THE HEDGING CAPABILITY BETWEEN NON-GREEN CRYPTOCURRENCY AND GREEN CRYPTOCURRENCIES TOWARDS U.S. STOCK MARKET: ANALYSIS EFFECT OF ECONOMIC POLICY UNCERTAINTY

HUNG XIN QI
KHOR SEANG YI
LAI JUN HAO
YAP SHUN QING

BACHELOR OF FINANCE (HONS)

UNIVERSITI TUNKU ABDUL RAHMAN

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MAY 2025

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BY

HUNG XIN QI
KHOR SEANG YI
LAI JUN HAO
YAP SHUN QING

A final year project submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF FINANCE (HONS)

UNIVERSITI TUNKU ABDUL RAHMAN

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Name of Student:	Student ID:	Signature:
1. Hung Xin Qi	22ABB04660	
2. Khor Seang Yi	21ABB02738	
3. Lai Jun Hao	22ABB04659	
4. Yap Shun Qing	22ABB02593	

Date: 24/04/2025

ACKNOWLEDGEMENT

First and foremost, we would like to take this opportunity to express our heartfelt gratitude to our research supervisor, Mr. Ng Cheong Fatt, for his continuous support, encouragement, and invaluable guidance throughout the course of this research project. His friendly nature and readiness to assist whenever we faced challenges have been truly motivating. We are deeply thankful for the time and effort he dedicated to sharing his expertise and insights, which have significantly enhanced the quality of our study. This research would not have been successfully completed without his expert supervision.

We also wish to extend our sincere appreciation to our examiner, Dr. Foo Chuan Chew, for her constructive feedback and thoughtful suggestions. Her guidance has been instrumental in helping us identify and correct our mistakes, thereby improving the overall standard and clarity of our research.

Our gratitude also goes to Universiti Tunku Abdul Rahman (UTAR) for providing us with the necessary resources and infrastructure to carry out this study. The access to various research databases and academic platforms greatly facilitated our literature review and data analysis. This opportunity has allowed us to deepen our understanding of the research area and enhance both our analytical thinking and problem-solving capabilities.

Lastly, we are truly grateful to our families and friends for their unwavering moral support and encouragement throughout this journey. We would also like to acknowledge the dedication and hard work of our team members, whose commitment and cooperation have been vital in completing this study. Each member’s contribution is deeply appreciated and has played a key role in the success of this research.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
ADA	Cardano
ALGO	Algorand
BTC	Bitcoin
CBOE	Chicago Board Option Exchange
CCR	Return on Cryptocurrency
DAX	Deutscher Aktienindex
EPU	Economic Policy Uncertainty
FGLS	Feasible Generalized Least Square
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GC / GCs	Green Cryptocurrency / Green Cryptocurrencies
LM	Langrage Multiple
MPT	Modern Portfolio Theory
OLS	Ordinary Least Square
OVX	Crude Oil Volatility Index
PoS	Proof-of-Stake
PoW	Proof-of-Work
P2P	Peer-to-Peer

PP	Philips-Perron
SVB	Silicon Valley Bank
S&P 500	Standard & Poor's 500 Index
VIF	Variance Inflation Factor
XCH	Chia
XLM	Stellar Lumens
XNO	Nano

ABSTRACT

This study examines, while accounting for Economic Policy Uncertainty (EPU), the relationship between green and non-green cryptocurrencies and the US stock market. A negative correlation between the returns of green cryptocurrencies and the U.S. stock market is found in the study, which uses daily time series data from May 3, 2021, to December 31, 2024. Numerous statistical tests were performed on the data, including the GARCH model, Feasible Generalised Least Squares (FGLS), Phillips-Perron (PP) test, Augmented Dickey-Fuller (ADF) test, Jarque-Bera test, Breusch-Godfrey LM test, and ARCH LM test. The absence of a unit root has been proven by employing the ADF test and PP test. The Newey-West Heteroscedasticity and Autocorrelation Consistent (HAC) method was employed to guarantee model resilience despite the presence of heteroscedasticity, autocorrelation, and error-term's normal distribution. According to the FGLS model, Bitcoin exhibits a positive but insignificant relationship with S&P 500 returns, whereas green cryptocurrencies have a significant negative relationship. Furthermore, whereas Bitcoin's hedging ability is unaffected by high EPU, green cryptocurrencies' hedging capacity is adversely harmed. In a nutshell, these results have important implications for future researchers, investors, and policymakers.

CHAPTER 1: RESEARCH REVIEW

1.0 Introduction

This chapter will provide the overview of the cryptocurrencies that are classified as green and non-green, including Bitcoin, Chia, Cardano, Nano, Stellar Lumens, and Algorand. Beyond that, the contrast between green and non-green cryptocurrencies, the relationship between green cryptocurrencies and the stock market in U.S., and the capability for hedging between cryptocurrencies and the equity market will all be presented. Problem statements, research objectives, research questions, hypothesis statement and significance of study will all be discussed in the chapter that follows. The chapter will conclude with an overview of the summary of the discussion of the research in each chapter.

1.1 Research Background

1.1.1 Non-green Cryptocurrency

A cryptocurrency is a digital exchange system that operates on a peer-to-peer (P2P) basis, using encryption to create and distribute units of currency (Farell, 2015). The value of this digital currency is based on the anonymity of an algorithm that can track every transaction, not on any physical item, a country's economy, or a company. It is infinitely divisible, has no physical representation, and is not linked to any higher authority, unlike the vast majority of other financial assets (Corbet et al., 2019). Cryptocurrencies are predicated on a data structure known as a secure distributed ledger, of which mining is a crucial component. By contributing historical transaction data to the Blockchain, a distributed ledger, mining enables users to come to a strong, safe agreement on every transaction. Miners are their main source of transaction validation. Its mining algorithm is known as the 'Proof-of-Work' (PoW) system (Mukhopadhyay et al., 2016).

These are factors contributing to cryptocurrencies' growing popularity and lead to increase in trade volume, price and volatility (Corbet et al., 2019). Within the short time it has existed, the cryptocurrency market has grown wildly and at an unprecedented rate. Since the initial anarchic cryptocurrency, Bitcoin (BTC), was introduced to the public in January 2009, more than 500 cryptocurrencies have been created (Farell, 2015). BTC and other cryptocurrency markets have expanded into captivating exchanges for investors for over a decade after being launched. There are billions of dollars that have been transacted and a futures market that provides the opportunity of risk hedging. Since cryptocurrencies are a novel class of trade asset, their price movements differ from those conventional financial assets (Wang et al., 2022).

By referring to the coinmarketcap.com, at the end of 2023, the global cryptocurrency market is worth $1.65 trillion, which has a growth of 206.68% on YoY compared to $798.321 billion global cryptocurrency market in 2022. Bitcoin is the largest market cap cryptocurrency and worth $830.81 billion, which approximately occupies 50.32% of the cryptocurrency market. There are more than 23,000 cryptocurrencies compared to decades before which only seven. However, the growth rate is not indicating good news to the market as there are only a few cryptocurrencies that account for the majority of market capitalization. A lot of these new coins exist only to enrich their developers. The fact that there is almost no entrance barrier is the main cause of the wide variety of cryptocurrencies. It is possible for anybody to establish a cryptocurrency (Daly, 2024).

