingering impact of the independent variables to the dependent variable i.e the short-run volatility impact and persistency of the standardised residuals from prior periods and persistency of the conditional correlation processes. It also has clear computational advantages in that the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated thus ensuring that potentially large correlation matrices can be estimated. It can also take different assumptions for error distribution including normal, student-t and skew Student t-distribution.

3.6.2 Model Diagnostic Tests

Several tests were performed to ensure that the fitted models best represent the study data and that the analysis performed was the most appropriate to draw statistically correct conclusions. These diagnostic tests are required before successful modelling with Vector Auto Regressive (VAR) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) methods. These tests are discussed below.

Influential Variables Test

Influential Outliers were identified using leverage and residual values as measured by Cook's Distance. Cook's distance is calculated by removing an i^{th} data point in the regression and summarising how the regression model changes when the i^{th} observation is removed. That is, it measures how much all of the model fitted values changes when the i^{th} data point is removed (Cook, 1977). The DFBETA test which measures the difference in each parameter estimate with and without the influential points was used to determine the influence that each variable datapoint has. A large value of DFBETA indicates that the observation is influential in estimating a given parameter.

Stationarity Tests

Stationarity is a necessary pre-condition for VAR models. A stationary time series is one whose properties do not depend on the time the series was observed i.e the statistical properties (mean, variance, covariance and standard deviation) of a process generating a time series do not change over time. The Augmented Dickey-Fuller (ADF) Test was performed on all the time series. Non-stationarity was addressed using differencing and log transformations. The ADF tests the presence of unit root in the time series. If a unit root exists, then the time series is non-stationary.

Residual Tests

Various tests were performed on residuals to test for heteroskedasticity, autocorrelation, the presence of ARCH effects and the type of error distribution. The Asymptotic Portmanteau Test was performed to determine if there is serial autocorrelation on the residuals. To test for the ARCH effect, the Autoregressive Conditional Heteroscedasticity (ARCH) Lagrange Multiplier

(LM) test is performed (Higgins & Bera, 1992). The ARCH LM test was used to detect the presence of time-varying phenomenon in conditional volatility and thus suggests the use of GARCH. A significant ARCH effect will identify time-varying conditional volatility, volatility clustering (or mean reversion) and the presence of fat-tails (Catani & Ahlgren, 2017). The Jarque-Bera test was used to test for the normality of residuals which was useful in informing the most optimum error distribution model (e.g normal, student t distributions or others).

ARCH Tests

To model conditional heteroskedasticity, 3 tests are performed. The ARCH LM test to test for heteroskedasticity in the error terms, the Weighted Ljung-Box Test on standardised square residuals to test for autocorrelation and the Adjusted Pearson Goodness-of-Fit test which compared the empirical distribution of the standardised residuals with the selected theoretical distribution to determine Goodness of Fit. The model with the highest log likelihood and the lowest information criteria (AIC or BIC) was selected.

3.7 Research Quality

All data used in the study is generated automatically from authoritative sources with minimal human intervention. This protects the data from testing and instrumentation errors that are common in survey-based approaches. Monetary policy data was obtained from the CBK website, while public Tweets were obtained directly from the Twitter API (now called X). Since, cryptocurrency transactions are recorded on a transparent blockchain, cryptocurrency data used is verifiable from different sources, greatly enhancing its integrity, transparency and accuracy.

3.8 Ethical Issues in Research

Cryptocurrencies though unregulated, are not illegal. The objective of this study is to understand the performance of cryptocurrency markets to contribute to the development of relevant regulatory interventions making them safer and more adaptable to a developing nation like Kenya. Secondly, the data obtained from the social media platforms conforms and complies with the respective platform’s privacy policies. Reasonable measures were

undertaken to prevent the disclosure of any private information that comes to the researcher attention during the study.

Further, the research output is licensed under Creative Commons (Attribution-ShareAlike 4.0 International (CC BY-SA 4.0)). This license facilitates the sharing and the unrestricted use of this research for educational purposes to guarantee future enhancements (Creative Commons, 2021)

The conduct of this research was guided by the Strathmore University ethical standards for graduate students as well as the standards issued by the National Commission for Science, Technology and Innovations (NACOSTI)

CHAPTER FOUR: DATA ANALYSIS AND FINDINGS

4.1 Introduction

The purpose of the study was to investigate the relationship between Kenya's monetary policy and local investor behaviour on cryptocurrency market performance. This chapter presents the research findings beginning with descriptive and correlation analysis followed by diagnostic and model fit tests then finally model test results and summary of findings.

4.2 Descriptive Analysis

The table below provides a summary of the descriptive statistics for each of the variables.

Table 4 - Descriptive Statistics

	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE	P2Coeff
CTV	186,418.27	180,530.82	102,899.93	4,917.86	815,301.44	1.11	0.03	5,799.49	1.39
USD	104.21	3.28	103.24	99.61	111.59	0.55	-1.16	0.11	0.89
IB	4.82	1.75	4.69	1.24	11.34	0.66	0.49	0.06	0.22
REPO	1.29	4.96	0.00	-11.94	9.97	-0.75	0.18	0.16	0.78
MPrice	13,928.79	14,894.69	8,518.91	449.38	61,792.30	1.75	1.84	478.49	1.09
NSE	2,725.35	717.33	2,720.97	1,729.46	4,089.00	0.15	-1.38	23.04	0.02
Gsent	0.09	0.06	0.10	-0.06	0.37	0.39	0.33	0.00	-0.47
Lsent	0.17	0.24	0.17	-0.77	0.98	-0.08	1.17	0.01	0.11
WUI	0.50	0.38	0.40	0.00	2.10	2.20	5.83	0.01	0.79

Note:

P2Coeff refers to Pearson's Second Coefficients is Standard Error, SD is Standard Deviation

Daily Cryptocurrency Trade Volumes (CTVs) have been rising over the years from a low of USD 4,917 (in July 2016) to a high of USD 815,301 (in September 2021). The characteristic high volatility of cryptocurrency trading is shown by the large standard deviation and spreads in CTVs (USD 810,383.58). Similar behaviour is observed with Momentum Price which has a mean of USD 13,928.79 with a high standard deviation (14,894.69) and large spreads (61,792.30). Thus, the Momentum Price was responding to CTV volatility. The average Foreign Exchange Rate of Kshs to the US Dollar (USD) was 104.21 with a standard deviation of 3.28. The lowest (99.61) and the highest (111.59) values of the USD Exchange Rate were recorded in March 2019 and December 2020 respectively. The average Interbank Exchange

Rate and Net REPO rates over the study period were 4.82 and 1.29 (i.e the Central Bank on average was clearing liquidity from the markets). The Nairobi Stock Exchange Index averaged 2,725.35 over the study period but with less volatility than the CTVs. The lowest NSE index was recorded in August 2020 (1,729.46) while the highest in August 2017 (4,089).

Global sentiment ranged from -0.06 in June, 2017 (attributed to the Ethereum Flash Crash (MarketWatch, 2017) and the cyberattack on 2 major cryptocurrency exchanges (CNBC, 2017)) and 0.37 in October, 2020 (largely due to a surge in the number of large institutions adopting Bitcoin as part of their business strategy e.g PayPal and DBS bank) (CoinGecko, 2023). The mean of 0.09 shows a relatively neutral to positive sentiment during the study period.

The Kenya's World Uncertainty Index (WUI) Score ranged from 0 in July 2019 and 2.10 in October 2017 (due to ongoing election tensions and insecurity in the north-eastern part of Kenya). A higher average CTV (USD 228,716.23) was reported during times of normal certainty (where Kenya's WUI indicator is less than its mean i.e 0.507) as compared to trade volumes in times of high uncertainty (USD 99,420.55). An increase in uncertainty leads to a reduction in trade volumes. This contrasts with the NSE index (NSE) where the mean of the index was highest during times of high uncertainty. The CTV investors significantly reduced their risks (as measured by the standard deviation reducing from 182,850.61 to 140,263.58) in times of increased local uncertainty. A similar result is obtained for the Momentum Price which is high in times of normal uncertainty as opposed to times of increased uncertainty. The NSE index rises in times of uncertainty implying that CTV investors shift their investment from Cryptocurrencies to NSE due to Fear, Uncertainty and Doubt (FUD). Both Global and Local Sentiments adjusts accordingly to reflect local uncertainty with the Local Sentiment responding predictably better than the Global Sentiments as seen by the higher means and standard deviations ($\mu = 0.20 \; and \; \delta = 0.25$ for Local Sentiment (LSent) during period of normal uncertainty as compared to $\mu = 0.11 \; and \; \delta = 0.06$ for Global Sentiment (GSent)). The impact on uncertainty in all the variables in summarised in Table 5 below.

Table 5 - Descriptive Statistics grouped by WUI Ranking

	WUI Rank	n	Mean	SD	Median	Min	Max
CTV1	0	652	228,716.23	182,850.61	140,075.81	6,948.86	815,301.44
CTV2	1	317	99,420.55	140,263.58	54,735.34	4,917.86	641,449.40
USD1	0	652	104.77	3.54	103.71	99.61	111.59
USD2	1	317	103.07	2.26	103.11	99.98	109.87
IB1	0	652	4.39	1.46	4.27	1.24	11.34
IB2	1	317	5.70	1.96	5.66	1.68	10.81
REPO1	0	652	1.64	4.84	-	(11.94)	8.99
REPO2	1	317	0.58	5.13	-	(11.17)	9.97
MPrice1	0	652	16,572.72	16,041.24	9,460.18	588.11	61,792.30
MPrice2	1	317	8,490.80	10,266.14	6,574.00	449.38	48,560.13
NSE1	0	652	2,444.74	594.08	2,442.27	1,729.46	3,862.27
NSE2	1	317	3,302.52	593.75	3,482.18	1,874.33	4,089.00
Gsent1	0	652	0.11	0.06	0.12	(0.06)	0.37
Gsent2	1	317	0.05	0.05	0.05	(0.04)	0.18
Lsent1	0	652	0.20	0.25	0.19	(0.77)	0.98
Lsent2	1	317	0.13	0.21	0.12	(0.60)	0.93

WUI Rank =0 implies normal uncertainty (where WUI < $\mu(WUI) = 0.5$

WUI Rank = 1implies higher than normal uncertainty where WUI > $\mu(WUI)$

4.3 Correlation Analysis

Correlation analysis was performed to establish the inter-relationships between the study variables. Spearman correlation was preferred because of its ability to handle both parametric and non-parametric variables. Table 6 summarises the correlation results.

Table 6 - Spearman's correlation results

	CTV	USD	IB	REPO	Mprice	NSE	Gsent	Lsent	WUI
1. CTV	-								
2. USD	.69***	-							
3. IB	-.30***	-.12***	-						
4. REPO	.28***	.33***	-.14***	-					
5. MPrice	.85***	.62***	-.20***	.19***	-				
6. NSE	-.83***	-.68***	.41***	-.35***	-.63***	-			
7. Gsent	.82***	.60***	-.35***	.28***	.73***	-.79***	-		
8. Lsent	.13***	.10**	-.10**	0.04	0.03	-.22***	.16***	-	
9. WUI	-.47***	-.18***	.26***	-.23***	-.35***	.56***	-.44***	-.12***	-

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

From this summary, there is a significant correlation between all the variables and CTV and between the variables themselves. The USD Exchange Rate is the strongest monetary policy variable affecting Cryptocurrency Trade Volumes. A fall in the value of Kenya Shillings as compared to the USD leads to increased investments in Cryptocurrencies. This indicates the presence of hedging opportunities against exchange rate falls. Interbank Rate and REPO rates significantly affect CTVs although not as strongly as the USD Exchange Rate. A fall in Interbank Interest Rate increases CTVs. Excess liquidity as indicated by the positive Net REPO co-efficient leads to an increase in CTVs thus, CTVs will rise whenever there is an increase in market liquidity. CTVs are significantly but negatively correlated to the NSE index. This implies that cryptocurrencies are hedging or acting as alternative investment for the NSE.

Net REPO, though weakly correlated with CTVs, is highly significant. It is also positively correlated with CTVs but negatively correlated with NSE. An increase in liquidity leads to an increase in CTVs in local cryptocurrency markets, however, excess market liquidity reduces the NSE index as investors can explore more risky investments. This short-term liquidity is better captured by CTVs than NSE stocks which may not be as sensitive to short-term economic changes. Thus, investors may choose to take advantage of the short-term liquidity before the CBK mops it out.

Momentum Price in the Cryptocurrency market is strongly and positively correlated to CTVs. An increase in Momentum Price leads to an increase in CTVs. On the other hand, Momentum Price is negatively correlated to the NSE indicating that an increasing cryptocurrency Momentum Price reduces NSE investments as more investment shifts to Cryptocurrencies. A

similar trend is seen with the Global Sentiment (GSent) and the Local Sentiment Score (LSent), although the Global Sentiment is more strongly correlated to CTVs than the Local Sentiment. An increase in cryptocurrency positive sentiments leads to an increase in CTV investments but a negative move on NSE. Reviewing the relationship between the global and local public sentiment, the study notes that they are weakly correlated even though the relationship is significant.

The World Uncertainty Indicator (WUI) for Kenya is negatively correlated to CTVs. That is, an increase in uncertainty leads to a reduction in CTVs. Most of cryptocurrency investments are made during times of normal certainty and Kenyan investors are risk averse. However, an increase in WUI leads to increase in NSE stocks in comparison to cryptocurrencies in times of uncertainties.

4.4 Diagnostic Test Results

This section contains diagnostic tests conducted before running the required models. The tests performed ascertains the viability of a VAR and GARCH model. These tests and diagnostic results are discussed below.

4.4.1 Test for influential variables

The dataset was analysed for influential variables using residual leverage and cooks' distance. Figure 5 and 6 below provides a visual representation of leverage and cook’s distance showing the 3 main outlier records which were removed. DFBETA test, which measures the difference in each parameter estimate with and without the outliers were also performed and similarly identified the 3 outlier points.

Figure 5 - Leverage influential variables test

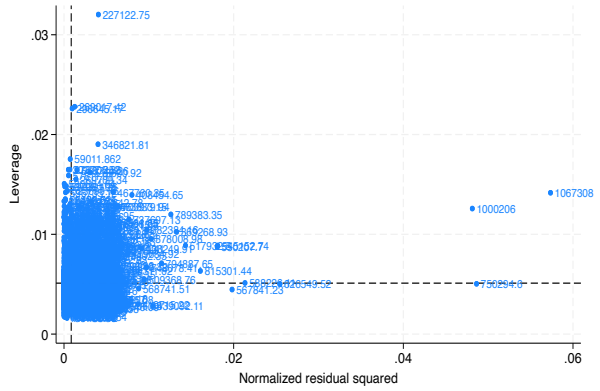
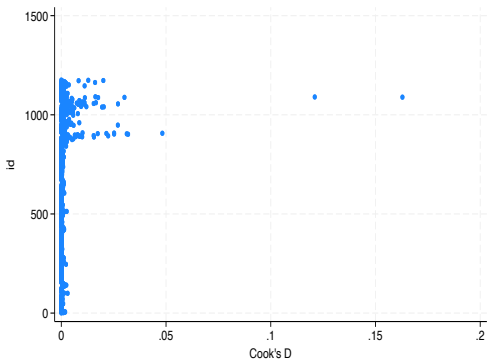


Figure 6 - Cooks Distance influential variable test



The removal of the outliers led to an increase in Adjusted R^2 from 0.8817 to 0.895 indicating that the model without outliers was better.

4.4.2 Stationarity Tests

Visual inspection, and the Augmented Dickey-Fuller (ADF)Test were performed on the data. Table 7 below summarises the results of the ADF test before and after log differencing for all the time series.

Table 7- ADF Test Results: Before & After series differentiation

	lnCTV	lnUSD	lnIB	REPO	lnMPrice	lnNSE	lnGsent	lnLsent	WUI
Before Differencing	-3.169 (0.093)	-1.896 (0.622)	-4.904 (0.01)	-5.928 (0.01)	0.303 (-2.651)	0.414 (-2.388)	-4.088 (0.01)	-7.011 (0.01)	-3.803 (0.019)
After Differencing	-12.059 (0.01)	-9.104 (0.01)	-10.659 (0.01)	-11.65 (0.01)	-7.896 (0.01)	-7.059 (0.01)	-14.379 (0.01)	-15.76 (0.01)	-9.866 (0.01)

p-values are in parenthesis.