1.1.1.1 Bitcoin

The initial emergence of cryptocurrencies, starting in 2008 when the anonymous Satoshi Nakamoto launched Bitcoin, sparked a lot of interest from the media, regulators, and investors alike. Since, they are a new type of digital currency that is not issued via banks or other traditional financial institutions but instead works on decentralized P2P networks (Farell, 2015). In the beginning of 2009, the open, P2P decentralized Bitcoin network launched worldwide (De Vries, 2020). Every transaction of Bitcoin is recorded in a distribution ledger called blockchain and transactions will be broadcast and verified by all nodes in the network through a particular consensus mechanism. The consensus mechanism needed in the blockchain to ensure trust across the network (IEA, 2015).

Bitcoin is characterized as a synthetic kind of commodity money that has characteristics with fiat currencies like the U.S. dollar as well as commodity currencies like gold. Fiat money is not inherently scarce; instead, it is issued by central banks and serves primarily as a means of trade. Commodity money, on the other hand, is naturally rare and has uses beyond simply becoming a medium of exchange. Furthermore, both kinds of money have the ability to be stored of value. In addition, it is a cross between fiat and commodity money. BTC lacks the "intrinsic" value of fiat money, but it is rare by design, its scarcity is dictated by an automated, prescriptive rule that is satisfied by competitive mining, much like commodity money like gold. The decentralized nature of BTC is another significant similarity to commodity money, most notably gold. However, the P2P payment network of BTC cannot equal the absence of risk of counterparty associated with gold (Baur et al., 2018).

Bitcoin is operated by a proof-of-work (PoW) consensus method and reward incentive engineering. Every node group transaction into blocks roughly every

10-minutes, which is linked to a challenging mathematical puzzle. Miners are nodes that mine currencies and mining is the process of finding a solution to that problem. The right to add the block to the longest block chain at the moment is obtained by the miner who solves the puzzle first. The updated block chain is then replicated to each node in the network after confirmation (Narayanan et al. 2016). The consensus of all nodes, which keeps track of all past transactions, creates the longest block chain. This mining process requires the highest computational power and leads to unsustainable consumption of energy and resource waste (Shi, 2016). Based on the Bitcoin Energy Consumption Index, the single transaction of Bitcoin consumes on huge resources including carbon footprint of 384.49kg CO_2, 44.20 grams electronic waste, 10,864 liters of water and electrical energy of 689.34kWh which comparable to the typical American household's electricity usage over 23.63 days. The annualized total bitcoin footprints in the end of 2023 are 148.91TWh, it is forecasted to increase in the following year (Digiconomist, 2024).

1.1.2 Green Cryptocurrencies

The green finance market consists of market-driven mechanisms and financial products that can regulate emissions of pollutants, establish an ecosystem, and protect businesses from unanticipated changes in the environment. The former is exemplified by emissions trading, while the latter involves a variety of products, including ecological options, environmental funds, nature-linked securities, weather derivatives, and ecological funds (Wang & Zhi, 2016). Green cryptocurrencies investments are recognized as one of the effective methods of achieving this goal among numerous forms of green financing (Ha, 2024).

The reason for Bitcoin's exorbitant energy consumption is its inefficient PoW mining mechanism, which necessitates the employment of extremely strong and energy-intensive machines. BTC, as a popular cryptocurrency, has consumed more than 140 TWH energy per year on mining price which is equivalent to twice Switzerland's power consumption per year. In the future, BTC was estimated to consume 60%-70% of total global electricity usage related to cryptocurrency while Ethereum was predicted to use 20%-39% of global electricity usage that relates to cryptocurrency in the mining process. As a result, the cryptocurrency has high transaction fees and scalability issues due to higher power consumption (Alzoubi & Mishra, 2023). Consequently, non-PoW cryptocurrency methods have seen a rise in acceptance lately. The market's growing demand for environmentally friendly cryptocurrencies has led to an increasing number of them being generated due to urgent needs on green and sustainable substitutes that best fit with cryptocurrency. The representation mechanism of green cryptocurrency (GC) as Proof of Stake (PoS). The PoS refers to validators of a blockchain by locking up set amounts of cryptocurrency or crypto tokens and validating transactions due to the entry of smart contracts in blockchain. On the contrary, they would lose some or all stake money, lock up crypto as a penalty since failure to validate bad or fraudulent data (Napoletano, 2022). The energy-efficient PoS technique, which provides validating devices rather than mining computers to defend the network without consuming a lot of power, is the foundation of green cryptocurrencies. Mining green cryptocurrencies uses less energy and nonrenewable resources than mining conventional cryptocurrencies due to the mechanism and protocol (Ergün, 2023). The change mechanism of Ethereum from PoW to PoS has resulted in the significant decrease of power consumption on the mining process after October 2022. However, many green cryptocurrencies still at an early stage and have limited projects and development. Green cryptocurrencies have their own protocol and mechanism consensus on their mining process, resulting in low annual energy consumption. The description of green cryptocurrency as XCH, ADA, XNO, XLM and ALGO on the mining process would be discussed in this study.

1.1.2.1 Chia (XCH)

Chia (XCH) is one of the green cryptocurrencies on their network blockchain. Their main technology for the operation of Chia is Proof of Space and Time, as the first new Nakamoto Consensus (Chia, 2024). Proof of Space and Time is the mix system that was established from Proof of Time (PoT) and Proof of Space, using their respective strengths to support their blockchain. According to Miller & Lawler (2023) article, this type of mechanism would lead to the users control their unused hard drive space and save their power consumption of mining in hardware. PoT allows additional protection on choosing the next block validator unpredictably, but no benefit on minimizing energy consumption. So, the party interested is unlikely to become the next validator in their current transaction. Farming, as another word of mining, stands out by low resource use, both in regard to processing power on the host's device or requesting reading for the supporting hard drive that manages the plots. Another Chia mechanism as Proof of Space provides efficient and fast proof's verification processes that cause lightweight farming processes (Houten, 2023).

1.1.2.2 Cardano (ADA)

Cardano (ADA), as the cryptocurrency that was founded by Charles Hoskinson uses a PoS consensus mechanism offering a more scalable and sustainable 3rd generation blockchain (Pham et al., 2022). ADA has a staking procedure in which individuals must deposit certain quantities of cryptocurrency in order to participate in the blockchain's operations (Rodeck & Adams, 2022). ADA is 1.6 million times more energy efficient than BTC, processes more than 250 transactions per second and consists of a peer reviewed network that maintain tight relationships with academics to generate peer-reviewed research to guide blockchain development. Napoletano (2022) indicates that PoS is the consensus mechanism that lets the participants get to handle the lucrative task as legitimate transactions and add into blockchain after signing a smart contract and lock up some cryptocurrency, called as stake. They would lose a certain amount of cryptocurrency if they failed to verify bad or fraudulent data (Napoletano, 2022).

1.1.2.3 Nano (XNO)

Nano (XNO) is a cryptocurrency that sets apart from its fee lessness, speed, and energy efficiency. It still has a minimal carbon footprint and has been in service since late 2015. XNO does not rely on mining, which adds to its scalability and lightweight design. XNO uses block-lattice technology, which goes beyond the standard Bitcoin notion. It maintains an account chain for each network user. Since Nano's block lattice technology is highly energy-efficient, verifying transactions is still performed using a PoW technique. The Nano platform's Open Representative Voting (ORV) approach enables account holders to vote for their chosen representatives, who then work to safely validate blocks of transactions. Nano can handle up to 125 TPS with just the sender and receiver account chains. A single Nano transaction has been seen to utilise as little as 0.111 Wh. Nano may be an excellent alternative for micropayments because users' chosen representatives are not compensated for their participation, resulting in free transactions (Alzoubi & Mishra, 2023).

1.1.2.4 Stellar Lumens (XLM)

Stellar Network was established as a separate company from Ripple with the goal of bridging the gap between digital currencies and traditional financial institutions. XLM is seen as a legitimate competitor to PayPal since it allows both individuals and organizations to utilize the network without incurring any fees. Stellar stands apart due to its open-source consensus procedure, which validates transactions by relying on a select group of reliable nodes rather than the whole network. This new consensus method, called Federated Byzantine Agreement (FBA), offers a shorter and faster authentication cycle, which reduces expenses and energy consumption. A single XLM transaction is expected to require around 0.22 Wh of energy. On a yearly basis, it is anticipated to utilize roughly 481 MWh, resulting in an output of around 173 tons of CO2 (Alzoubi & Mishra, 2023).

1.1.2.5 Algorand (ALGO)

Same with the features of other cryptocurrency as quick, decentralized, and security, Algorand is a cryptocurrency that focuses more on payment features. Its characteristics are able to process over 1000 transactions per second within five seconds and are more energy efficient. Their main core technology on their operation is Pure PoS, as a highly democratized version of the PoS model. This novel consensus protocol permits any ALGO currency holder to participate in the network's operation, with only 1 coin to engage it. The 2-phase block in this novel consensus mechanism function is proposing and voting (Miller, 2023). Staking process is similar to locking the money in the fixed deposit for a certain period. Anyone engaging in these operations on the Algorond network by staking ALGO coins and computing a valid participation key to become a Participation Node. Relay nodes manage and share messages among Participation Nodes but indirectly participate in voting or proposing activities. (Miller, 2023). Bassi & Ihsanullah (2022) mentioned that Algorand has lower energy consumption per transaction (kWh/tx) as 0.00021, while Bitcoin and Ethereum have 1700kWh/tx and 290kWh/tx respectively by using PoW.

1.1.3 Comparison between green cryptocurrency and non-green cryptocurrency

The proof-of-work (PoW) consensus processes used by non-green cryptocurrencies, notably Bitcoin, are energy-intensive and have received a lot of flak for their effects on the environment (Sedlmeir et al., 2020; Ren & Lucey, 2022). This has led to a rising concern about how it contributes to greenhouse gas emissions and global warming, which has prompted people to seek out alternatives that are more sustainable.

As a result, GCs that use proof-of-stake (PoS) consensus techniques or other consensus algorithms have surfaced. In this study, we will mainly focus on the proof-of-stake consensus algorithm because not only is it a frequently discussed consensus method by previous research, but it is also the consensus method for two of the green cryptocurrencies in the chosen variables. PoS considerably reduces energy consumption and environmental impact compared to PoW by verifying transactions based on the shares held by the verifier instead of computational power (Sedlmeir et al., 2020; Rebello et al., 2021). Research contrasting various consensus methods evaluates their technical and economic viability in the cryptocurrency arena in addition to looking at their effects on the environment (Roeck & Drennen, 2022).

One important way to distinguish between GCs and non-GCs is through the mining process. Because of this technological distinction, they may be less appealing to investors and of value for certain industries, which could have an impact on how their prices fluctuate in comparison to non-green cryptocurrencies (Roeck & Drennen, 2022). Investor sentiment can also cause independent price changes in green cryptocurrencies relative to non-green cryptocurrencies. These price movements reflect larger market tendencies towards sustainability (Sedlmeir et al., 2020; Rebello et al., 2021).

Bitcoin is able to be used as a speculative investment as well as a hedge against stock market risk. Because of its dominant market position, Bitcoin's high volatility also noticeably affects other cryptocurrencies, including green alternatives. Because of their greater dominance and volatility, non-green cryptocurrencies' actions can have an impact on green alternatives, highlighting the intricate dynamics of the cryptocurrency market. GCs and non-GCs' progress in quite different directions, but there remains weak interconnectedness in this dynamic market (Rao et al., 2022; Kılıç & Althan, 2023; Ali et al., 2024).

1.1.4 The co-movement between U.S. stock market and green cryptocurrencies

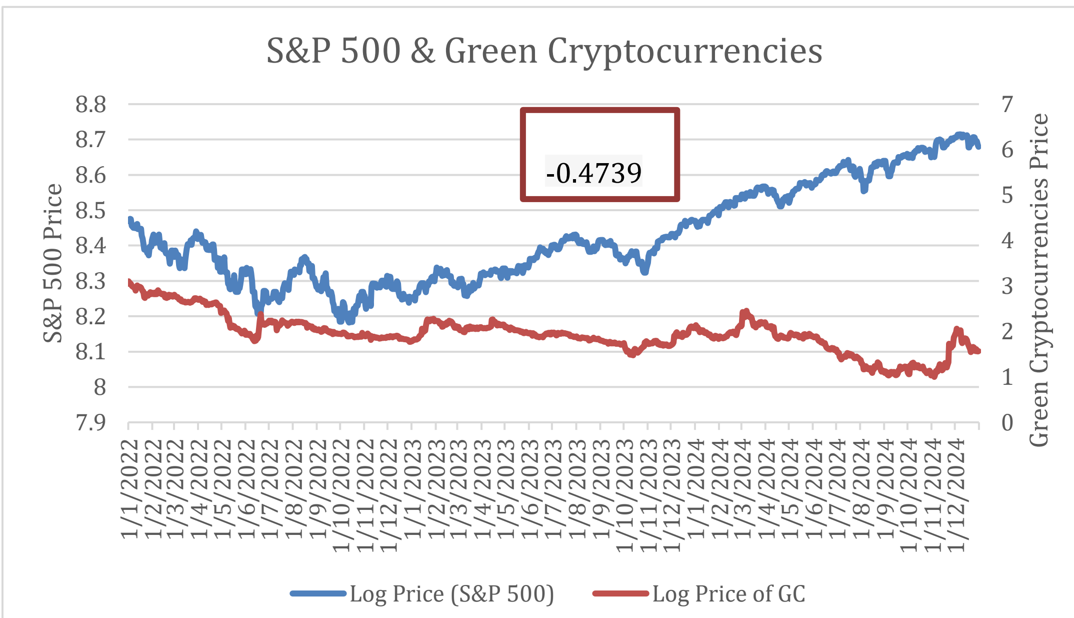

Figure 1.1.4 S&P 500 and Portfolio of Green Cryptocurrencies (including, Algorand, Cardano, Chia, Nano, Stellar) from Jan 2022 to December 2024

The graph below illustrates the price changes of the US stock market, represented by the S&P 500, and green cryptocurrencies during a four-year period spanning May 2021 to May 2025.