As also confirmed by the visual representation in Appendix 1 and 2, the p-values after differencing are lower than 0.05, thus, it was concluded that the series were stationery after differencing.

4.4.3 Tests on residuals

Various tests were performed on the model residuals (i.e The Portmanteau Test, Multivariate ARCH test and the JB-Tests). The residuals were heteroskedastic as expected. Table 8 summarises the results.

Table 8 - VAR model residual tests statistics

	1	2	3	4	5	6	7
Portmanteau Test (asymptotic)	54.02 (0.009)	219.9 (0.001)	54.283 (0.002)	82.264 (0.0005)	33.868 (0.006)	46.722 (0.109)	1218.9 (1.34E-12)
ARCH (multivariate)	130.75 (2.69E-10)	818.14 (< 2.2e-16)	121.16 (6.59E-09)	471.61 (< 2.2e-16)	95.441 (1.73E-05)	145.34 (1.70E-12)	14020 (2.20E-16)
JB-Test (multivariate)	13797 (< 2.2e-16)	8295 (< 2.2e-16)	1847.1 (< 2.2e-16)	11263 (< 2.2e-16)	16649 (< 2.2e-16)	225763 (< 2.2e-16)	99582 (2.20E-16)

P-values are in parenthesis.

Model 1: lnCTV & lnNSE

Model 2: lnCTV & Monetary Policy Variables (lnUSD, lnIB, REPO)

Model 3: lnCTV & Momentum Price (lnMprice)

Model 4: lnCTV & Sentiments (lnGsent & lnLsent)

Model 5: Global and Local Sentiments (lnGsent & lnLsent)

Model 6: lnCTV & Uncertainty (WUI)

Model 7: lnCTV & All variables

The Portmanteau Test (Asymptotic) test was used to determine if there is serial autocorrelation on the residuals. The null hypothesis (no autocorrelation) is rejected for all models except Model 6 (i.e CTV and Uncertainty) since p-values are less than the significant level alpha of 0.05. Therefore, there is residual correlation all the models except Model 6. The Jarque-Bera Test low p-values provide strong evidence that the residuals do not follow a normal distribution. However, the ARCH (Autoregressive Conditional Heteroscedasticity) test low p-values (i.e less than 0.05) indicate the presence of ARCH effects, a key pre-requisite for a GARCH model.

4.4.4 ARCH Tests

Additional ARCH tests were performed on the respective univariate time series (i.e the ARCH LM and the Box-Ljung tests) which indicated the presence of ARCH effects. The results are summarised in Table 9 below

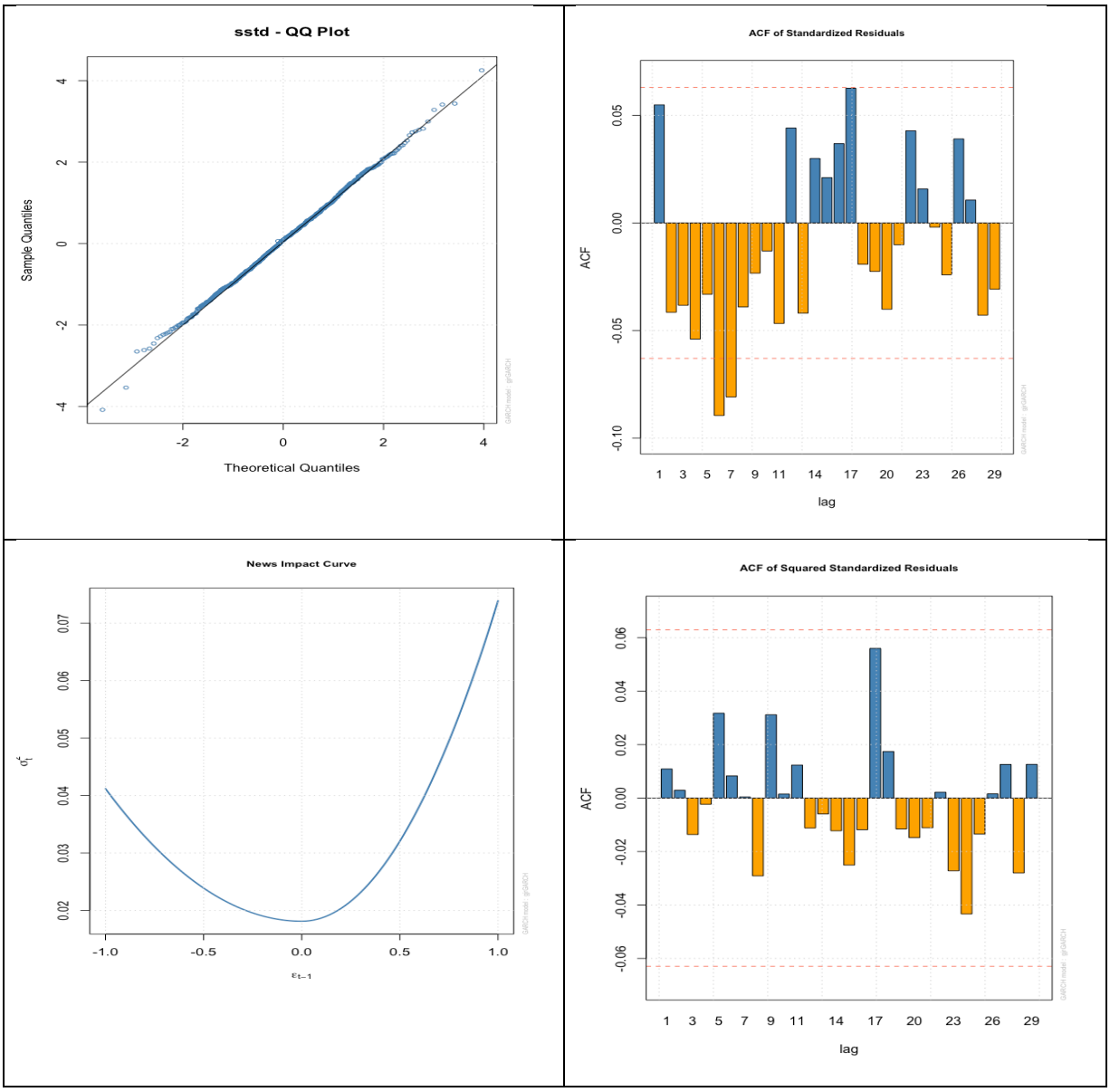
Table 9-ARCH Test results for all the series

	lnCTV	lnUSD	lnIB	lnMPrice	lnGsent	lnLsent	lnNSE
Arch LM-test - Chi Squared (p-value)	119.48	108.93	101.15	29.298	206.44	20.581	60.755
	< 2.2e-16	< 2.2e-16	3.31E-16	0.003557	< 2.2e-16	0.05686	1.64E-08
Box-Ljung Test - X-Squared (p-value)	449.91	449.91	338.18	85.164	926.63	77.586	178.37
	< 2.2e-16	< 2.2e-16	< 2.2e-16	4.23E-13	< 2.2e-16	1.19E-11	< 2.2e-16

A combination of Standard GARCH and the GJR (Glosten, Jagannathan, and Runkle) GARCH models (sGARCH(1,1), sGARCH(2,1), GJR-GARCH(2,1) and GJR-GARCH(1,1) with student t-distribution and sGARCH(1,1) with normal distribution) were evaluated using 3 tests: Weighted Ljung-Box Test on Standardized Squared Residuals, the ARCH LM test to test the presence of ARCH effects (the best model will not have ARCH effects as all serial autocorrelations should be accounted for) and the Adjusted Pearson Goodness-of-Fit Test for selection of best of fit model. The results are summarised in **Appendix 3 – GARCH Model selection test results.**

The Weighted Ljung-Box Test on Standardized Squared Residuals which defines a null hypothesis that a series of residuals exhibit no autocorrelation for a fixed number of lags had p-values > 0.05 indicating the absence of autocorrelation in the errors. Similarly, all the ARCH LM tests generated a p-value > 0.05 implying that the models do not exhibit the ARCH effect, thus these are the optimal models. The Adjusted Pearson Goodness-of-Fit test which compares the empirical distribution of the standardized residuals with the selected theoretical distribution had p-values > 0.05. This implies that the models have Goodness-of -Fit. Figure12 provides a visualisation of the errors for Model 5 (i.e the GJR-GARCH(1,1) with student t-distribution) which was selected as the best model based on the highest log likelihood and lowest information criteria variables (AIC & BIC).

Figure 7 - Visual representation of residuals for GJR-GARCH (1,1) model



4.5 Results

The study results are presented in 2 parts based on the analysis model used and the research question being answered. The VAR model analysed the inter-relationship between CTV and the various Monetary Policy, investor behaviour and public sentiment independent variables. The VAR results are supported by Granger and Instantaneous Causality tests and Impulse Response Functions (IRF) for visualisation. Univariate and Multivariate GARCH results will further clarify the volatility relationship within CTV itself and with the other independent variables.

4.5.1 Vector Autoregressive (VAR) analysis results

Monetary Policy Influence

A VAR model for log of CTV (lnCTV) was fitted with the 3 monetary policy variables (lnUSD, lnIB and REPO). The table below summarises the relationships obtained from the VAR analysis.

Table 10-Monetary Policy VAR results

	Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
1	lnCTV= 0.579 lnCTV.l1(***) -0.449 lnCTV.l2(***)- 0.276 lnCTV.l3(***) + 0.136 lnIB.l3(**)- 0.188 lnCTV.l4(***) + 7.969 lnUSD.l4(*) -0.110 lnCTV.l5(***) + -0.058 lnCTV.l6(*)	962	0.253	2.2E-16	0.216
2	LnUSD= 0.324 lnUSD.l1(***) -0.063 lnUSD.l2(*) -0.070 lnUSD.l4(**) -0.00003 REPO.l6(*)	962	0.095	1.985E-14	0.002
3	lnIB = 0.035 lnCTV.l1(**) 0.115 lnIB.l1(***) -0.002 REPO.l1(*)- 0.059 lnCTV.l2(***) -0.002 REPO.l2(**) -0.061 lnCTV.l3(***) -0.002 REPO.l3 (**) -0.039 lnCTV.l4(*) -0.002 REPO.l5(**) -0.002 REPO.l6(*)	962	0.028	0.000922	0.114
4	REPO = 0.597 REPO.l1(***) -0.462 REPO.l2(***)- 0.343 REPO.l3(***) +1.513 lnCTV.l4(*)- 0.180 REPO.l4(***)- 0.138 REPO.l5(***) -0.117 REPO.l6(***)	962	0.270	< 2.2e-16	4.306

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

The future value of Cryptocurrency Trade Volumes (CTV) is strongly and significantly determined by its own 6 lags (a contribution of 6/8 = 0.75 i.e prob = 0.75), 1 lag of lnIB

(moderately) and 1 lag of lnUSD (weakly). USD Exchange Rate (LnUSD) is predicted by 3 of its own lags (prob=0.75) and weakly by REPO (prob = 0.025). REPO is a significant predictor of Interbank Rates (prob = 0.5) together with Cryptocurrency Trade Volumes (prob = 0.4). REPO is predicted 6 out of 7 times (prob = 0.857) from its own lags. 25.3% variability in CTV is accounted for by itself, USD Exchange Rate and Interbank Rates. CTVs strongly predicts Interbank Rates but has weak prediction for REPO and USD.

On further causality analysis, we can reject Granger Causality null hypothesis (since p-value < 0.05) and conclude that both past and present values of USD Exchange Rate and Interbank Rate, granger cause Cryptocurrency Trade Volumes. This means that knowing the past values of USD and IB rates is helpful in predicting the future values of CTV. The results also indicate the existence of instantaneous causality between lnUSD and lnIB and lnCTV implying that knowing the future values of USD Exchange Rate and IB Rate is useful in predicting CTV. Table 11 below, summarises the results.

Table 11-CTV & Monetary Policy Causality Tests

Ho	Test Statistic	P-Values	Conclusion
G: lnUSD lnIB do not Granger-cause lnCTV	2.3219	0.01756	lnUSD lnIB -> lnCTV
I: No causality between lnUSD lnIB and lnCTV	13.192	0.001366	lnUSD lnIB -> lnCTV
G: lnCTV do not cause lnUSD lnIB	1.3854	0.1275	lnCTV ≠> lnUSD lnIB
I: No causality between lnCTV and lnUSD lnIB	14.012	0.002889	lnCTV -> lnUSD lnIB

Upon closer examination of the Impact Response Function (IRF) between the Monetary Policy variables and CTV, we note that the impact of a shock on USD will affect CTV between the 4^{th} and 6^{th} days with a 1 standard deviation increase in USD causing a 0.01 standard deviation increase in lnCTV within this period. Similarly, a shock on IB will reflect within 2 time periods with a dip and sharp increase on the 5^{th} and 6^{th} day with a 1 standard deviation increase causing a 0.014 standard deviation increase in lnCTV within the period. In both cases, the effects of the shock begin to die on the 10th day. Figure 13 and 14 below illustrates these relationship.

Figure 8 - Impact of Shock of USD on CTV

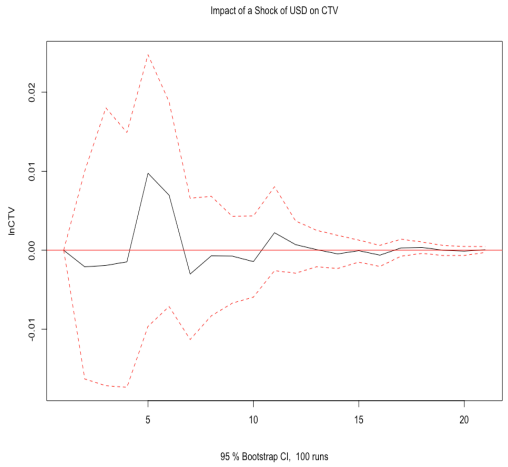
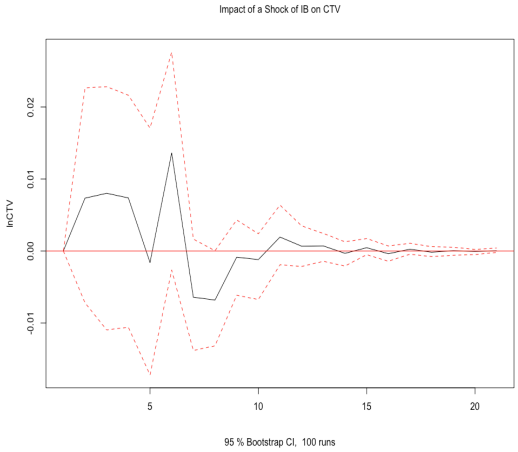


Figure 9 - Impact of Shock on IB on CTV



Thus, the study concludes that USD and IB jointly have a significant predictive power on CTV. Knowing the past or future values of USD and IB have a predictive power on CTV. Shocks on both USD and IB affects CTVs within first 5 days and begin to decay on the 10th day. REPO has very weak predictive power on CTVs. This implies that the KSHS/USD Exchange Rate and Interbank Rates as components of the local monetary policy have predictive power on cryptocurrency trade volumes. This is consistent with studies by (Auer & Claessens, 2018), (Giudici, Milne, & Vinogradov, 2020), (Nguyen T. , Nguyen, Nguyen, Pham, & Nguyen, 2022), (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) and (Elsayed & Sousa, 2022)

Investor behaviour based on Herding and Hedging Strategies

The study carried out a VAR analysis on both Momentum Price, as a measure of several behavioural biases (overconfidence, regret, bounded rationality and chasing trends), and hedging against the NSE Index.. The results are discussed in 2 parts: CTV with MPrice and CTV with NSE. Table 12 and 13 below summarises the significant VAR results.