The S&P 500 has a general increasing trend with occasional fluctuations, commencing near 8.4 points, dropping slightly about 2022, and then steadily rising to a peak of roughly 8.7 points by 2025. In contrast, green cryptocurrencies display a mostly downward trend. They begin the era with a price close to 3, then progressively decrease to around 1 by the end of 2024, despite a small rise in late 2024. From the graph, we observe that green cryptocurrencies consistently decline in value, while the S&P 500 mostly trends upward over the same time frame.

The relationship between the two markets tends to be negatively correlated. While the S&P 500 is rising, green cryptocurrencies are falling, indicating that these two asset classes are impacted by distinct economic factors. Over time, green cryptocurrencies appear to behave primarily independently or negatively to the regular stock market.

S&P Dow Jones Indices was founded in 1957. S&P 500 is a significant financial benchmark that analyses the performance of 500 prominent firms listed on the stock exchanges of the United States, providing they fulfil particular criteria defined by the index committee (Kenton, 2024). The S&P 500, which is generally acknowledged as an important metric of the U.S. equities market, can be used as a performance measure for assessing the performance of U.S. stocks as well as a representation of the U.S. equity market as a whole (Asem & Alam, 2012). The market capitalization of each company determines its weight in the index because this index is built using a free-float market capitalization approach (S&P Dow Jones Indices LLC, 2023).

The emergence of the Russian Ukrainian War, the fall of the Silicon Valley Bank, and the Black Swan event of COVID-19 all caused notable fluctuations in the movement of the S&P 500. US stocks have plummeted multiple times since March 2020, creating a risk to liquidity and an unusual situation where riskier assets and hedging assets declined at the same time (Liu et al., 2022). Due to indirect and transmission-dependent non-financial causes, the COVID-19 pandemic's outbreak and Russia's invasion of Ukraine may have comparatively less detrimental effects but resulting in short-term, significant swings of the index (Chen, 2023). The SVB failure, however, did not have a long-lasting impact on the price of the S&P 500 stock. According to anecdotal evidence, the federal government and the Federal Deposit Insurance Corporation (FDIC) intervened immediately to guarantee deposits to depositors, including uninsured portions of the deposits, which caused a short-term effect on the S&P 500 only (Ngwakwe, 2023).

Beyond that, in the recent research, there was a significant increase in the interrelationships between volatility indexes (VIX) and the values of the S&P 500 index especially at large scales during the COVID-19 outbreak. This suggests that during this time, the S&P 500 saw high levels of volatility and correlation with other markets, reflecting the general unrest and uncertainty in the economy. Furthermore, it shows that the COVID-19 pandemic has had a more severe effect on the economy than the Spanish Flu of 1918–1919, particularly on the U.S. stock markets, which include the S&P 500 (Younis et al., 2022).

On the other hand, the fluctuations in the S&P 500, both positive and negative, will also affect cryptocurrency volatility and make it more unstable, finding from the recent study. More specifically, for all five of the cryptocurrencies under such study, the discontinuity component of realized volatility is significantly impacted negatively by upside surges in the S&P 500. It reveals a strong correlation between the volatilities of the cryptocurrency market and the S&P 500, demonstrating the influence of established financial market dynamics on relatively new digital asset classes such as cryptocurrencies. In this study, it was found that various cryptocurrencies are affected differently by the S&P 500 (Gkillas et al., 2022).

In this study, it constructed a portfolio that included the five GCs to represent the whole cryptocurrency market based on their different unique characteristics, market presence, and environmental concern which is energy efficient. From figures 1.1.4, the data show the trend of different fluctuations between GCs and the S&P 500. In line with the findings of Gkillas et al. (2022).

GCs have gained popularity in the midst of mounting worries about carbon emissions and ecological effects. They are characterized by their dedication to environmental sustainability through PoS consensus or other sustainable methods. This segment of the cryptocurrency market not only attracts eco-aware investors, but it also has a subtle relationship with the U.S. stock market. The demand for green cryptocurrencies can be influenced by investor sentiment towards sustainability, which might affect their pricing separately from regular stocks. Recent research (Ali et al., 2024b) indicates different levels of association between the performance of green cryptocurrencies and different sectors of the U.S. stock market, which are indicative of the overall dynamics of the market and the actions of investors.

1.1.5 Hedging capabilities between cryptocurrency and equity market

1.1.5.1 Green cryptocurrencies

The GCs are not only environment-friendly, energy-efficient, sustainable, clean, but also capable of providing weak safe-haven protections against the equity market (Ali et al., 2024a). The green bonds are the most effective hedger for the U.S. dollar based on the outcomes of their hedging (Naeem et al., 2021). The U.S. stock market and U.S. dollar have a positive relationship. A positive growth in the U.S. stock market is correlated with the dollar strengthening the same day, whilst a downward trend in the market is associated with the currency weakening. The stock market return plus the shift in the dollar's value in terms of the foreign investor's home currency make up the exchange rate adjusted rate of return, which has a compounding impact for foreign investors in U.S. stocks

(Johnson et al., 2004). This connection stems from the observed correlation where movements in the U.S. stock market often correspond with changes in the strength of the U.S. dollar. Therefore, if green bonds could hedge to the U.S. dollar, it can also hedge the U.S. stock market, assuming these correlations persist. According to research on the short and long run effect of crude oil price and economic policy on green finance, the fluctuation of crude oil price and economic policy uncertainty have a negative impact on the green finance since the investors are more sensitive to risks and choose green bonds as hedging asset. However, there is a short run effect of crude oil price and economic policy uncertainty are less significant in the case of China because the researchers indicate that long-run policy support and economic fundamentals support the green bond index in China (Wang et al., 2023).

1.1.5.2 Non-green cryptocurrencies

The majority of relevant research indicates that there is weak correlation between BTC and stocks. Some cryptocurrencies are a safe-haven property against U.S. market-wide and sector level equity indices by using the daily data from the U.S. market-wide and sector level equity indices and cryptocurrencies, especially Bitcoin (Bouri et al., 2020). Bitcoin has a definite role in the market for portfolio analysis and risk management, since it may be used as a hedge against the stock market and minimize the particular specific risks (Dyhrberg, 2016). Additionally, the cryptocurrencies have weak correlation with equity markets. During worldwide crisis such as Covid-19 pandemic and Russia-Ukraine War, the relationship between the equity market and crypto market is independent. Stock market index has a significant and positive impact on Bitcoin in the long run. In contrast, Bitcoin is stable and is not much impacted by the financial market (Fareed et al., 2022; Mgadmi et al., 2023).

Previous studies also examined that the daily and monthly correlation between Bitcoin (BTC), Ethereum (ETH) and benchmarking which includes S&P 500, SPDR Gold Shares (GOLD), and CBOE Volatility Index (VIX) from 1 May 2017 to 30 June 2019 (Karl Härdle et al., 2019). This result indicates that BTC and ETH are low hedging ability giants in the portfolio. However, there is a different result from identifying the hedging capabilities of Bitcoin and Ethereum influence on bond, stock and gold market from 5 October 2013 to 8 January 2018 (Wee et al., 2018). BTC and ETH have slightly negatively correlated with bonds, stocks and gold. Compared to other assets, BTC has a strong hedge with stocks (Wong et al., 2018).

1.2 Problem statement

The Global Risk report has consistently recognized climate change and other environmental concerns as the most serious risk on a global scale (WEF, 2021). The financial industry is essential to enabling humanity to address these enormous challenges (Bhattacharyya, 2021). Mining cryptocurrencies has turned into an unfavorable environmental indicator. Blockchain technology and cryptocurrency mining contribute to environmental problems even in spite of financial advancements. Thus, the following are the study's motivations. First off, investors in renewable energy and environmentalists are influenced by the fact that cryptocurrencies are filthy money. Second, a lot of power is needed for mining cryptocurrencies, like Bitcoin. Notably, the Cambridge Centre of Alternative Finance (CCAF) estimates that the annual energy usage of Bitcoin is currently equal to around 0.55% (110 TWh) of the world's power use. Consequently, focusing on the green financial markets has become increasingly crucial.

Investors intending to hedge their portfolios and protect themselves from market risk perceive cryptocurrencies to be an appealing alternative asset as they are thought to be uncorrelated with the US stock market (Gan et al, 2023). There is a positive correlation between Bitcoin and the S&P 500 when BTC signifies excessive volatility, suggesting that changes in the cryptocurrency market might influence the trend of the U.S. stock market (Doumenis et al., 2021). However, Figure 1.1.4 shows a negative correlation between the green cryptocurrencies and S&P 500, implying that with the rise in S&P 500 caused an increase in green cryptocurrencies, which are in line with (Gkillas et al., 2022). Various cryptocurrencies are affected differently by the S&P 500.

Recent research has found that green cryptocurrencies perform better as hedging instruments than non-green ones and that volatility spillovers from the bitcoin market to green financial assets occur more frequently (Ali et al., 2024b; Naeem & Karim, 2021; Pham et al., 2022). Nonetheless, there are small spillovers between green cryptocurrencies and Bitcoin (Pham et al., 2022). Dirty markets and clean markets have high correlation during short period, but these relationships would eventually disappear in the long term. This demonstrates that there is weak correlation in terms of investment between the non-green and green markets (Sohag et al., 2023).

In essence, safe haven assets act as a hedge that improve the risk-return trade-off of asset portfolios during volatile markets. They function to mitigate the impact of negative shocks on the primary asset classes of fund managers. In bear markets, safe-haven assets typically exhibit negative correlations, while in bull markets, they show positive correlations. Identifying safe-haven assets is crucial during periods of turmoil, as investors seek assets that can preserve the value of their investments. Safe haven investments enhance portfolio risk-return trade-offs amid market volatility and help investors recover losses by increasing in value when other assets decline (Hampl et al., 2024). Cryptocurrencies are among these safe haven assets and can serve as hedges against downside risk in equity investments (Bouri et al., 2020b; Ji et al., 2020). For instance, Bitcoin has been identified as an effective safe haven asset compared to other financial assets and a robust hedge against changes in the U.S. Dollar index (DXY). During dramatic swings in SPDR S&P 500 ETF Trust (SPY) amid the Russia-Ukraine

War, BTC has proven to be a solid safe haven (Hsu et al., 2024). Additionally, found that clean energy stocks are more likely to act as a safe haven during recessions against dirty cryptocurrencies than green cryptocurrencies (Ren & Lucey, 2021; Pham et al., 2022; Esparcia et al., 2024).

However, the effectiveness of green and non-green cryptocurrencies as safe havens is complicated by economic policy uncertainty, which has become a significant global issue due to economic shocks such as COVID-19 variants, trade tensions between the US and China, and the Russia-Ukraine conflict. These severe economic disruptions have led to higher unemployment rates, inflation, and other adverse effects. The impact of such upheavals on economic policy is significant. Specifically, the U.S. EPU has been found to have a long-term negative effect on Bitcoin returns, reflecting the U.S.'s dominant role in the global economy and its broader implications for traditional financial markets. While cryptocurrencies might serve as safe havens during short-term economic uncertainties, they do not provide equivalent protection during extended periods of high EPU. This asymmetric impact suggests that although cryptocurrencies may offer temporary risk mitigation, their long-term performance is adversely affected by prolonged economic policy uncertainty. Further examination reveals that the relationship between EPU and the cryptocurrency market is predominantly positive, particularly heightened after the onset of the COVID-19 pandemic. This positive correlation is especially pronounced for "dirty" cryptocurrencies, such as Bitcoin and Ethereum, compared to "clean" cryptocurrencies, indicating a greater vulnerability of dirty cryptocurrencies to EPU-induced uncertainty (Duan et al., 2023; Simran & Sharma, 2023). In summary, while EPU has a notable effect on traditional financial markets, its impact on cryptocurrencies demonstrates a complex dynamic that varies between short-term safe haven properties and long-term vulnerabilities.

Most of the studies are solely focused on the hedging capability of non-green cryptocurrency on the stock market. Although there were researchers studying the hedging ability of non-green and green cryptocurrency, they combined both cryptocurrency in portfolios to examine their hedging ability toward the stock market. The hedging ability of each cryptocurrencies has an unclear insight. Furthermore, non-green cryptocurrency and green cryptocurrency are different in the mining process and attract investors with different risk acceptance levels. The volatility is different between the non-green cryptocurrency and green cryptocurrency, non-green cryptocurrency provides higher Sharpe ratios compared to green cryptocurrency. An aggressive investor may prefer the non-green cryptocurrency with higher volatility for a better return. Therefore, this study will concern the hedging capability between the non-green cryptocurrency and green cryptocurrency. The effect on EPU towards the hedging capability will be examined in this study. By providing a detailed analysis of cryptocurrency markets, this research will offer valuable insights for investors and policymakers seeking to navigate the complex interplay between environmental concerns, financial risk management, and economic uncertainty.

1.3 Research Objectives

The goal of this study is to explore at how green cryptocurrency performs in comparison to non-green cryptocurrency on the U.S. stock market, as well as to compare the hedging capabilities of green and non-green cryptocurrencies.