Table 12-CTV with MPrice VAR Analysis

	Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
1	lnCTV= 0.415 lnCTV.l1(***) + 0.111 lnCTV.l2(**) + 0.13 lnCTV.l3(***)+ 0.066lnCTV.l4 (.) + 0.086lnCTV.l8(*)+ 0.058lnCTV.l0(.)	959	0.997	2.2e-16	0.212

2	lnMPrice = 0.034 lnCTV.l1 (***) + 1.35 lnMPrice.l1(***) - 0.29 lnMPrice.l2(***) - 0. 02 lnCTV.l4(**) - 0.09 lnMPrice.l4(.) - 0. 009 lnCTV.l5(.) - 0. 01 lnCTV.l8 (*) - 0. 01 lnCTV.l9 (**) + 0. 01 lnMPrice.l9 (**) - 0. 08 lnMPrice.l10(**)	959	1	2.2e-16	0.030

Table 13-CTV with NSE VAR Analysis

	Equation with Significant Lagged Variable	**Obs**	**Adj R^2**	**p-value**	**Residual Error**
1	lnCTV= 0.58305 lnCTV.l1 (***) +2.35714 lnNSE.l1(**)-0.2992 lnCTV.l3(***)- 1.9004 lnNSE.l3(*)-0.23576lnCTVl4(***)-0. 17328lnCTV.l5(***) +1.4387 lnNSE.l5(.)-1.45E-01lnCTV.l6(***)-1.24E-01lnCTV.l7(***)	960	0.270	2.2e-16	0.213
2	lnNSE=0.23097 lnNSE.l1(***) +0.0561.14 lnNSE.L5(.)+0.004839 lnCTV.l7(**) +0.002163 lnCTV.l8(.)+0.134353 lnNSE.L8(***)	960	0.0088	7.659E-15	0.009

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

CTV is strongly predicted by its own lags (6) when compared with Momentum Price. But when compared with NSE, NSE moderately but significantly (i.e 3 lags) predicts the values of CTV. On the other hand, Momentum Price is not a predictor of CTV at any lag. This is expected because the Momentum Price is derived from historical CTV performance, where investors would prefer to stick to their positions based on what they already know. However, CTV strongly predicts Momentum Price (with 5 lags). CTV predicts the future value of NSE moderately by 2 lags. Therefore, both NSE and CTVs are joint predictors. The significant values of Adjusted R^2 and the low p-values indicate that both models are good fit.

On causality, we note that the past values of CTV can predict the future value of Momentum Price and NSE. It is also seen that NSE index granger causes CTV, however, past values of Momentum Price do not cause CTVs. This is summarised in Table 14 below:

Table 14-CTV with MPrice and NSE Causality Results

Ho	**Test Statistic**	**P-Values**	**Conclusion**
G: H0: lnCTV do not Granger-cause lnMPrice	8.4398	1.893e-12	lnCTV -> lnMPrice

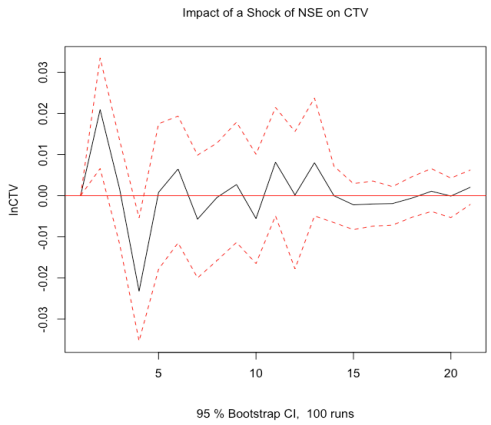
I:H0: No instantaneous causality between: lnCTV and lnMPrice	17.59	2.74e-05	lnCTV -> lnMPrice
G:H0: lnMPrice do not Granger-cause lnCTV	1.1714	0.3091	lnMPrice ≠> lnCTV
I: No causality between lnMPrice and lnCTV	17.59	0.0000274	lnMPrice-> lnCTV
G: lnCTV do not cause lnNSE	2.3257	0.0175	lnCTV -> lnNSE
I: No causality between lnCTV and lnNSE	0.3356	0.5624	LnCTV≠> lnNSE
G: lnNSE do not cause lnCTV	2.8435	0.003847	lnNSE -> lnCTV
I: No causality between lnNSE and lnCTV	0.3356	0.5624	lnNSE ≠>lnCTV

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

A shock on CTVs will impact the NSE within 8 days with a moderate increase in NSE as investors hedge against further loses in Cryptocurrency Markets. The shock will last about 20 days before it flattens out. On the other hand, a shock on NSE will immediately impact the Cryptocurrency Markets as NSE investors hedge against short-term losses in the NSE market with Cryptocurrency investments. This is seen by the sharp increase in CTV volatility within the first 2 days. The shock will stabilise earlier than NSE within 13 days.

Figure 10 - Impact of a shock of CTV on NSE

Figure 11 - Impact of a shock of NSE on CTV



In conclusion, both the NSE and the CTVs are strong predictors of one another. With shocks in one variable affecting the other significantly although within different time frames. The CTV market is more sensitive to shocks in the NSE index than vice versa while past values of Momentum Price have no significant predictive power on CTVs. However, knowing the future values of Momentum Price has predictive power on cryptocurrency trade volumes.

Uncertainty Analysis

The WUI has a strong predictive power on CTVs. 42% of all CTV's lags can be predicted by WUI. CTV has no predictive power on WUI. R^2 value for lnCTV isq approximated 27.2%. The low residual error on lnCTV indicates a good fit between the predicted values and the actual data. The results are summarised in Table 18 below:

Table 15 - Uncertainty Analysis

	Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
1	lnCTV =0.575lnCTV.l1(***) -0.181WUI.l1(**) -0.437lnCTV.l2(***) -0.287 lnCTV.l3(***) -0.174 WUI.l3(**) -0.211lnCTV.l4(***) -0.221WUI.l4(***) -0.156 lnCTV.l5(***)+ 0.128WUI.l5(*) -0.137lnCTV.l6(***) +0.140 WUI.l6(*) -0.118lnCTV.l7(***)	961	0.272	< 2.2e-16	0.213
2	WUI= 0.124 WUI.l4(***) -0.039 lnCTV.l6(***) -0.058 WUI.l6(*)	961	0.021	0.0017	0.087

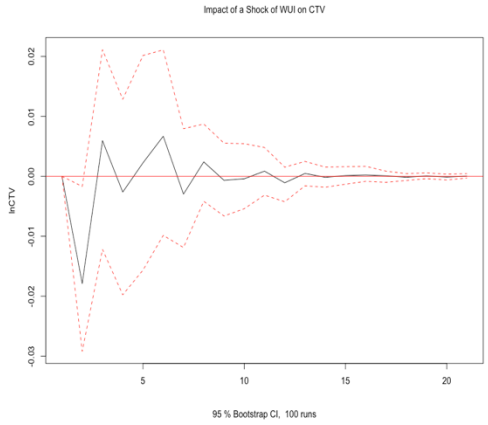
On causal analysis, past and present values of WUI have a causal effect on CTV and vice versa. Future values of WUI or CTV have no predictive effect on current values of CTV or WUI. This is summarised in Table 19 below:

Table 16 - WUI and CTV Causality Analysis

Ho	Test Statistic	P-Values	Conclusion
G: H0: WUI do not Granger-cause lnCTV	3.8868	0.0003265	WUI -> lnCTV
I: H0: No instantaneous causality between: WUI and lnCTV	0.37878	0.5383	WUI ≠> lnCTV
G:H0: lnCTV do not Granger-cause WUI	2.058	0.04497	lnCTV -> WUI
I: No instantaneous causality between: lnCTV and WUI	0.37878	0.5383	WUI ≠> lnCTV

A shock of WUI on CTV is felt immediately with a negative surge in CTVs. A 1 standard deviation in WUI will cause a 0.018 drop in CTV within the first 2 days. A shock of WUI on CTV will die off in the next 7 days. This is shown in Figure 16.

Figure 12 - Impact of WUI's shock on CTV



In conclusion WUI has strong predictive power on CTVs. A shock on WUI has an immediate effect on CTVs . .

Sentiment Analysis

To answer the 3rd research question, sentiment analysis was performed at 2 levels: Sentiment analysis influence on CTV and Global Sentiment influence on Local Sentiments. As summarised in Table 15, CTV is strongly predicted by its own lags (9/13=0.692 i.e 69.2%) and Global Sentiment (31%). CTVs on the other hand predict the future values of Global Sentiments (20%) although Global Sentiments strongly rely on its own past lags (73%). On the other hand, CTV does not significantly predict Local Sentiments. The significant lags account for the model's variability of about 26.5% for CTV,37.3% for Global Sentiment and 43.1% for Local Sentiment. The models have low p-values and low residual errors indicating good fit.

Table 17-Sentiment and CTV Analysis

Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
LnCTV= 0.536 lnCTV.l1(***) -0.400lnCTV.l2(***)-0.214lnCTV.l3(***)+ 0.065lnGsent.l3(**)- 0.229lnCTV.l4(***)-0.208lnCTV.l5(***)+ 0.100 lnGsent.l5 (***) -0.198 lnCTV.l6(***)+ 0.055 lnGsent.l6(**)+ 0.060lnGsent.l7(**)-0.083lnCTV.l9(*)+ -0.075 lnCTV.l10 (*) -0.085lnCTV.l11(**)	756	0.265	2.2e-16	0.203

lnGsent = 0.746 lnGsent.l1(***)- 0.624 lnGsent.l2 (***) -0. 541lnGsent.l3 (***) -0.439 lnGsent.l4 (***) -0.346 lnGsent.l5 (***)- -0.181 lnCTV.l6 (**) -0.296 lnGsent.l6(***) - 0.305 lnGsent.l7 (***) -0. 184lnCTV.l8(**)- 0. 204lnGsent.l8 (***)- 0. 227lnCTV.l9 (***)- 0. 193lnGsent.l9(***)- 0. 035lnLsent.l9- 0.139 lnGsent.l10 (***)- 0. 063lnGsent.l11(*)	756	0.373	2.2e-16	0.400
LnLsent= 0.867lnLsent.l1 (***) -0.298 lnGsent.l2(**)- 0.751lnLsent.l2(***) - 0.677lnLsent.l3(***)-0.652lnLsent.l4(***)- 0.631lnLsent.l5(***)-0.504 lnLsent.l6(***)-0.425 lnLsent.l7(***) - 0.345 lnLsent.l8(***) -0.269 lnLsent.l9(***) -0.214 lnGsent.l10 (**) -0.180 lnLsent.l10(***) -0.391 lnLsent.l11(**)-0.156 lnGsent.l11(*)	756	0.431	2.2e-16	1.040

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

Global Sentiments significantly predict Local Sentiments while Local Sentiments weakly predict global sentiments (6.7%) as shown in Table 16 below.

Table 18- Global and Local Sentiment analysis

Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
LnGsent= 0.24 lnGsent.l1(***) +0.13 lnGsent.l2 (***) + 0.08 lnGsent.l3(*) -0.09 lnGsent.l4(*) + 0.08 lnGsent.l5(***)+ 0.032 lnLsent.l6(*) + 0.097 lnGsent.l8(**) + 0.06 lnGsent.l2(.) +0.03 lnLsent.l2(.)	756	0.9766	< 2.2e-16	0.403
LnLsent= 0.11 lnLsent.l1 (**) + 0.27 lnGsent.l2(**) -0.09 lnLsent.l2(*) - 0.17 lnGLsent.l4(.)+ 0.1 lnLsent.l6(**) -0.207 lnGsent.l9(*) -0.07 lnLsent.10(.) -0.09 lnLsent.l11(*) + 0.18 lnGsent.l12(*)	756	0.743	2.2E-16	1.038

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

On causality analysis we note that past and present known values for global sentiment can predict the future values of CTVs. Secondly, past and present global sentiments have a predictive causal effect on local sentiments, but the vice versa is not applicable. Local sentiments have no predictive value on global sentiments. These causal relationships are summarised in Table 17 below:

Table 19-Sentiment Causal Analysis

Ho	Test Statistic	P-Values	Conclusion

G: lnGsent lnLsent do not Granger-cause lnCTV I: No causality between lnGsent lnLsent and lnCTV	2.1945 5.1735	0.001095 0.07526	lnGsent lnLsent -> lnCTV lnGsent lnLsent ≠> lnCTV
G: lnLsent do not Granger-cause lnGsent I: No instantaneous causality between: lnLsent and lnGsent	1.4695 0.041515	0.1288 0.8385	lnLsent ≠> lnGsent lnLsent ≠>lnGsent
G: lnGsent do not Granger-cause lnLsent I: No instantaneous causality between: lnGsent and lnLsent	3.2606 0.041515	0.0001159 0.8385	lnGsent -> lnLsent lnLsent ≠> lnGsent

The impact of a shock on Global Sentiments to CTV will be felt within 2 time periods. A change of 1 standard deviation in Global Sentiments will lead to a 0.012 change in lnCTV. Inversely, since CTVs also have an impact on Global Sentiment, a shock on CTVs will propagate within 5 days to Global Sentiments generally dying off after 10 days. Local Sentiments will pick up a shock on Global Sentiments within 4 days dying off after about 12 days. It thus takes, 4 days to transmit Global Sentiments into Local Sentiments. These observations are visually illustrated in the Impact Response Functions in Figures 17, 18,19 and 20 below:

Figure 13 - Impact of shock on Global Sentiments on CTV

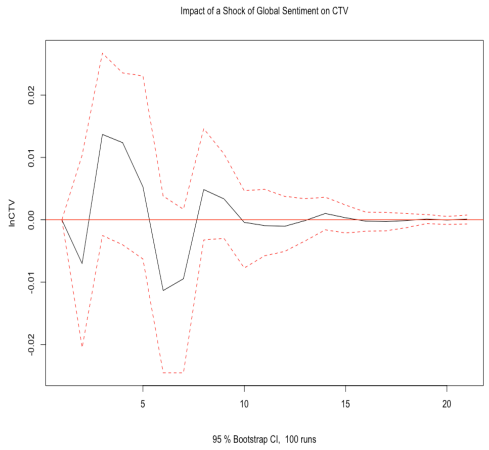


Figure 14 - Impact of Shock of CTV on Global Sentiment

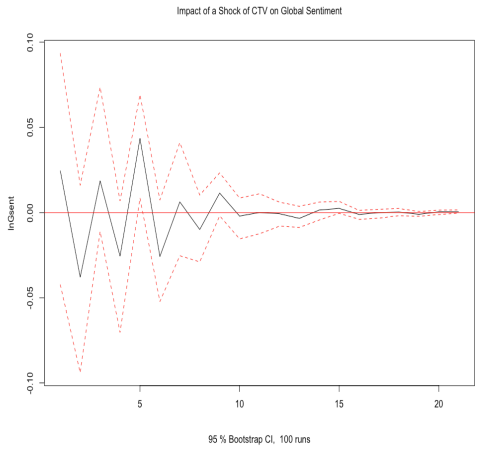


Figure 15 - Impact of a shock on CTV on Local Sentiment

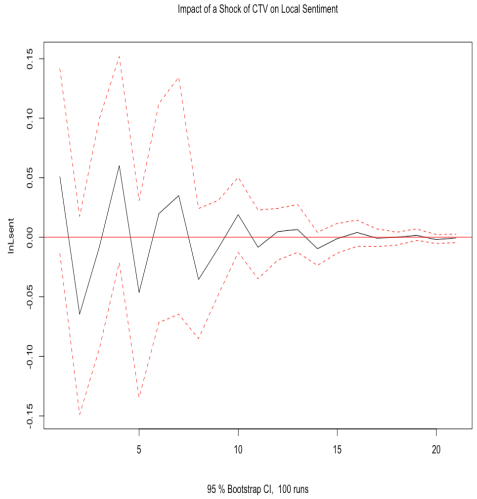
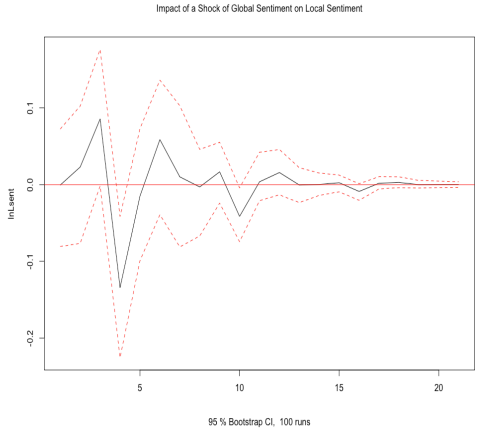


Figure 16 - Impact of a shock on Global Sentiment on Local Sentiment



In conclusion, past and present global sentiments values have more predictive power on CTVs than local sentiments even though local sentiments are also significantly influenced by global sentiments.