Specifically:

1. To investigate the hedging capability of non-green cryptocurrency (BTC) in the U.S stock market.
2. To investigate the hedging capability of green cryptocurrencies in the U.S. stock market.
3. To investigate the hedging effectiveness between green cryptocurrencies and non-green cryptocurrency in the U.S. stock market, taking into account the impact of EPU.

1.4 Research Questions

The following research questions were derived from the research's problem statement:

1. Does there have the same hedging capability between non-green cryptocurrency and green cryptocurrencies?

2. How does the EPU impact on hedging capability of non-green cryptocurrency?

3. How does the EPU impact on hedging capability of green cryptocurrencies?

1.5 Hypothesis Statements

With the purpose which response to the research question stated above, hypothesis statements have been generated as below:

H_1: There is the same hedging capability between non-green cryptocurrency and green cryptocurrencies.

H_2: The EPU has an impact on the hedging capability of non-green cryptocurrency.

H_3: The EPU has an impact on the hedging capability of green cryptocurrencies.

1.6 Significance of study

The present study will benefit several parties involved in the equity market and cryptocurrency market. In the recent past, green cryptocurrency is upending Bitcoin's historical high energy usage as the market drives for more environmentally friendly investing strategies. The relationship between the BTC and green cryptocurrencies has drawn the attention of the participants in the crypto market. By referring to previous studies, the researchers solely showed that a combination of Bitcoin and green cryptocurrencies are able to serve as safe haven assets to hedge against the equity market. They should investigate the hedging capability for each non-green cryptocurrency and green cryptocurrency as it is essential for those involved in the financial market. To fulfill the literature gap, this study will investigate the hedging capability of each non-green cryptocurrency and green cryptocurrency towards the U.S stock market. Meanwhile, this study also examines the impact of EPU on the hedging capability for BTC and green cryptocurrencies including XCH, ADA, XLM, ALGO, XNO. Throughout this study, useful and valuable information will be given to different participants such as researchers, investors and policymakers.

Initially, this research will contribute to the researchers for their further examination of study in this area. Despite numerous studies concentrated on the hedging capability in combination of non-green cryptocurrencies and green cryptocurrencies towards the stock market. Nonetheless, more research is needed into the independent hedging capabilities of BTC and green cryptocurrencies. It could be a challenge for other researchers to enter this field since it is still relatively new and there are limited researchers who have conducted research on this field. Therefore, this study may be used as a reference by other researchers interested in studying the hedging capability for BTC and green cryptocurrencies towards the U.S. stock market with consideration the impact of EPU on hedging capability. Additionally, this research will aid scholars in developing more insightful concepts for pertinent field studies and might provide more significant results down the road.

On top of that, the outcomes will be significant to the investors and fund managers. As well known, the goals of investors and the fund managers always desired to maximize profit within the acceptable risk level. Investors and fund managers will have better knowledge in mitigating their risk in the U.S. equity market by utilized the BTC and GCs as hedging tools. Moreover, they will comprehend the correlation and return between the Bitcoin, green cryptocurrencies and U.S. equity market. A clearer view on the impact of EPU on the return and hedging capability will be given. Hence, the findings of this study will give investors and fund managers some guidance in selecting safe haven assets that are appropriate for dealing with uncertainty and lowering their risk exposure.

Last but not least, the policymakers may benefit from this study. A deep understanding will be required in policy making to ensure the effectiveness and efficiency of policies on the market. By referring to this study, policymakers will expand their understanding in the hedging capabilities of BTC and GCs against U.S. stock markets and the impact of EPU on the hedging capability for each category of cryptocurrency. Thus, they are able to develop new effective policies related to stock market in U.S. and cryptocurrency market in the future which can respond to the market condition and prevent the issues or crisis happening.

1.7 Chapter Outline

This research has five chapter, the remaining chapters follows as:

Chapter 2: This chapter would discuss the theoretical framework, empirical results and literature gap on the past studies about this study field.

Chapter 3: This chapter include the methodology used, the research design, the data collection method and the ways of conducting this research.

Chapter 4: The chapter would discuss the results' analysis and interpretation from EViews result.

Chapter 5: This chapter summarizes the findings in this research and explore the implications and limitations of the study with recommendations for future research.

CHAPTER 2 LITERATURE REVIEW

2.0 Literature review

Hedging now covers most markets in the current financial world, including cryptocurrency. This occurs at a time when investors are looking for alternative risk-hedging strategies since conventional hedges are under investigation, volatile, and, more lately, have been reluctant to accept underperforming financial assets. This chapter focuses on a particular area within this emerging field thereby evaluating the potential of green and non-green cryptocurrencies to hedge against the U.S. stock market, particularly during periods of high Economic Policy Uncertainty (EPU).

2.1 Theoretical Framework

2.1.1 Safe Haven and Hedging Theory

A safe haven constitutes an asset that exhibits an inverse correlation with alternative assets or portfolios amidst episodes of specific periods and events, especially financial crises. In the long run, hedges retain their value on average. During financial instability or economic distress, safe haven assets are negatively correlated with stocks but normally move in tandem with stock. Safe havens may only be demanded by investors during periods of extreme market turmoil when they are facing losses on their portfolio. In contrast, hedges are typically employed as a long-term investment to lower risk and return volatility (Kopyl & Lee, 2016). Dyhrberg (2016) stated that an asset that has inverse relationship with alternative assets can serve as a hedging tool to mitigate the risk from portfolio. However, there are no hedging capability for an asset that is uncorrelated with other assets.

Finding an appropriate asset to hedge their portfolio is crucial for investors. A strong safe haven asset indicates that even if another asset or portfolio is experiencing an extreme decline during a period of uncertainty events, investors will still get a positive return. Positive returns from an asset during stressful financial times might improve market stability by lowering the overall losses. A weak safe haven asset offers protection during certain financial crises and periods, unless assets are uncorrelated (Nguyen et al., 2020).

Few studies have mentioned the features of Gold such as resilience to inflation, value preservation, and strong market acceptability making it serve as both hedge and safe-haven asset for the stock market (Baur & Lucey, 2009; Baur & Lucey, 2010; Baur & McDermont, 2010; Miyazaki et al., 2012). Due to investors' reluctance to trade on the stock market, gold may become a desirable alternative investment during financial turbulence. Gold can perform as safe haven since it doesn't lose value during these periods (Baur & McDermont, 2010). However, its hedging capability depended on uncertainty events and economic conditions, a safe haven asset may lose its safe haven features during the global financial crisis, its characteristics of negative correlation with alternative assets became more correlated with the market return (Kopyl & Lee, 2016). The study revealed that gold provides a very robust safe haven during financial crises in developed markets, but it has a limited safe haven impact in emerging markets, it might not protect the overall losses on investors' portfolio.