Overall Analysis

All the variables were combined into a single model to assess their overall influence on CTV and to determine if there is any significant deviation to the conclusions drawn above. A summary of the VAR analysis is shown in Table 20 below:

Table 20 - Overall VAR model summary

	Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
1	LnCTV=0.520 lnCTV.l1(***) -0.372 lnCTV.l2(***) - 0.212 WUI.l1(***)+ 1.496 lnNSE.l1(*) - 0.191 lnCTV.l3(***) + 0.127 lnIB.l3(**) + 0.039 lnGsent.l3(*)- 0.151 lnCTV.l4(***)-0.060 lnGsent.l4(***) -0.070 lnCTV.l5(*)-0.159 lnIB.l5(***)+ 0.032 lnGsent.l5(*)	762	0.245	2.2e-16	0.206
2	LnUSD=0.259 lnUSD.l1(***) +0.002 WUI.l1(***) -0. 003lnMPrice.l2 - 0.0004 lnGsent.l2(*) -0.015 lnNSE.l2(*) -0.0004 lnGsent.l3(*) -0.015 lnNSE.l3(**) -0.0003 lnGsent.l4(*) -0.014 lnNSE.l4(*) -0.00004 REPO.l5(**) + 0.004 lnMPrice.l5(*) -0.0003 lnGsent.l5(*)	762	0.105	0.0000000009778	0.002
3	lnIB =0.081 lnCTV.l1(***) -0.002 REPO.l1(*) + 0.090 lnIB.l1(**) - 0.056 lnCTV.l2(**) -0.003 REPO.l2(**)- 0.062 lnCTV.l3(**) -4.373 lnUSD.l3(*) -0.004 REPO.l3(***) + 5.342 lnUSD.l4 -0.004 REPO.l4(***) -0.070 lnIB.l5(*)	762	0.046	0.001111	0.131
4	REPO= 0.626 REPO.l1(***) -0.448 REPO.l2(***) + 1.199 lnGsent.l2(***) + 188.057 lnUSD.l3(**) -0.296 REPO.l3(***) + 1.638 lnGsent.l3(***) + 0.314 lnLsent.l3(*) + 2.089 lnCTV.l4(**) -165.231 lnUSD.l4(**) -0.145 REPO.l4(***)+ 1.576 lnGsent.l4 (***) -0.112 REPO.l5(***)	762	0.281	2.2E-16	4.329
5	LnMPrice= 0.031 lnCTV.l1(***)+ 0.253 lnMPrice.l1(***) + 0.011 lnGsent.l1(***) + 0.288 lnNSE.l1(***) + 0.039 lnCTV.l2(***)+ 0.081 lnMPrice.l2(**)+ 0.007 lnGsent.l2+ 0.034 lnCTV.l3(***) -0.003 lnLsent.l3(*)+ 0.026 lnCTV.l4+ 0.069 lnMPrice.l4(*) + 0.014 lnGsent.l4(***) -0.392 lnNSE.l5(***)	762	0.164	2.2E-16	0.042
6	LnGsent=0.737 lnGsent.l1(***) -0.556 lnGsent.l2(***) + 20.392 lnUSD.l3(***) -0.402 lnGsent.l3(***) -0.242 lnGsent.l4(***) -0.007 REPO.l5(*) -0.106 lnGsent.l5(***)	762	0.372	2.2E-16	0.424

	Equation with Significant Lagged Variable	Obs	Adj R^2	p-value	Residual Error
7	lnLsent = 2.029 lnMPrice.l1(**) -0.749 lnLsent.l1(***) + 1.762 lnMPrice.l2(*) + 0.293 lnGsent.l2(***) -0.555 lnLsent.l2(***) -0.420 lnLsent.l3(***) -0.324 lnLsent.l4(***) -0.230 lnLsent.l5(***)	762	0.369	2.2E-16	1.095
8	WUI= 0.031 lnCTV.l1+0.001 REPO.l1 -0.036 lnCTV.l2(*)- 0.022 lnGsent.l2(**) -0.182 lnMPrice.l3 -0.420 nLsent.l3(***)- 0.706 lnNSE.l3(**) + 0.046 lnIB.l4(*) -0.196 lnMPrice.l4(**) -0.016 lnGsent.l4(*) -0.177 WUI.l4(***) +3.554 lnUSD.l5(**) -0.022 lnGsent.l5(***)	762	0.073	0.00000339	0.096
9	NSE=0.426 lnUSD.l1(**) + 0.022 lnMPrice.l1(**) + 0.270 lnNSE.l1(***) -0.021 lnMPrice.l2(**) +0.002 lnGsent.l2(**) +0.001 lnLsent.l2(*) -0.016 WUI.l2(***) -0.320 lnUSD.l3(*) +0.001 lnLsent.l3(***) + 0.165 lnNSE.l3(***) + 0.346 lnUSD.l5(*) -0.001 lnGsent.l5(*)	762	0.139	4.256E-14	0.010

Note. * p < 0.05; ** p < 0.01; *** p < 0.001

A summary of the significant interactions based on the number of lags for each variable with itself and with others in provided in Table 21 below.

Table 21-Summary of significant lags analysis

	LnCTV	LnUSD	lnIB	REPO	LnMPrice	LnGsent	lnLsent	WUI	NSE
LnCTV	5	0	3	1	4	0	0	2	0
LnUSD	0	1	2	2	0	1	0	1	3
lnIB	2	0	2	0	0	0	0	1	0
REPO	0	1	4	5	0	1	0	2	0
LnMPrice	0	2	0	0	3	0	2	2	2
LnGsent	3	4	0	3	3	5	1	3	2
lnLsent	0	0	0	1	1	5	5	1	2
WUI	1	1	0	0	0	0	0	1	1
NSE	1	3	0	0	2	0	0	1	2
Total	12	12	11	12	13	12	8	14	12

From the summary, CTV main predictors are its own lags (5 = 42%), Global Sentiments (3=25%), Interbank Rate (17%), Uncertainty(8.5%) and the NSE index (8.5%). REPO, Local Sentiment and Momentum Price are not significant CTV predictors for the overall model. Global Sentiments and NSE are best predictors of the USD exchange rate. The Interbank Rate

is best predicted by REPO, the USD exchange rate and the CTVs. Momentum price is strongly predicted by sentiments and CTVs. Global sentiments are strongly predicted by local sentiments, while local sentiments are predicted by both global sentiments and momentum price. The NSE index is strongly predicted by the USD exchange rate, sentiments, and the performance of Momentum price. Uncertainty is significant in all the other variables. Overall, the model is statistically significant hence is a good model.

In considering overall Granger and Instantaneous Causality, we note that both present and future values of the combined independent variables have a causal effect on CTV. Similarly, CTV has a causal effect on all the combined independent variables. Interestingly, although the main Monetary Policy variables (USD and IB) have a causal effect on CTV, they do not have a similar effect on the other independent variables in the model. However, knowing the future monetary policy variables has a predictive effect on all the other variables. Both future and past values of Momentum Price, the NSE index and the WUI have a predictive causal effect on all other variables. Past and present sentiment have a causal effect on all the other variables in the model.

Table 22-Overall model causality test results

Ho	Test Statistic	Conclusion
G: H0: CTV do not Granger-cause all the other variables	2.093 (0.00006832)	CTV -> All other Variables
I: H0: No instantaneous causality between: CTV and all the other variables	35.284 (2.37E-05)	CTV -> All other variables
G:H0: All other variables do not Granger-cause CTV	1.8227 (0.00119)	All other variables -> CTV
I: No instantaneous causality between: All other variables and CTV	35.284 (0.00002373)	All other variables -> CTV
G:H0: All Monetary Policy variables (USD, IB, REPO) do not Granger-cause all other variables (CTV, MPrice, NSE, Gsent, Lsent, WUI)	1.0831 (0.2786)	All Mmonetary Policy variables ≠> All other variables
I: No instantaneous causality between: All Monetary Policy variables and other variables (CTV, MPrice, NSE, Gsent, Lsent, WUI)	37.646 (0.004313)	All Monetary Policy variables -> All other variables
G:H0: Momentum Price (MPrice) does not Granger-cause all other variables	1.4886 (0.02449)	MPrice -> All other variables
I: No instantaneous causality between: Momentum Price and all other variables	31.462 (0.0001162)	MPrice -> All other variables

Ho	Test Statistic	Conclusion
G:H0: NSE Index (NSE) does not Granger-cause all other variables	1.4409 (0.03563)	NSE -> All other variables
I: No instantaneous causality between: NSE index and all other variables	20.349 (0.009092)	NSE -> All other variables
G:H0: All Sentiment variables (Lsent & Gsent) do not Granger-cause all other variables (MPrice, NSE, Gsent, Lsent, WUI)	2.2253 (2.43E-08)	Sentiments -> All other variables
I: No instantaneous causality between: All other variables and CTV	17.39 (0.236)	Sentiments ≠> All other variables
G:H0: Uncertainty (WUI) do not Granger-cause all other variables	1.3083 (0.09251)	WUI -> All other variables
I: No instantaneous causality between: WUI and all the other variables	38.249 (6.77E-06)	WUI -> All other variables

Note: p-values are in parenthesis

In conclusion, the overall model analysis has produced similar and consistent results with the conclusions drawn from the thematic models earlier presented. Monetary policy variables of USD and IB have causal effects on CTV but not on any other variables in the model. On the other hand, uncertainty as measured by WUI has an effect on all the other variables in the model.

4.5.2 GARCH Model Estimation Results

5 GARCH models were fitted on the variance data. The GARCH models and their estimated parameters are summarised in Table 23 below. The GJR-GARCH (1,1) model with Student-t distribution was selected as it had the lowest information criteria and highest log-likelihood values.

Table 23-Estimated GARCH model parameters

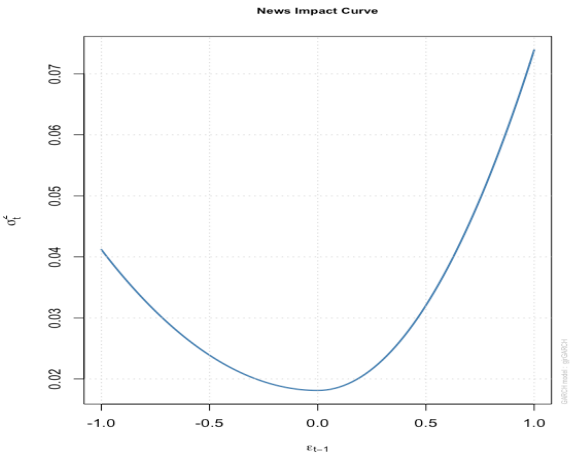
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
GARCH Model	**sGARCH(1,1)**	**sGARCH(2,1)**	**sGARCH(1,1)**	**gjrGARCH(2,1)**	**gjrGARCH(1,1)**
Mean Model	**ARFIMA(1,0,0)**	**ARFIMA(1,0,0)**	**ARFIMA(1,0,0)**	**ARFIMA(1,0,1)**	**ARFIMA(1,0,1)**
Distribution	sstd	sstd	norm	sstd	sstd
mu	0	0	0	9.51***	9.02***
	0	0	0	-0.09	-0.33
ar1	-0.38***	-0.39***	-0.38***	1.00***	1.00***
	-0.03	-0.03	-0.03	0	0
ma1				-0.62***	-0.63***
				-0.03	-0.03
omega	0	0	0	0	0
	0	0	0	0	0
alpha1	0.05***	0.01	0.04***	0.05***	0.06**
	-0.01	-0.02	-0.01	0	-0.02
alpha2		0.04		0	
		-0.02		-0.01	
beta1	0.95***	0.95***	0.96***	0.95***	0.96***
	-0.01	-0.01	-0.01	-0.01	0
gamma1				-0.10***	-0.03
				0	-0.07
gamma2				0.09***	
				-0.02	
skew	1.02***	1.02***		1.03***	1.07***
	-0.05	-0.05		-0.05	-0.05
shape	13.71**	13.33**		12.50**	14.84**
	-4.76	-4.52		-4.32	-5.53
Log likelihood	149.46	148.85	143.7	197.98	199.09
AIC	-0.29	-0.29	-0.29	-0.39	-0.39
BIC	-0.26	-0.25	-0.26	-0.33	-0.35

Note. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$, Standard errors are indicated below the fitted model parameters

In the selected GJR-GARCH(1,1) model (i.e Model 5), alpha1(α_1) is the ARCH coefficient. It is positive and significant confirming the presence of volatility clustering in CTV. Beta1 (β_1)on the other hand is the GARCH co-efficient which is also positive and significant, in addition, it is also greater than alpha1(α_1) which indicates that volatility clustering is persistent. In the mean equation, the value of the intercept mu (9.02) is positive and significant implying that CTV returns are likely to be positive and will increase in the long run. In all the models the value of $\alpha_1 + \beta_1 < 1$ which implies that CTVs exhibit high volatility persistence (high uncertainty and shock propagation) and that the shock volatility response function decays at a relatively slow rate (i.e unexpected external shocks will tend to last longer).

The GJR GARCH model allows for asymmetric response of variance to positive and negative news. The news impact curve is a helpful tool to visualize the response of the variance to the surprise in returns. The News Impact Curve from the GJR-GARCH model shows the asymmetric effect of shocks where a positive news/shock causes a large effect on the CTV volatility/conditional variance. (Kumar & Anandarao, 2019)

Figure 17 - GJR-GARCH Model News Impact Curve



Further analysis on spill-over effects was performed using DCC-GARCH which is a multivariate time series analysis tool. Table 24 summarises the results of the DCC-GARCH analysis for all the independent variables with CTV. As already seen in the GARCH model, the mean value mu is positive indicating that CTV returns will likely be positive and persist into the future. The largest long-term persistent spill overs are noted for Local Sentiment ($\beta_1 = 0.997$), MPrice ($\beta_1 = 0.92$), NSE ($\beta_1 = 0.896$) and USD ($\beta_1 = 0.78$). The highest short-term shocks are with IB ($\alpha_1 = 0.364$), Global Sentiment ($\alpha_1 = 0.29$) and USD ($\alpha_1 = 0.22$). The effect of the constant omega is not significant across the series. This observation is consistent with other studies ((Bhatnagar, Taneja, & Rupeika-Apoga, 2023)).

Table 24-Multivariate GARCH spill over effects analysis

X spill over to Y	USD -> CTV	IB -> CTV	MPrice -> CTV	NSE -> CTV	Gsent->CTV	Lsent -> CTV
[dlnCTV].mu	0.003218	0.003218	0.003218	0.003218	0.0035	0.0014
	(0.446)	(0.446)	(0.446)	(0.446)	(0.409)	(0.786)
dlnCTV].ar1	-0.381578	-0.381578	-0.3815	-0.38158	-0.372	-0.31
	(0.000)	(0.000)	(0.000)	(0.00)	(0.000)	(0.000)
[dlnCTV]. omega	0.000121	0.000121	0.000121	0.000121	0.00014	0.0001
	(0.2448)	(0.245)	(0.245)	(0.245)	(0.229)	(0.494)
[dlnCTV]. alpha1	0.040909	0.040909	0.040909	0.040909	0.044061	0.043866
	(0.00)	(0.00)	(0.00)	(0.00)	(6e-6)	(0.003)
[dlnCTV]. beta1	0.955748	0.955748	0.955748	0.955748	0.952269	0.95227
	(0.00)	(0.00)	(0.00)	(0.000)	(0.00)	(0.00)
[dlnX].mu	0.000006	0.001631	0.003814	-	-0.006217	-0.017
	(0.932)	(0.675)	(0.0478)	0.000074	(0.360)	(0.634)
				(0.802)		
[dlnX].ar1	0.221018	0.273191	0.518704	0.243979	-0.227	-0.415
	(0.001905)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)
[dlnX].omega	0.000000	0.000908	0.000031	0.000	0.0034	0.004
	(0.78)	(0.019)	(0.401)	(0.645)	(0.207)	(0.531)
[dlnX]. alpha1	0.222398	0.363958	0.045592	0.09163	0.289512	0.00
	(0.000116)	(0.044)	(0.378)	(0.189)	(0.006)	(1.00)
[dlnX.beta1	0.776354	0.635033	0.919738	0.895805	0.709488	0.997491
	(0.000)	(0.000)	(0.00)	(0.000)	(0.000)	(0.00)
[Joint]dcca1	0.019124	0	0.046878	0.590036	0.077039	0.00
	(0.1496)	(0.996)	(0.049)	(0.184)	(0.088)	(0.78)
[Joint]dccb1	0.942724	0.918839	0.400095	0.001957	0.489664	0.879068
	(0.000)	(0.000)	(0.06)	(0.000)	(0.003)	(0.006)

p-values in parenthesis

Considering the joint parameters, all series short-run volatility persistence (ARCH) is lower than long-run persistence (GARCH) except for the NSE (i.e the Joint $\alpha_1 < \beta_1$ for all independent variables beside the NSE ($\alpha_1 = 0.59\ which\ is < \beta_1 = 0.002$)). The highest correlation is between the USD/KSHS exchange rate and the CTVs, followed by Interbank Rates and the Local Sentiments. IB ($\alpha_1 = 0.364$), Global Sentiment ($\alpha_1 = 0.29$) and USD ($\alpha_1 = 0.22$) have the highest and significant short-term volatility spill-over to CTV in comparison to all the other variables. Local Sentiments ($\beta_1 = 0.997$) have the highest long-

term persistent spill over effect to CTV followed by MPrice and NSE. Beside Local Sentiment ($\beta_1 = 0.997$), MPrice ($\beta_1 = 0.92$) and NSE ($\beta_1 = 0.896$) have the highest long-term persistent spill-over effect on CTV. This implies that fear factors raised in MPrice and NSE have a long term and persistent effect on Cryptocurrency investors.

USD ($Joint\ \beta_1 = 0.943$) and IB($Joint\ \beta_1 = 0.919$), have the highest joint volatility correlation with CTV that have a long-run persistency. NSE($Joint\ \beta_1 = 0.002$) have the lowest joint correlation on volatility with long-term persistency than all the other variables. This supports the conclusion that NSE can be used as an effective hedge for Cryptocurrency volatilities and vice versa.

4.5.3 Time varying correlation and covariance graphs

The analysis above, demonstrate that conditional correlations are time varying. To ascertain that, key events that affected the cryptocurrency and other financial markets in Kenya and globally were identified and mapped to the correlation and covariance graphs obtained from the DCC GARCH analysis. These events are in Table 25 below:

Table 25-Key events affecting cryptocurrency markets in Kenya

DURATION	EVENT	MAPPING TO GRAPHS
2017-08-21 to 2017-11-27	August 2017 elections & subsequent elections annulment and repeat in September 2017 Repeat Presidential Elections with failure of opposition leader to participate	80-150
2019-01-15 to 2019-01-20	DusitD2 Bombing	420-450
2019-04-09 to 2019-04-30	US-China Trade Tensions	470-478
Nov-19	Abolishment of interest rates caps / Announcement by KRA of Digital Service Tax for Cryptocurrencies	568-585
2020-03-05 to 2020-03-16	COVID-19 outbreak & Lock downs	627-700

2020-09-20 to 2021-01-30	School close due to COVID-19 / CBK CBDC Paper High COVID-19 Death rates Announcements/Coming into effect of Digital Service Tax	733-820
2021-03-25 to 2021-05-12	Morgan Stanley and other Wall Street Banks adopts BitCoin	840-886
2021-05-12 to 2021-07-21	China Crackdown on Cryptocurrency Trading/China Banned Cryptocurrencies	850-950

The impact of the August 2017 election, COVID 19 in April 2020 with the China Crackdown on Cryptocurrencies influenced the return co-movements of the 2 key monetary policy variables (USD and IB) on CTVs. As shown in Appendix 4, the conditional correlations between CTV with USD and CTV with IB are increasing with significant spill-over effects lasting through the period of the analysis. Similar conclusions are drawn for Momentum Price and NSE where on observing the time carrying corelation graphs in Appendix 5, we see co-movements especially in the later part of the graphs (Days > 600) that is after the COVID-19 outbreak.

Both the Global Sentiment and the Local Sentiment are correlated with CTVs. The volatility spill over of Global Sentiment with CTVs was only present up to September 2017 after which the spill-over is negligible. Similarly local sentiments also provided volatility spill over at the beginning of the series of which this gradually reduced to the end of September 2021. See Appendix 6 for a visual representation.

4.6 Summary of Findings

The study used a combination of models to achieve its objectives. Descriptive statistics and correlations (Spearman, ACF and PACF), Vector Autoregressive (VAR), GARCH and Multivariate GARCH models (i.e DCC GARCH) accompanied by Causality Tests and Impact Response Functions (IRFs) analysis were used to arrive at statistically sound and repeatable findings. This section provides a summary of the key findings captured from the analysis.

The analysis indicates that both present and future values of the combined independent variables have a causal effect on CTV. Uncertainty as measured by WUI is significant in predicting all the other variables (i.e all other variables are affected by uncertainty). Similarly, CTV has a causal effect on all the combined independent variables. The main Monetary Policy variables (USD and IB) have a causal effect on CTV, but do not have a similar effect on the other independent variables. However, knowing the future monetary policy variables has a predictive effect on all the other variables (i.e there is instantaneous causality). Both future and past values of Momentum Price, the NSE index and the WUI have a predictive causal effect on all other variables. Past and present sentiment have a causal effect on all the other variables in the model.

There is high volatility persistence on CTVs with CTV returns likely to be positive and increasing in the long run. Positive news/shock has a large effect on CTV volatility.

Table 26 provides a summary of the key findings.

Table 26 - Summary of Findings

Research Objective	Findings
To investigate the influence of Kenya's monetary policy on the local	CTVs are strongly predicted by USD Exchange Rate and Interbank Rate but weakly predicted by REPO. CTVs strongly predict Interbank Rates but have weak prediction ability on REPO and USD. There is both granger and instantaneous causality between CTV, USD and IB but no

Research Objective	Findings
cryptocurrency market performance	causality with REPO. Monetary Policy variables (USD and IB) have a causal effect on CTV, they do not have a similar effect on the other independent variables in the model. The impact of a shock on USD will affect CTV between the 4th and 6th days with a 1 standard deviation increase in lnUSD causing a 0.01 standard deviation increase in lnCTV within this period. Similarly, a shock on IB will reflect within 2 time periods with a dip and sharp increase on the 5th and 6th day with a 1 standard deviation increase causing a 0.014 standard deviation increase in lnCTV within the period. In both cases, the effects of the shock begin to die on the 10th day. Therefore, a shock on USD has a bigger impact on CTV than a shock on IB. Both IB ($\alpha_1 = 0.364$ and USD ($\alpha_1 = 0.22$) have the highest and significant short-term volatility spill-over to CTV in comparison to all the other variables except Global Sentiment ($\alpha_1 = 0.29$). USD ($Joint\ \beta_1 = 0.943$) and IB($Joint\ \beta_1 = 0.919$), have the highest long-term persistent joint volatility correlation with CTV implying that there are significant time varying correlations supported by shock events between USD, IB and CTV
To investigate how investor behaviour, measured by momentum price and stock market hedging affects Kenya's	Both MPrice (0.85) and NSE (-0.83) have the highest correlation to CTV although the NSE is negatively correlated to CTV. Local uncertainty affects the number of CTV trades with an increase in uncertainty accompanied by reductions in mean CTV trades (USD 182,850.61 to USD 99,420). The CTV investors also reduce the size of their trades to manage the risk as measured by reduction in CTVs standard deviation. A similar result is obtained for the Momentum Price which is high in

Research Objective	Findings
cryptocurrency market performance	times of normal uncertainty as opposed to times of increased uncertainty. The NSE index rises in times of uncertainty. Thus, in times of uncertainty investors shift their investments into the NSE, preferring to invest more in cryptocurrencies in times of normal uncertainty. This implies that the investors are rational and risk averse as they are taking measures to avoid uncertainty. Momentum Price (MPrice) is not a CTV predictor at any lag. This means that investor behavioural biases of overconfidence and chasing trends do not apply and that the investor is rational and taking deliberate measures to accommodate local uncertainty and doubt. Both the NSE and the CTVs are strong predictors of one another. With shocks in one variable affecting the other significantly although within different time frames. The CTV market is more sensitive to shocks in the NSE index than vice versa while past values of Momentum Price have no significant predictive power on CTVs. A shock on CTVs will impact the NSE within 8 days with a moderate increase in NSE as investors hedge against further loses in Cryptocurrency Markets. While a shock on NSE will immediately impact the CTV market (i.e within 2 days). Knowing the future values of Momentum Price has however predictive power on cryptocurrency trade volumes. Uncertainty as measured by WUI has a strong predictive power on Cryptocurrency Trade Volumes. A shock on WUI is immediately reflected on CTVs dying off in the next 7 days. Local Sentiment ($\beta_1 = 0.997$), MPrice ($\beta_1 = 0.92$), NSE ($\beta_1 = 0.896$) have the highest long-term persistent spill-over effect on CTV. This

Research Objective	Findings
	implies that fear factors raised in MPrice and NSE have a long term and persistent effect on Cryptocurrency investors. NSE($Joint\ \beta_1 = 0.002$) have the lowest joint correlation on volatility with long-term persistency than all the other variables. This supports the conclusion that NSE can be used as an effective hedge for Cryptocurrency volatilities and vice versa
To investigate the extend in which local and global public cryptocurrency sentiments affect cryptocurrency market trade volumes	Both Global and Local Sentiments adjusts accordingly to reflect local uncertainty with the Local Sentiment responding predictably better than the Global Sentiments to uncertainty as seen by the higher means and standard deviations ($\mu = 0.20\ and\ \delta = 0.25$ for Lsent during period of normal uncertainty than $\mu = 0.11\ and\ \delta = 0.06$ for Gsent) Global Sentiment predicts CTVs significantly (prediction contribution of at least 31%). CTVs on the other hand can predict the future values of Global Sentiments (20%), however, Global Sentiments relies heavily on its own lags (73%). Local sentiments weakly predict global sentiments (6.7%) while CTV does not significantly predict Local Sentiments. On the other hand, local sentiments, weakly predicts global sentiment while global sentiment has a moderately strong prediction effect on local sentiment. On average it takes about 4 days for global sentiments to influence local sentiments. Past and present sentiments have a causal effect on all the other variables in the model. The impact of a positive sentiment shocks causes a large effect on the variance or volatility of CTVs as compared to negative sentiments. The potential for super normal gains drives cryptocurrency investors as opposed to fear of losing returns.

Research Objective	Findings
	Global sentiments have a higher short-term spill-over effect on CTVs as compared to local sentiments which have a more long-term persistency. Local Sentiments ($\beta_1 = 0.997$), have the highest long-term persistent spill over effect to CTV followed by MPrice and NSE. Local sentiments ($Joint\ \beta_1 = 0.879$) have a higher correlation to CTV volatilities than Global Sentiment. It is a better predictor of CTV volatilities than Global Sentiments($Joint\ \beta_1 = 0.49$) on the long term.

CHAPTER FIVE: DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The purpose of this chapter is to present the conclusions drawn from the study as well as the various policy recommendations that the study advances. It also links the study findings to prior literature, highlighting the areas of divergence as appropriate.

5.2 Discussions on Findings

5.2.1 The influence of Kenya's Monetary Policy on Cryptocurrency Market Performance

One of the study's specific objectives was to investigate the influence of Kenya's monetary policy on local cryptocurrency market performance. Correlation analysis reveals that the USD to Kshs Exchange rate is positively correlated to Cryptocurrency Trade Volumes while Interbank Rates are negatively correlated. The findings further reveal that both the past and future values of USD to Kshs Foreign Exchange Rate (USD) and the Interbank Rate (IB) have a strong predictive effect on Cryptocurrency Trade Volumes (CTV). Additionally, the USD Exchange Rate jointly with IB have a significant causality effect on CTV. REPO on the other hand has no significant effect on CTVs. The strong effect of USD Exchange Rate and Interbank Rate is also seen in the high but significant short-term volatility spill-over effects of IB and USD to CTV in comparison to all the other independent variables except Global Sentiment. There is also long-term persistency of volatility correlation between CTV, USD and IB an indicator of consistently significant time varying correlations between the 3 variables.

Monetary Policy Theory dictates that a weaker local currency boosts exports. A devaluing Kenya Shilling leads to increased CTVs. This implies that more local cryptocurrency investors begin to hedge the devaluation of the Kenya Shillings with Cryptocurrencies. On the other hand, falling interbank rates mean more liquidity in the market which means that investors can invest the excess liquidity in cryptocurrency markets. Thus, the research findings are consistent with monetary policy theory.

In considering empirical research, the study findings are consistent with (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) and (Karau, 2021) who found out the US , Eurozone and Chinese Monetary Policies have an effect on Bitcoin Prices and Cryptocurrency Returns respectively. The (Nguyen T. , Nguyen, Nguyen, & Phama, 2019) study further found out that US OMO rates have no significant effect on Cryptocurrency Returns while Chinese OMO rates had a positive effect on cryptocurrency returns leading them to conclude, similarly to (Karau, 2021) that monetary policy effect is different from one market or zone to another.

5.2.2 Investor behaviour, measured by herding and risk hedging in times of uncertainty

Momentum Price is a measure of several behavioural biases (overconfidence, regret, bounded rationality and chasing trends) while hedging indicates the presence of an active and rationale risk-averse investor. These 2 variables help define the main behavioural aspects of a Kenya's Cryptocurrency Investor. The study findings indicate the Momentum Price is not a strong predictor of CTVs as compared to the NSE Index. The performance of the NSE Index is a stronger predictor of CTV performance than Momentum Price (MPrice). Further the study notes that NSE is negatively correlated to CTV implying that investors will prefer to invest in a well-functioning stock market than in a more volatile and thus risky cryptocurrency market. In considering local uncertainty, the study notes that an increase in uncertainty is accompanied by reduction in CTV while NSE index rises in times of uncertainty. Thus, in times of uncertainty investors shift their investments into the NSE, preferring to invest more in cryptocurrencies in times of normal uncertainty. On causality analysis, the study concludes that NSE index causes CTV and vice versa. Indeed, a shock on CTV will impact the NSE within 8 days while a shock on NSE will immediately impact CTVs. In considering volatility, MPrice and NSE have significant long-term spill-Over effects on CTV. NSE index has the lowest joint volatility correlation with CTVs thus the NSE is a good hedge to cryptocurrency volatilities.

The conclusion of the study is consistent with behavioural asset pricing theory in terms of risk management. . The investors are opting to invest less in CTV in times of increased uncertainty while invest more in the stable and less volatile NSE. Thus, emotionally hedging against losses in

the financial markets all together. This is more evident when looking at the significant long-term spill-over effects of both MPrice and NSE which implies that behavioural aspects are present but not deducible in the short-term when using the Momentum Price indicator.

The study findings are also supported by empirical studies by (Sami & Abdallah, 2020), (Caferra & Vidal-Tomás, 2021) , (Bhullar & Bhatnagar, 2020), (Maitra, Rehman, Dash, & Kang, 2022), (Nkrumah-Boadu, Junior, Adam, & Asafo-Adjei, 2022) and (Jiang, Lie, Wang, & Mu, 2021). The (Sami & Abdallah, 2020) study concluded that a 10% increase in CTVs is matched with a 0.17% decrease in market returns in 6 gulf countries and that the higher the returns in global cryptocurrency markets, the lower the returns in the stock market. The study findings deviate from (Liu & Tsyvinski, 2020) study which concluded that Momentum Price and Investor Attention (captured by public sentiments) have a significant time series effect on Cryptocurrency Trade Volumes. This difference in conclusion can be attributed to the fact that an investor in a developing economy is in very unstable markets and more vulnerable to local conditions as compared to an investor in a stable and large developed economy. It also means that because of cryptocurrency markets volatilities, the local investor chooses not to make decisions using short-term momentum information.