To summarize, the overall risk from the portfolio can be hedged by alternative assets in the long run. During times of financial turmoil, including a strong safe haven asset in a portfolio might provide a positive return even if other assets have negative return. Furthermore, a weak safe haven asset will still protect the portfolio as long as it is correlated. The research found that gold functions as a safe haven and hedge in developed countries, but not for emerging markets (Baur & McDermont, 2010). Henriques & Sadorsky (2018) and Corbet et al. (2018) stated that Bitcoin can be a hedge and safe haven asset as its similarity of features with Gold which can hedge against inflation.

2.1.2 Modern Portfolio Theory (MPT)

Harry Markowitz developed Modern Portfolio Theory (MPT) in 1952. It is a fundamental framework for investing that maximizes portfolio allocation to provide the highest return for a specific degree of risk. MPT means that the combinations of two or more assets in a portfolio with correlated relationships but low or negative correlations. Investors are suggested to hold a portfolio that maintain the risk at acceptable levels and portfolio efficiency. The risk acceptable levels depend on the inventors' behavior, a risk averse investor might maintain his portfolio at lower risk, but with such lower expected return. In contrast, the higher risk level must be accepted by risk taker investors as they demand for greater expected returns (Markowitz, 1952; Fabozzi et al., 2002). Expected portfolio return is one of the essential concepts in Modern Portfolio Theory (MPT), it is a weighted average return of each individual asset in the combined portfolio. Moreover, the correlations between the different combinations of individual assets have an impact on the volatility of the portfolio.

Based on the Modern Portfolio Theory (MPT), a traditional portfolio may consist of different asset classes such as stocks, bonds, commodities, etc. Few studies have shown that investors can mitigating risk by combining cryptocurrencies with stock and debt securities in their investing portfolio. Equity and debt markets have no cointegration with cryptocurrency for both short and long run, the result remains during the times of uncertainty events such as COVID-19. Therefore, incorporating cryptocurrency in a portfolio allows investors to maximize rewards while reducing volatility in their portfolio (Allen & Macdonald, 1995; Gilmore & McManus, 2002; Voronkova, 2004; Dangi, 2022; Jayawardhana & Colombage, 2024).

2.2 Hedging capability of non-green cryptocurrency against U.S. stock market

There are different perspectives and data result on the hedging capability of non-green cryptocurrency due to data constraints. Common representative cryptocurrency data on research is Bitcoin since their large capitalization and their popularity on the market. Bitcoin was established in the midst of the financial crisis in 2018 and became an increasingly well-known investment due to its unique characteristics and the uses of cryptography technology to manage its monetary system. The blockchain created on cryptocurrency mechanism consists of faster transactions in a few minutes, security since decentralized and limited supply, compared to traditional money supply as manipulation that causes currency devaluation over the period. Investors have made new choices on safe-haven assets for adapting to the financial crisis and market volatility, instead of gold (Asian Marketcap Official, 2020).

Some of the arguments and different result interpretations on the hedging capabilities of the U.S. stock market. Wong et al., (2018) examine the safe haven and hedge properties of Bitcoin against stocks, bonds, USD and commodities with dynamical conditional correlation (DCC) model from 2014 to 2018. The data results interpret that Bitcoin and Litecoin are negatively correlated with bonds, gold and S&P 500, but Bitcoin can be a stronger hedge with stock in comparison of gold and bond since it has the highest negative correlation with S&P 500 as -0.013. Thamrongsak et al. (2021) also indicates that the Bitcoins seem to improve their hedging capabilities against S&P 500 during economic uncertainty and market turmoil. Especially, the correlation of Bitcoin and S&P 500 still negative when the US-China trade war, the pre-Covid-19 pandemic and cryptocurrency bubble in 2018. Bouri et al. (2020a) found that Bitcoin can perform as a hedge against the U.S. stock market during trade policy uncertainty.

In some cases, non-green cryptocurrency reduces the risk in the U.S. equity market. For instance, Bouri et al. (2016) indicated that Bitcoin reduced stock market risk in weekly and daily analysis from July 2011 to December 2015 due to the positive correlation, but Bitcoin’s safe haven and hedge properties are different due to the time horizon. Karl Härdle et al. (2019) capture the positive and weak correlation between Bitcoin’s return, S&P 500 and Gold, but it is negatively correlated with CBOE Volatility Index (VIX) in the period from May 2017 to June 2019 with monthly and daily data. Ali et al. (2024a) provide evidence that Bitcoin performs as has reduced downside risk and expected shortfall than other non-green cryptocurrency in the portfolio since the non-green cryptocurrencies are more related with equity indices than green cryptocurrencies. As stated by Dyhrberg (2016), bitcoin has a definite role in the market for portfolio analysis and risk management, since it may be used as a hedge against the FTSE Index and the US dollar.

Another perspective indicates that Bitcoin cannot perform as hedge against US. stock market in certain circumstances. Stensås et al. (2019) indicate that Bitcoin suitable perform as hedge asset on developing countries as Russia, India and South Korea, but cannot perform as hedge for S&P500 as US. stock market. Bouri et al. (2017) also examines the dynamic conditional correlation in the daily and weekly return series to determine whether the hedging capabilities of Bitcoin. As result provided, Bitcoin only can act as stronger hedge on Japanese and Asia Pacific stock market based on daily analysis. Bitcoin cannot provide hedging role on US. stock market for both analysis due to significant positive coefficient. Oosterlinck et al. (2023) also highlighted that Bitcoin cannot perform as hedger for all assets including European and US. stock market. The findings from Gil-Alana et al (2020), Tiwari et al (2019), Hao et al. (2021) and Kristjanpoller et al. (2020) indicate that Bitcoin cannot perform as a hedger due to positive coefficient in most cases.

2.3 Hedging capability of green cryptocurrencies against U.S. stock market

The research resulted in hedging abilities of green cryptocurrency towards the stock market in U.S. is limited in terms of types of green cryptocurrency on research. The correlation of the return of green cryptocurrencies with other asset classes will influence their characteristics to serve as a hedge or safe haven asset. Ali et al. (2024a) mentioned that the correlation of equity indices with green cryptocurrency are more diverse than the correlation of equity indices with another non-green cryptocurrency. The result indicates that green cryptocurrency might provide investors with protection and reduce the risk of their portfolio risk due to weak safe haven properties against equity indices both at regional and global level. Bouri et al. (2020a) stated that green cryptocurrencies such as Ripple and Stellar have significant function as safe-haven assets against US market-wide and sector level equity indexes. Ali et al. (2024a) highlighted that adding green cryptocurrencies into a portfolio, they can serve as a hedging to reduce the risk and expected shortfall. Portfolios with a larger allocation to the green cryptocurrency - EOS are more likely to achieve global minimum-variance. By comparing green cryptocurrencies and non-green cryptocurrencies, green cryptocurrencies have lower Sharpe ratio and volatility. This shown that green cryptocurrencies provide better hedging capability and safe haven benefits compared to non-green cryptocurrencies in some cases. However, its performance of hedging and safe haven may change towards different equity indices.