5.2.3 Local and Global Sentiments effects on Cryptocurrency Market Performance

Global sentiments are better predictors of CTVs than local sentiments. The past and present known values of global sentiments have a strong causal effect on future CTV values. This means that local investors rely more on global sentiments than local sentiments in their short-term investment decision making. Additionally, global sentiments moderately predict local sentiment while local sentiments weakly predict global sentiments. The past and present global sentiments have a predictive causal effect on local sentiments but the vice versa is not true. The impact of a positive sentiment shocks causes a large effect on the volatility of CTVs as compared to negative sentiments. This implies that the potential for super normal gains is a bigger motivation for cryptocurrency investors than the fear of losing returns. Global sentiments have a higher short-term spill-over effect on CTVs as compared to local sentiments which have long-term persistency. In the long-term, CTV volatility correlation is more clear and pronounced with local sentiments

than with global sentiments. This implies that local cryptocurrency investors consider local sentiments in making long-term cryptocurrency investments.

This study findings are consistent with behavioural finance theory on investors biases. Based on herding bias theory, investors tend to follow and copy what other investors are doing regardless of their own conclusions or beliefs as shown by local investors relying on global sentiments in making short-term investment decisions in a local cryptocurrency market. Information cascades increase herding behaviour due to perceived informational differences between local and developed nations investors. As seen from the findings, hindsight, experience and the arrival of new information eventually leads the local investor to rely on local sentiments due to long-term volatility persistence.

On comparison with other empirical studies, we note that other studies by (Kraaijeveld & De Smedt, 2020), (Abraham, Higdon, Nelson, & Ibarra, 2018), (Nie, Cheng, & Yen, 2020) and (Lyocsa, Molnar, Plihal, & Siranova, 2020) had similar conclusions on the impact of social media sentiments on cryptocurrency prices. Notably is the (Kraaijeveld & De Smedt, 2020) study which concluded that twitter sentiment can be used to predict price returns for 9 largest cryptocurrencies. However, this study extends these findings by showing than the CTV market is affected by both global and local sentiments. It also demonstrates that investors consider local sentiments in the long-term while their short-term decisions are based on global sentiments.

5.3 Conclusions

The study demonstrated that Cryptocurrency Markets are affected by similar conditions to stock and other financial markets. Current cryptocurrency markets, although unregulated, are responding to monetary policy interventions and behavioural factors that affect other types of markets. This means that existing regulators like the Central Bank of Kenya and the Capital Markets Authority can successfully regulate Cryptocurrency Markets using existing regulatory policies. Similarly to (Auer & Claessens, 2018) and (Giudici, Milne, & Vinogradov, 2020) studies, this study has affirmed that cryptocurrency markets are within the control of national policies and therefore can

be successfully regulated. This will increase public trust and create a safer investment environment for cryptocurrencies.

An effective monetary policy will be a pertinent tool in controlling cryptocurrency markets. Stable interest rates will enable investors to create pure or mixed cryptocurrency investment portfolios having a stable cost of capital which in turn reduces uncertainty and increases investment. Investors will be able to benefit from the high-risk high return cryptocurrency market at the same time benefit from the more stable stock exchange markets.

Behavioural factors as captured by public sentiment are increasingly becoming an important factor in investment decision making. Fortunately, public sentiment can be measured and successfully modelled to predict market performance. The incorporation of both global and local sentiments will enable the development of better predictive models by capturing investor opinion and their return expectations. The transmission of global sentiments to local sentiments can be modelled as shown in this study to predict the short-term direction of local cryptocurrency markets. This will predict arbitrage opportunities which can be exploited for higher returns.

Finally, the study has also highlighted the importance of the Stock Exchange as an investment hedge for cryptocurrency investments and vice versa. This means that the government can reduce investment in risky unregulated cryptocurrency markets by ensuring an effective and efficient alternative stock exchange market.

5.4 Recommendations

For investors, the study recommends the studying of local market conditions associated with both monetary policies and investor behaviour in making investment decision. In the short-term, the investor should consider global sentiments and incorporate models that capture and analyse global sentiments in their decision-making process. A more accurate predictive model can be derived which in turn will provide valuable information enabling the investor to make optimum return decisions. To manage uncertainty a local investor can make more short-term investments in cryptocurrency markets during times of normal uncertainty as modelled by the World Uncertainty Index (WUI) and global sentiments. The investor should exploit the hedging opportunities with the NSE to further manage their risks based on their risk appetites. The study has shown that exchange rates and interbank rates have a significant effect on cryptocurrency markets. Thus, the government should strengthen its strategy to revive the interbank foreign exchange market. This will provide a good indicator on market liquidity and a better predictor of cryptocurrency markets direction. This will lead to better predictive models which will in turn improve returns and address market uncertainty.

For regulators, the study has shown that the cryptocurrency markets are affected by local monetary policy decisions and thus are within the control of national policies. The study recommends that cryptocurrency markets should be regulated just like for the other financial markets. Proper registration and compliance to monetary policy statutory requirements like reserves and depositor protection will ensure a safe environment for cryptocurrency investments. Financial regulators are increasingly required to address information asymmetries and provide relevant information to ensure informed decision making. To achieve this, regulators can incorporate public sentiments and monetary policy parameters in publicly accessible models which generate relevant information for local investors in both mainstream and alternate markets. Measurable behavioural finance factors should be incorporated. Monetary Policy Committee (MPC) meetings must also incorporate a brief on alternate or emerging cryptocurrency and other alternate investment markets. This will strengthen the regulatory authority function of communication and ensuring transparent markets. A functioning cryptocurrency market will be a necessary pre-cursor for the potential launch of CBDCs.

5.5 Suggestions for Further Research

The study focussed on one aspect of the dual nature of cryptocurrencies i.e as an investment asset and not as a currency. As the study has shown, cryptocurrency investment assets are viable as they are within the control of national regulation. The use of cryptocurrency as a currency needs to be studied further especially its application and impact on retail and cross border payments and remittances. Because of their global nature, cryptocurrencies will need to be studied in a regional context. This will be highlighting the interconnectedness of cryptocurrency markets in various countries and address various systemic risks through joint regulatory interventions.

Additionally, a potential future study can look at the role that cryptocurrencies play in remittances and cross-border trade. The study may incorporate other types of cryptocurrencies including stable coins, CBDCs and Ethereum.

5.6 Study Limitations

Lack of regulations means that current cryptocurrency market players have not been subjected to registration or any regulatory disclosure. This reduced the set of available information making it difficult to supplement the secondary data analysis with survey or primary data. Therefore, the validation with primary data was not possible.

REFERENCES

Abraham, J., Higdon, D., Nelson, J., & Ibarra, J. (2018). Cryptocurrency Price Prediction Using Tweet Volumes and Sentiment Analysis. SMU Data Science Review, 1(3), 1-21.

Acatrinei, M., Gorun, A., & Marcu, N. (2013). A DCC-GARDH model to estimate the risk of the capital market in Romania. Romanian Journal of Economic Forecasting, 1(2013), 136-148.

Africa Growth Initiative. (2022). Foresight Africa: Top Priorities for the continent in 2022. Brookings Institute.

Agbo, E., & Nwadialor, E. (2020, June). Cryptocurrency and the African Economy. Economics And Social Sciences Academic Journal, 2(6), 84-100.

Aharon, D. Y., Demir, E., Lau, C., & Zaremba, A. (2022). Twitter-Based uncertainty and cryptocurrency returns. Research in International Business and Finance, 59(101546).

Ahir, H., Bloom, N., & Furceri, D. (2022, Feb). World Uncertainty Index. NBER Working Paper Series, 29763, pp. 1-114.

Ampountolas, A. (2022, Jul 8). Cryptocurrencies Intraday High-Frequency Volatility Spillover Effects Using Univariate and Multivariate GARCH Models. International Journal of Financial Studies, 10(51), 1-22.

Auer, R., & Claessens, S. (2018). Regulating cryptocurrencies: assessing market reactions. BIS Quarterly Review September 2018, 51-68.

Avramov, D., Cheng, S., & Hameed, A. (2016, Dec). Time-Varying Liquidity and Momentum Profits. The Journal of Financial and Quantitative Analysis, 51(6), 1897-1923.

Baddeley, M. (2010). Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses. Philosophical transactions of the Royal Society, 365(1538), 281-290.

Bank of England. (2018, May). Broadening narrow money: monetary policy with a central bank digital currency. Staff Working Paper No. 724(724), p. 4.

Bank of Russia. (2022). Cryptocurrencies: Trends, Risks and Regulation. Central Bank of the Russian Federation. Moscow: Central Bank of the Russian Federation.

Bhatnagar, M., Taneja, S., & Rupeika-Apoga, R. (2023, Feb 17). Demystifying the Effect of the News (Shocks) on Crypto Market Volatility. Journal of Risk and Financial Management, 16(136), 1-16.

Bhullar, P., & Bhatnagar, D. (2020). Bitcoins as a determinant of stock market movements: A comparison of Indian and Chinese Stock Markets. Theoretical and Applied Economics, 27(3), 193-202.

Bird, R., & Yeung, D. (2012, April). How do investors react under uncertainty? Pacific-Basin Finance Journam, 20(2), 310-327.

Bjordal, A., & Opdahl, E. (2017). Portfolio optimization in the cryptocurrency market. Norwegian School of Economics Thesis: Master of Science in Economics and Business Administration, Financial Economics, 1-78.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. The Journal of Political Economy, 81(3), 637-654.

Blinder, A., Ehrmann, M., Fratzscher, M., Haan, J., & Jansen, D.-J. (2008). Central Bank Communication and Monerary Policy: A survey of theory and evidence. European Central Bank - Working Paper Series (No. 898).

Bohte, R., & Rossini, L. (2020, Sep 18). Comparing the Forecasting of Cryptocurrencies by Bayesian Time-Varying Volatility Models. Journal of Risk and Financial Management, 12(150), 1-18.

Bollerslev, T. (1990). Modeling the coherence in short-run nominal exchange rates: A multivariate Generalised ARCH model. Review of Economics and Statistics, 72, 498-505.

Borgards, O., & Czudaja, R. (2020). The prevalence of price overreactions in the cryptocurrency market. Journal of International Financial Markets, Institutions and Money, 65.

Bouri, E., Das, M., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. Applied Economics, 50, 1-50.

Bouri, E., Gil-Alana, L., Gupta, R., & Roubaud, D. (2019). Modelling long memory volatility in the Bitcoin market: Evidence of persistence and structural breaks. International Journal of Finance & Economics, 412-426.

Bouri, E., Lau, C., Lucey, B., & Roubaud, D. (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. Finance Research Letters, 340-346.

Brauneis, A., Mestel, R., Riordan, R., & Theissen, E. (2021). How to measure the liquidity of cryptocurrency markets? Journal of Banking and Finance, 124, 1-26.

Brima, S., & Brima, A. (2017). Monetary Policy Effects on Private Sector Investment: Evidence from Sierra Leone. International Journal of Economics and Financial Issues, 7(1), 476-488.

Caferra, R., & Vidal-Tom√°s, D. (2021, Feb 1). Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. Finance Research Letters.

Caporale, G., & Plastun, A. (2020). Momentum effects in the cryptocurrency market after one-day abnormal returns. Financial Markets and Portfolio Management, 34, 251-266.

Catani, P., & Ahlgren, N. (2017, Jan). Combined Lagrange multiplier test for ARCH in vector autoregressive models. Econometrics and Statistics, 1, 62-84.

CBK. (2015, December 18). Banking Circular No. 14 of 2015 : Virtual Currencies. Retrieved April 2021, from Central Bank of kenya: https://www.centralbank.go.ke/uploads/banking_circulars/2075994161_Banking%20Circular%20No%2014%20of%202015%20-%20Virtual%20Currencies%20-%20Bitcoin.pdf

CBK. (2022). Discussion Paper on Central Bank Digital Currency. Central Bank of Kenya. Nairobi: Central Bank of Kenya.

CBK. (2023, Feb 10). Central Bank of Kenya Monetary Policy. Retrieved from Central Bank of Kenya: https://www.centralbank.go.ke/monetary-policy/#

Chainalysis. (2021). The 2021 Geography of Cryptocurrency Report - Analysis of Geographic Trends in Cryptocurrency Adoption, Usage and Regulation. Chainalysis. Chainalysis.

Chainalysis. (2023). The 2022 Geography of Cryptocurrency Report. Chainalysis Inc.

Cheng, Q., Liu, X., & Zhu, X. (2019). Cryptocurrency momentum effect: DFA and MF-DFA analysis. Physica A: Statistical Mechanics and its Applications, 526.

Cheong, C. (2019). Cryptocurrencies vs global foreign exchange risk. The Journal of Risk Finance, 20(4), 330-351.

CMA. (2019, January 3). CMA warns against Kenicoin Initial Coin Offering and Trading. Retrieved April 2021, from Capital Markets Authority: https://www.cma.or.ke/index.php?option=com_content&view=article&id=509:cma-warns-against-kenicoin-initial-coin-offering-and-trading&catid=12&Itemid=207

CNBC. (2017, Jun 15). Major bitcoin exchanges hit by cyberattacks as record rally makes them a target . Retrieved from CNBC: https://www.cnbc.com/2017/06/14/major-bitcoin-exchanges-hit-by-cyberattacks-as-record-rally-makes-them-a-target.html

Coin Dance. (2021, April 3). Coin Dance Paxful Volume (Kenya). Retrieved 3 2021, from Coin Dance: https://coin.dance/volume/paxful/KES

Coin Dance. (2021, April 3). Coin Dance: LocalBitcoins Volume(Kenya). Retrieved April 2021, from Coin Dance: https://coin.dance/volume/localbitcoins/KES

CoinDesk Research. (2022). CoinDesk 2021 Annual Crypto Review. CoinDesk Research.

CoinGecko. (2023). October 2020 Monthly Crypto Report. CoinGecko. Retrieved from https://www.coingecko.com/learn/coingecko-monthly-crypto-report-october-2020#:~:text=Here%20are%20our%204%20key,of%20bullish%20sentiment%20on%20Bitcoin

CoinMarketCap. (2022, Jan 29). Global Cryptocurrency Charts. Retrieved from CoinMarketCap - Total Cryptocurrency Market Cap : https://coinmarketcap.com/charts/

CoinMarketCap. (2023, Feb 11). Global Cryptocurrency Charts - Total Cryptocurrency Market Cap. Retrieved from CoinMarketCap: https://coinmarketcap.com/charts/

Cook, D. (1977, Feb). Detection of Influential Observation in Linear Regression. Technometrics, 19(1), 15-18.

Corbet, S., McHugh, G., & Meegan, A. (2017). The influence of central bank monetary policy announcements on cryptocurrency return volatility. Investment Management and Financial Innovations, 14(2), 60-72.

Creative Commons. (2021, May 9). Creative Commons- Attribution 4.0 International-CC BY 4.0. Retrieved from Creative Commons: http://creativecommons.org/licenses/by/4.0/

Creswell, J. (2009). Research Design - Qualitative, Quantitative, and Mixed Method Approaches. California: Sage Publications,Inc.

Das, D., & Kannadhasan, M. (2018, Nov 5). Do global factors impact bitcoin prices? evidence from wavelet approach1. Journal of Economic Research, 23, 227-264.

Dennis, N., & Griffin, P. (2018, June). The wider impact of a national currency. Global Policy, 5880(1), 1-18.

Elsayed, A., & Sousa, R. (2022). International monetary policy and cryptocurrency markets: dynamic andspillover effects. The European Journal of Finance, 1-21.

Fasanya, I., Onakoya, A., & Agboluaje, M. (2013). Does Monetary Policy Influence Economic Growth in Nigeria? Asian Economic and Financial Review, 3(5), 635-646.

Fauzi, M., Paiman, N., & Othman, Z. (2020). Cryptocurrency Bitcoin: Disruption, challenges and opportunities. Journal of Asian Finance Economics and Business, 7(8), 695-704.

French, J. (2021, May). #Bitcoin, #COVID-19: Twitter-Based Uncertainty and Bitcoin Before and during the Pandemic. International Journal of Financial Studies, 9(28), 1-7.

Friedman, M. (1968, Mar). The Role of Monetary Policy. The American Economic Review, 58(1), 1-17.

Gabauer, D. (2020, Jan 3). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. Journal of Forecasting, 788-796.

Gaffard, J. (2018, November). Monetary theory and policy: The debate revisited. LEM Working Paper Series, 2018/37, pp. 1-33.

Giudici, G., Milne, A., & Vinogradov, D. (2020). Cryptocurrencies: Market analysis and perspectives. Journal of Industrial and Business Economics, 47(1), 1-18.

Glosten, L., Jagannathan, R., & Runkle, D. (1993, Dec). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. The Journal of Finance, 48(5), 1779-1801.

Governor: CBK. (2021, October 24). Central Bank of Kenya Governor on Bitcoin, Cryptocurrencies, and Central Bank Digital Currencies. Retrieved from Youtube: https://www.youtube.com/watch?v=SkAptgCdfvQ

Guler, D. (2021). The Impact of Investor Sentiment on Bitcoin Returns and Conditional Volatilities during the Era of Covid-19. Journal of Behavioral Finance, 1-14.

Gunay, S. (2019). Impact of Public Information Arrivals on Cryptocurrency Market: A Case of Twitter Posts on Ripple. East Asian Economic Review, 23(2), 149-168.

Hassan, O. (2015). The Impact of Monetary Policy on Private Capital Formation in Nigeria. Journal of Empirical Economics, 4(3), 138-153.

He, J. (2020). Capturing Four Stylized Facts of Financial Time Series in GARCH and Stochastic Volatility Models. 2020 3rd International Conference on Economic Management and Green Development (ICEMGD 2020) (pp. 388-400). CSP.

Hicks, J. (1937, Apr). Mr. Keynes and the "Classics"; A Suggested Interpretation. Econometrica, 147-159.

Higgins, M., & Bera, A. (1992, Feb). A class of nonlinear ARCH models. International Economic Reiew, 33(1), 137-158.

Holovatiuk, O. (2020). Cryptocurrencies as an asset class in portfolio optimisation. Central European Economic Journal, 7(54), 33-55.

Hutto, C., & Gilbert, E. (n.d.). A Parsimonious Rule-based Model for Sentiment Analysis of Social Media te.

Ibrahim, A., Kashef, R., Li, M., Valencia, E., & Huang, E. (2020, Aug 19). Bitcoin Network Mechanics: Forecasting the BTC Closing Price Using Vector Auto-Regression Models Based on Endogenous and Exogenous Feature Variables. Journal of Risk Financial Management, 13(189), 2-21.

Issing, O., & Wieland, V. (2012). Monetary Theory and Monetary Policy: Reflections on the development over the last 150 years. Working Paper Series(67), 1-34.

Jiang, Y., Lie, J., Wang, J., & Mu, J. (2021, February). Revisiting the roles of cryptocurrencies in stock markets: A quantile coherency perspective. Economic Modelling, 95(1), 21-34.

Jovani*f*á , T. (2020, Mar). An Overview of Regulatory Strategies on Crypto-Asset Regulation - Challenges for Financial Regulators in the Western Balkans. EU Financial Regulation and Markets - Beyond Fragmentation and Differentiation (Eds. I. Bajaki*f*á, M. Bo≈æina Bero≈°), pp. 130-177.

Kaggle. (2023, Feb 15). Bitcoin tweets - 16M tweets- Tweets for sentiment analysis. Retrieved from Kaggle: https://www.kaggle.com/datasets/alaix14/bitcoin-tweets-20160101-to-20190329

Kamaan, C. (2014, Apr). The Effect of Monetary Policy on Economic Growth in Kenya. International Journal of Business and Commerce, 3(8), 11-24.

Kamau, C. G. (2022, Aug 26). The Cryptocurrency Market in Kenya: A review of awareness and participation by the Youth. Journal of Asian Business Strategy, 12(1), 49-56.

Kaminska, I., Mumtaz, H., & Roman, S. (2021, March 5). Monetary Policy Surprises and their Transmission Through Term Premia and Expected Interest Rates. Bank of England Working, 124, 1-40.

Karau, S. (2021, Nov 19). Monetary Policy and Bitcoin. Deutsche Bundesbank Discussion Paper, pp. 1-50.

Kessa, O., & Mahoro, V. (2019). Rwandacoin: Prospects and challenges of developing a cryptocurrency for transactions in Rwanda. ArXiv, Abs/1901(6249).

Keynes, J. (1936). The General Theory of Employment, Interest and Money. Macmillan.

Keynes, J. (1937, February). The General Theory of Employment. The Quartely Journal of Economics, 51(2), 209-223.

Khalfaoui, R., Hammoudeh, S., & Rehman, M. (2023, Feb 2). Spillovers and connectedness among BRICS stock markets, cryptocurrencies, and uncertainty: Evidence from the quantile vector autoregression network,. Emerging Markets Review, 54.

Kimolo, N. (2023, Dec 2). Data. Retrieved from OneDrive: https://1drv.ms/f/s!Ans_zFey4D2ljaVxQYTZHv5cXg0Uqw?e=ArYfN1

Kimolo, N., & Machua, A. (2022, April 27). NK-Bitcoin - Sentiment Analysis. Retrieved from Google Collab: https://bit.ly/nicholus-mdf-sbs

Kr√ºckeberg, S., & Scholz, P. (2019). Cryptocurrencies as an Asset Class. In S. Goutte, K. Guesmi, & S. Saadi, Cryptofinance and Mechanisms of Exchange -The Making of Virtual Currency .

KRA. (2020, October 15). Taxing Cryptocurrencies in Kenya - Kenya Revenue Authority. Retrieved from Youtube: E-lABZ: https://youtu.be/8j1TR4Bvv0M

KRA. (2021, January 1). Introducing Digital Service Tax. Retrieved April 2021, from Kenya Revenue Authority: https://www.kra.go.ke/images/publications/Brochure--Digital-Service-Tax--final.pdf

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. Journal of International Financial Markets, Institutions and Money, 65(C).

Kumah, S., Odei-Mensah, J., & Amanamah, R. (2022, Sept 11). Co-movement of cryptocurrencies and African stock returns: A multiresolution analysis. Cogent Business & Management, 9(1), 1-29.

Kumar, A., & Anandarao, S. (2019, June 15). Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. Physica A: Statistical Mechanics and its Applications, 524, 448-458.

Lee, C., & Swaminathan, B. (2000). Price Momentum and Trading Volume. The Journal of Finance, 55(5), 2017-2069.

Liu, Y., & Tsyvinski, A. (2020, Sep 26). Risks and Returns of Cryptocurrency. The Review of Financial Studies, 34(6), 2689,Äì2727.

Lyocsa, S., Molnar, P., Plihal, T., & Siranova, M. (2020). Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin Author links open overlay panel. Journal of Economic Dynamics and Control, 119, 1-20.

Maitra, D., Rehman, M., Dash, S., & Kang, S. (2022, Jul 18). Do cryptocurrencies provide better hedging? Evidence from major equity markets during COVID-19 pandemic. The North American Journal of Economics and Finance, 62, 1-27.

Makarov, I., & Schoar, A. (2020, Feb). Trading and arbitrage in cryptocurrency markets. Journal of Financial Economics, 135(2), pp. 293-319.

Malmsten, H., & Ter√§svirta, T. (2004, Aug). StylizedFactsofFinancialTimeSeriesand ThreePopularModelsofVolatility. SSE/EFIWorkingPaperSeriesinEconomicsandFinance, 563, 1-44.

MarketWatch. (2017, Jun 24). What caused the ethereum flash crash? Retrieved from Market Watch: Stock Market & Financial News: https://www.marketwatch.com/story/what-caused-the-ethereum-flash-crash-2017-06-22

Markowitz, H. (1952). Portfolio Selection. The Journal of Finance,, 7(1), 77-91.

Martens, M., & Poon, S.-H. (2001). Returns synchronization and daily correlation dynamics between international stock markets,. Journal of Banking & Finance, 25(10), 1805-1827.

McCallum, B., & Nelson, E. (1997, Jan). An Optimizing IS-LM Specification for Monetary Policy and Business Cycle Analysis. NBER Working Paper, 5875(JEL Nos E10,E30,E40).

MICT. (2019). Emerging Technologies for Kenya: Exploration & Analysis. Nairobi: Ministry of Information,Communications and Technology.

Mozahem, N. (2019). Logistic Regression using Stata: Theory and Application.

Mutwiri, N., & Jagongo, A. (2017, Jan). Monetary Policy Tools and Inflation in Kenya. International Journal of Academic Research in Accounting, Finance and Management Sciences, 7(1), 86-97.

Nanayakkara, N., Nimal, P., & Weerakoon, Y. (2019, July 07). Behavioural Asset Pricing: A Review. International Journal of Economics and Financial Issues, 9(4), 101-108.

Nguyen, P., Schinckus, C., Nguyen, B., & Tran, D. (2022, Aug 17). International portfolio investment: does the uncertainty matter? Journal of Economics and Development, 24(4), 309-328.

Nguyen, T., Nguyen, B., Nguyen, K., & Phama, H. (2019). Asymmetric monetary policy effects on cryptocurrency markets. Research in International Business and Finance, 48(1), 335-339.

Nguyen, T., Nguyen, T., Nguyen, T., Pham, T., & Nguyen, Q. (2022). Stablecoins versus traditional cryptocurrencies in response to interbank rates. Finance Research Letters.

Nie, W.-Y., Cheng, H.-P., & Yen, K.-C. (2020). Investor Sentiment and the Cryptocurrency Market. The Empirical Economics Letters, 19(11), 1254-1262.

Nkrumah-Boadu, B., Junior, P., Adam, A., & Asafo-Adjei, E. (2022, Aug 29). Safe haven, hedge and diversification for African stocks: cryptocurrencies versus gold in time-frequency perspective. Cogent Economics & Finance, 10(1), 1-22.

Norman-William, E. (2018). Africa's Cryptocurrency Boom: The Bitcoin Craze. Abuja: Centre for Democracy & Development.

O. T., & Chiluwe, M. (2012, April 15). The Effect of Monetary Policy on Private Sector Investment in Kenya. Journal of Applied Finance & Banking, 2(2), 239-287.

Olusegun, V., & Olaniyi, E. (2019, July 9). Can cryptocurrency, mobile phones, and internet herald sustainable financial sector development in emerging markets? Journal of Transnational Management, 24(3), 259-279.

Oprean, C., & Tanasescu, C. (2014). Effects of Behavioural Finance on Emerging Capital Markets. Procedia Economics and Finance, 15, 1710-1716.

Orskaug, E. (2009, June). Multivariate DCC-GARCH Model-With Various Error Distributions. Master Thesis, Norwegian University of Science and Technology, Department of Mathematical Sciences.

Ozdamar, M., Akdeniz, L., & Sensoy, A. (2021). Lottery like preferences and the MAX effect in the cryptocurrency market. Financial Innovation, 1-27.

Pal, R. (2017). Issues and Concepts of Economics. In R. Pal, Issues and Concepts of Economics. New Delhi: Adhyayan Publishers.

Raissi, N., & Missaoui, S. (2015). Role of investor sentiment in financial markets: an explanation by behavioural finance approach. International Journal of Accounting and Finance, 5(4), 362-401.

Ram, A. (2019). Bitcoin as a new asset class. Meditari Accountancy Research, 27(1), 147-168.

Sami, M., & Abdallah, W. (2020, April 21). Cryptocurrency and Stock Market: Complements or Substitutes? Applied Financial Letters, 9(4), 25-35.

Saunders, M., Lewis, P., & Thornhill, A. (2007). Research Methods for Business Students. London: Prentice Hall.

Saunders, M., Lewis, P., & Thornhill, A. (2012). Research Methods for Business Students. Essex, England: Pearson Education Limited.

Sharpe, W. (1964). Capital Asset Prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425-442.

Shefrin, H. (2009). Behavioralizing Finance. Foundations and Trends in Finance, 4(1), 1-184.

Shnier, M. (1996). Dictionary of PC hardware and data communications terms.

Sifat, I. (2021). On cryptocurrencies as an independent asset class: Long-horizon and COVID-19 pandemic era decoupling from global sentiments. Finance Research Letters, 43(102013).

Smales, L. (2021, Oct 15). Volatility Spillovers among Cryptocurrencies. Journal of Risk and Financial Management, 14(493), 1-12.

Statman, M. (1999). Behaviorial Finance: Past Battles and Future Engagements. Financial Analysts Journal, 55(6), 18-27.

Thapar, R. (2006). Volatility and Value at Risk modelling using univariate GARCH models. Stockholm School of Economics , 1-35.

Twinoburyo, E., & Odhiambo, N. (2018). Monetary Policy and Economic Growth: A Review of International Literature. Journal of Central Banking Theory and Practice, 7(2), 123-137.

Veni, P., & Kandregula, R. (2020). Evolution of Behavioural Finance. International Journal of Scientific Development and Research, 5(3), 209 -215.

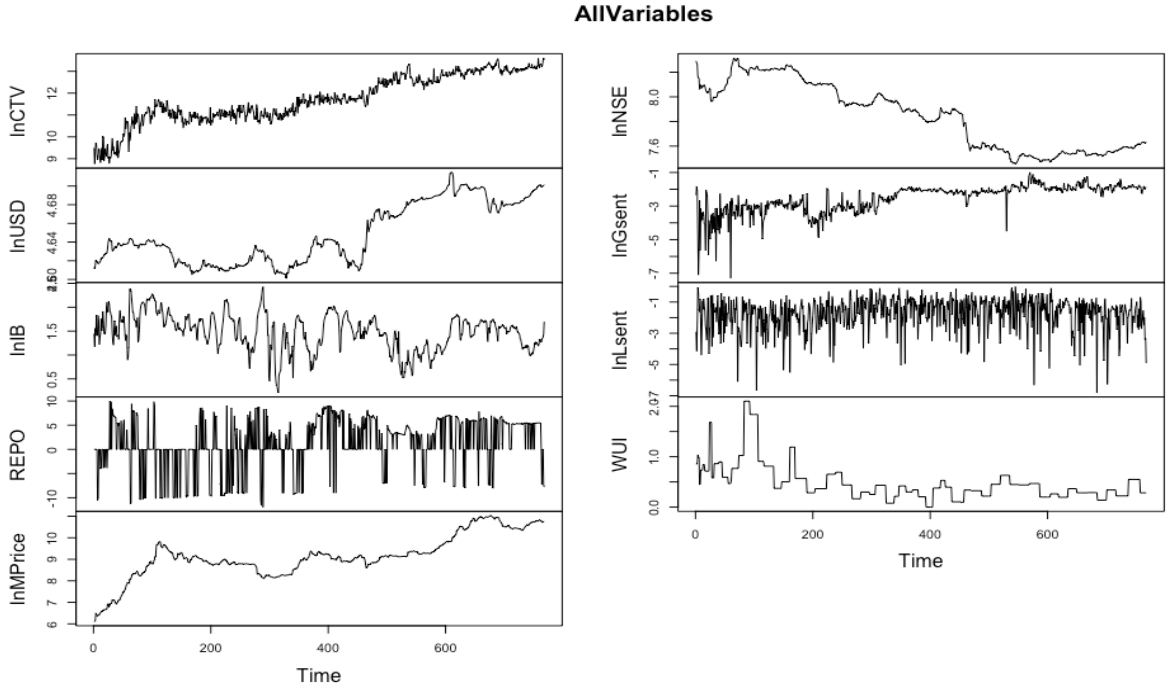
Vidal-Tomas, D., & Ibanez, A. (2018). Semi-Strong Efficiency of Bitcoin. Finance Research Letters, 27(c), 259-265.

Wei, C.-C. (2008, Oct 10). Multivariate GARCH modeling analysis of unexpected U.S. D, Yen and Euro-dollar to Reminibi volatility spillover to stock markets. Economics Bulletin, 3(64), 1-15.

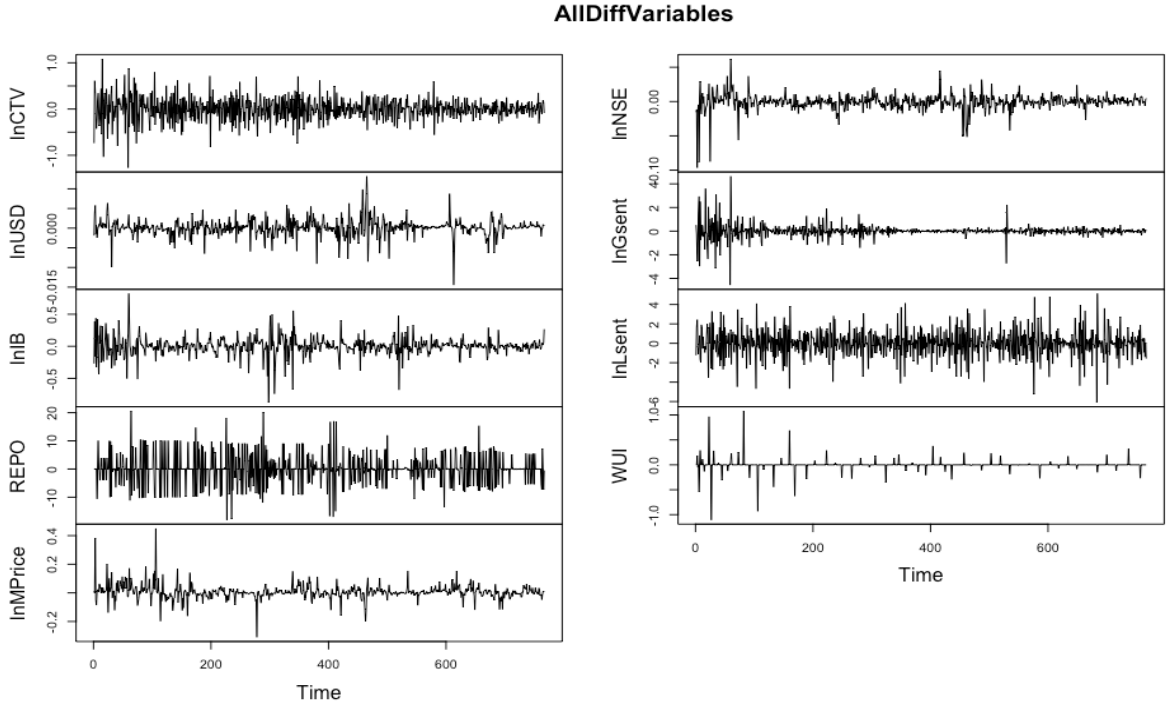
Xiao, L., & Dhesi, G. (2010, September). Volatility spillover and time-varying conditional correlation between the European and US stock markets. Global Economy and Finance Journal, 3(2), 148-164.

APPENDICES

Appendix 1 - Time Series before differencing



Appendix 2 - Variables Time Series after differencing



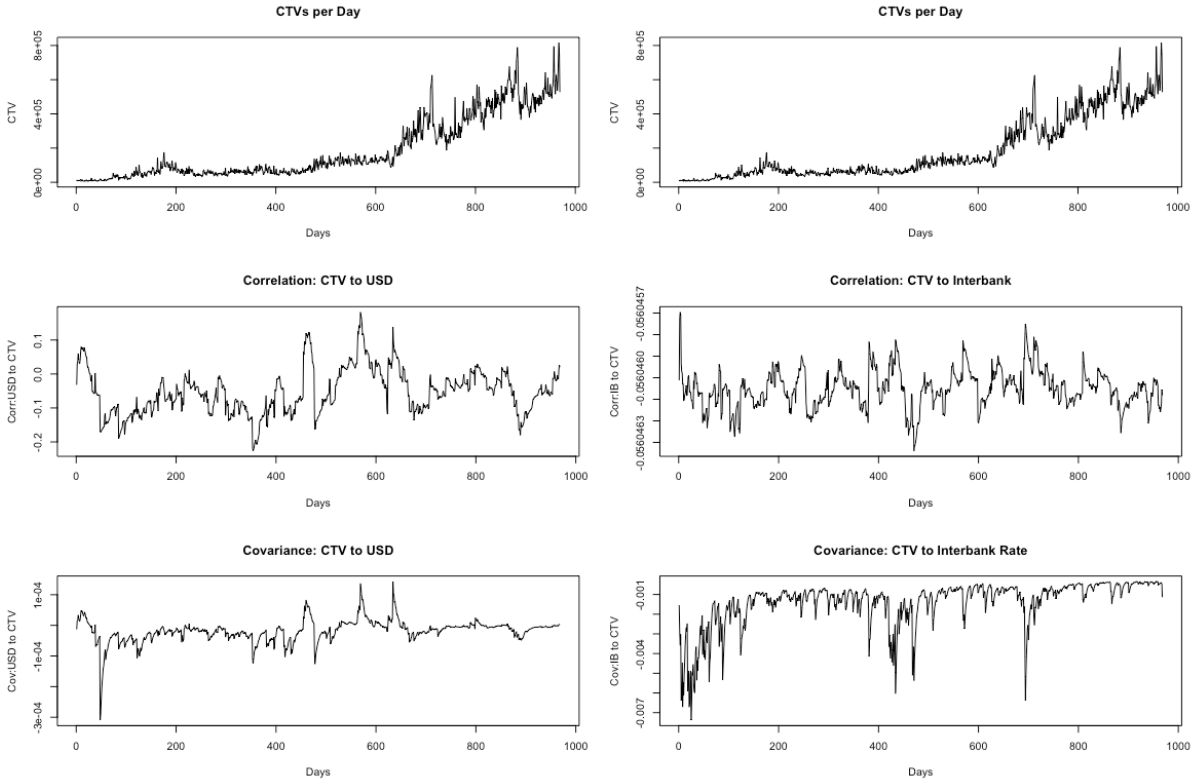
Appendix 3 – GARCH Model Selection Test Results

	1	2	3	4	5
GARCH Model	sGARCH(1,1)	sGARCH(2,1)	sGARCH(1,1)	gjrGARCH(2,1)	gjrGARCH(1,1)
Mean Model	ARFIMA(1,0,0)	ARFIMA(1,0,0)	ARFIMA(1,0,0)	ARFIMA(1,0,1)	ARFIMA(1,0,1)
Distribution	sstd	sstd	norm	sstd	sstd
Weighted Ljung-Box Test on Standardized Squared Residuals: (All p-values > 0.05)	Yes	Yes	Yes	Yes	Yes
Lag[1]	0.006	1.086	7.638e-06	1.352	0.1154
	(0.938)	(0.297)	(0.998)	(0.245)	(0.7341)
Lag[2*(p+q)+(p+q)-1][5]	3.364		3.735	1.905	0.4297
	(0.3445)		(0.289)	(0.873)	(0.968)
Lag[2*(p+q)+(p+q)-1][8]		4.741			
		(0.389)			
Lag[4*(p+q)+(p+q)-1][9]	4.145		4.6	2.328	1.1345
	(0.564)		(0.49)	(0.983)	(0.98)
Lag[2*(p+q)+(p+q)-1][14]		5.811			
		(0.664)			
Weighted ARCH LM Tests (All p-values >0.05)	Yes	Yes	Yes	Yes	Yes
ARCH Lag[3]	0.07885		0.03788		0.1798
	(0.779)		(0.846)		(0.6715)
ARCH Lag[4]		0.2736		0.004753	
		(0.601)		(0.945)	
ARCH Lag[5]	0.5817		0.54196		0.7710
	(0.859)		(0.871)		(0.8019)
ARCH Lag[6]		0.6939		0.785882	
		(0.837)		(0.81)	
ARCH Lag[7]	0.75188		0.7565		0.9213
	(0.9503)		(0.95)		(0.926)
ARCH Lag[8]		0.7774		0.837697	
		(0.942)		(0.947)	
Adjusted Pearson Goodness-of-Fit Test Per	Yes	Yes	Yes	Yes	Yes

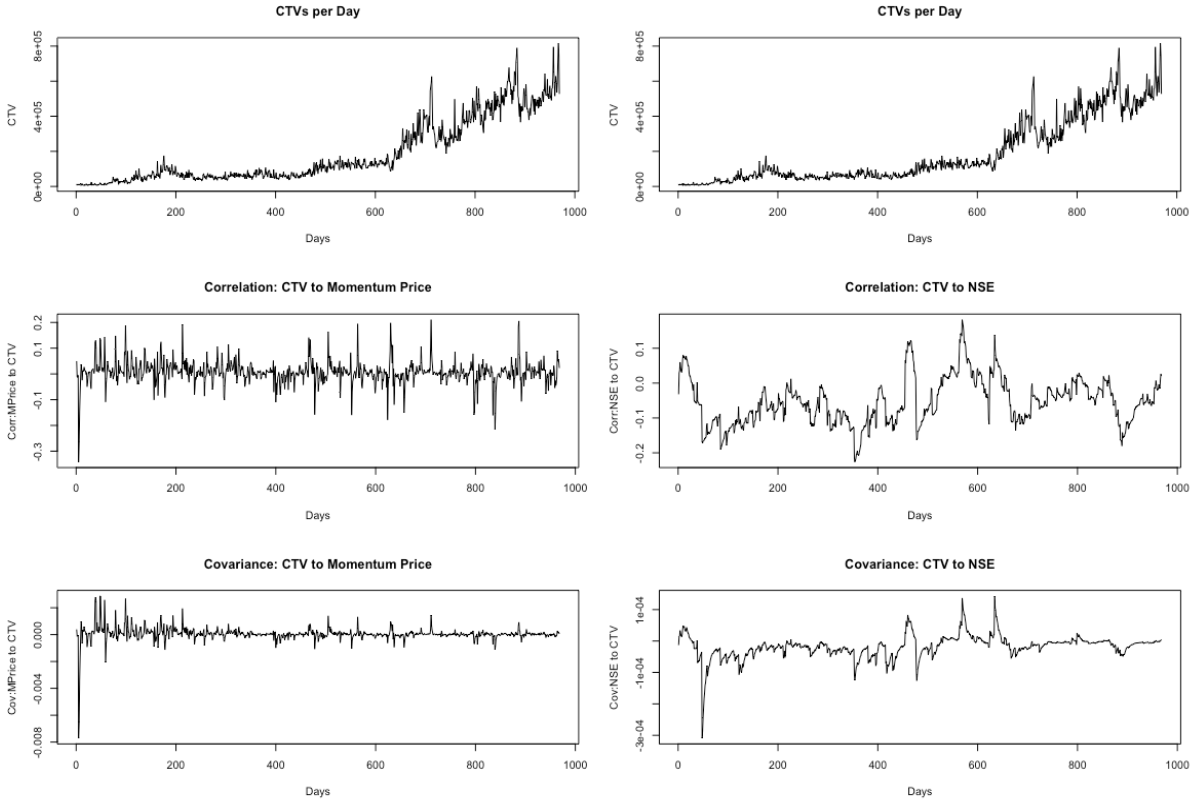
	1	2	3	4	5
Group (All p-values > 0.05)					
20	19.23	15.88	15.76	13.6	14.14
	(0.4421)	(0.665)	(0.673)	(0.807)	(0.776)
30	32.29	24.67	26.28	18.59	21.31
	(0.307)	(0.696)	(0.612)	(0.932)	(0.848)
40	38.53	25.06	33.98	29.43	33.72
	(0.4912)	(0.959)	(0.698)	(0.867)	(0.709)
50	43.78	38.61	35.72	36.42	49.73
	(0.684)	(0.857)	(0.9218)	(0.908)	(0.444)
Log likelihood	149.46	148.85	143.7	197.98	199.09
AIC	-0.29	-0.29	-0.29	-0.39	-0.39
BIC	-0.26	-0.25	-0.26	-0.33	-0.35

p-values in parenthesis

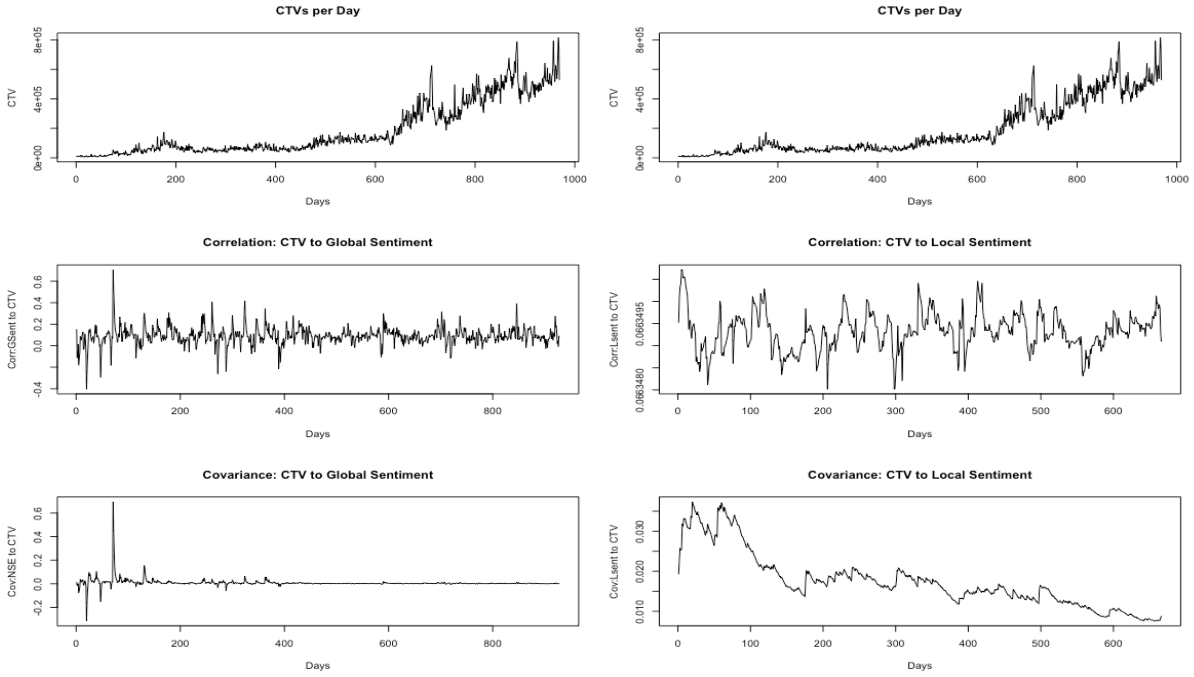
Appendix 4 - Time varying correlation between CTV & Monetary Policy



Appendix 5 - Time varying correlation between CTV & Investor Behaviour factors



Appendix 6 - Time varying correlation between CTV & Sentiment Analysis



Appendix 7: Ethical Review Committee Letter

Strathmore UNIVERSITY

27th March 2023

Mr Kimolo Nicholus Mutua,
nicholus.kimolo@strathmore.edu

Dear Mr Kimolo,

RE: The Associative Relationship between Kenya's Monetary Policy and Investor Behavior with its Cryptocurrency Market Performance

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU- master's** research proposal. Your application reference number is **SU-ISERC1660/23.** The approval period is from **27th March 2023 to 26th March 2024.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 48 hours of notification
iv. Any changes, anticipated or otherwise, that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 48 hours
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: **Dr Ben Ngoye,**
Secretary; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
27-Mar-2023
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
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Cc: Mr Ambrose Rachier,
Chairperson; SU-ISERC

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Appendix 8: NACOSTI Research License

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 246650

Date of Issue: 05/April/2023

RESEARCH LICENSE

This is to Certify that Mr.. Nicholus Mutua Kimolo of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: The Associative Relationship between Kenya's Monetary Policy and Investor Behavior with its Cryptocurrency Market Performance for the period ending : 05/April/2024.

License No: NACOSTI/P/23/24949

246650

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

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