Conversely, Ali et al., (2024b) identified that the green cryptocurrencies as Cardano, MIOTA, Stellar, Nano and XRP have weak positive correlation with U.S. stock market. As a result, the green cryptocurrencies only can reduce portfolio risk on stock portfolios during the early phase of uncertainty events such as Covid-19 pandemic. Husain et al. (2023) indicate that green cryptocurrencies do not have hedge or safe haven properties against conventional assets including gold, equities, oil and green environment friendly investment options. Wong et al. (2018) mentioned that the characteristics and function of Ripple could have an impact on hedging capabilities on other asset classes. The research data mention the slightly positive correlation between Ripple with bond and gold at the 1% confidence level while the correlation with stock at the 10% interval. This signifies that Ripple cannot perform as a hedger of portfolio because this cryptocurrency return moves the same direction with these asset classes.

2.4 Hedging capability of non-green cryptocurrency during economic policy uncertainty (EPU)

The study of Shaikh (2020) observed that Economic Policy Uncertainty (EPU) does influence Bitcoin returns, contrary to initial assumptions that EPU does not affect the cryptocurrency market. They also reveal that Bitcoin serves as a hedge and safe haven against broader market uncertainties, such as those related to FOMC decisions, GDP data, and other macroeconomic factors. The research examines how the leverage effect and EPU affect the volatility of bitcoin. They discover that EPU does affect Bitcoin volatility using high-frequency data (Yu, 2019). EPU influenced the return and volatility of Bitcoin and affected hedging capability of Bitcoin. This means that the information on EPU can be utilized by the investors in allocating BTC into their portfolio (Paule-Vianez et al., 2020).

Based on the study of Yen et. al (2021), they discovered an adverse association between EPU's and BTC’s future volatility, implying that higher EPU correlates with lower Bitcoin volatility. Demir et al. (2018), Mokni et al. (2020) and Fareed et al. (2022) observed that the return of BTC and the changes in EPU are negatively correlated. BTC may be utilized as a hedging mechanism against uncertainty in severe situations, since they discovered that there is positive and significant effect when higher quantiles.

Besides, Jiang et al. (2021) and Wang et al. (2019) discovered that non-green cryptocurrencies perform as superb hedging strategies against high EPU, but it is unsuitable to use as a hedge during moderate to low EPU's period. This indicates that the hedging capability and EPU have a positive correlated relationship, the lower the EPU will cause the weakness in cryptocurrencies to hedge against losses (Paule-Vianez et al., 2020).

The conclusion in Fang et al. (2019) highlighted that EPU has a major effect on long-term volatility in BTC, stocks, and commodities. During times of economic instability, Bitcoin may be used to hedge against equities and commodities. They also show that BTC volatility is impacted by the status of economic uncertainty, meaning that investors and practitioners in the BTC market must actively watch the level of global economic policy uncertainty (GEPU) while making investment decisions based on BTC volatility. Nouir et. al (2023)'s study concludes that EPU from the U.S. significantly affects BTC volatility, with BTC hedging ability evolving from reducing volatility in response to individual EPU increase before June 2014 to a more complex, long-term negative relationship with EPU from both the U.S. and China after this date. Additionally, Colon et al. (2021) established that the cryptocurrency market actively responds to GEPU, but cryptocurrencies' responses to uncertainty are diverse. They observed that the cryptocurrency market might act as a safe haven and a weak hedge against GEPU during a bull market.

According to Umar et. al (2021), BTC shows a variable relationship with economic uncertainty (EPU). While Bitcoin can sometimes act as a safe haven asset during high EPU's period, this behavior is inconsistent, with Bitcoin also experiencing negative impacts from EPU at times. This variability suggests that Bitcoin's effectiveness as a hedge against economic uncertainty fluctuates with different market cycles. As indicated by Wu et al. (2019), Bitcoin can only act as a weak hedge and safe haven against EPU during severe bearish and bullish markets, implying that Bitcoin cannot hedge effectively against the EPU. The Khan et al (2021) study found that the relationship between EPU and Bitcoin Cryptocurrency Price (BCP) fluctuates considerably over time. In general, EPU can affect BCP in positive as well as negative ways depending on the presence of state interventions. When there are no restrictions, higher EPU tends to increase BCP, suggesting Bitcoin can act as a hedge against uncertainty. Conversely, during periods of state intervention, EPU may negatively impact BCP. Additionally, BCP can influence EPU, particularly in cases of manipulative trading.

2.5 Hedging capability of green cryptocurrency during economic policy uncertainty (EPU)

Simran & Sharma (2023) has applied the Nonlinear Autoregressive Distributed Lag (NARDL) approach to examine the long period and short period's relation of EPU with cryptocurrency. As a result, ripple (XRP) has positive correlation with the increase of EPU in the short run while it is negatively correlated with the rising of EPU in the long run. This cryptocurrency only can act as a safe-haven asset in the short period. Jiang et al. (2021) concluded that some cryptocurrencies can contribute properties as a serve haven asset during serious financial market incident with quantile coherency methodology. Notably, XLM can provide as a hedge against high EPU and stock market volatility within COVID-19. Individual or institutional investors might select XLM as a good choice of a hedging asset.

Aftab et al. (2023) found that XRP, acts as a hedge against EPU in some emerging countries and global but has led positive correlations with EPU in some countries such as Australia, Italy and the United States and lag positive correlation with EPU in Russia, France and the U.S. on pre-Covid-19 pandemic with holding other variables constant. However, XRP serves as safe-haven assets since there is a positive correlation between EPU and XRP. According to Yatie (2022), ADA has contributed more safe haven properties than gold on Europe equities indices before and after market crashes in Covid-19. Ul Haq et al. (2023) research also indicates that green cryptocurrencies have seen safe-haven behavior for EPU in China, U.S. as well as U.K. since maintaining weak positive or negative correlation with three countries' EPU. Most of the sustainable cryptocurrencies such as Nano, ADA, XRP, and XLM perform as safe haven on China's EPU since the correlation of sustainable crypto is maintained weakly positive or negative with China EPU. The researchers suggest that institutional investors may choose energy and sustainable cryptos to reduce higher risks of economic instability.

2.6 Literature gap

Despite the growing body of research on the hedging capabilities of green and non-green cryptocurrencies against the stock market in U.S. and economic policy uncertainty (EPU), several gaps remain. One of the key inconsistencies in the literature is the conflicting findings regarding the safe-haven properties of green cryptocurrencies. While some researches, such as Bouri et al. (2020) and Ali et al. (2024a), suggest that cryptocurrencies like Ripple and Stellar can serve as safe-haven assets, others, including Wong et al. (2018) and Husain et al. (2023), argue that green cryptocurrencies are unable to hedge against equities. This inconsistency indicates the need for further empirical research to establish a more definitive understanding of their hedging potential.

Additionally, existing studies provide limited insight into the performance of green cryptocurrencies across different market conditions. Most research examines broad trends without considering specific scenarios such as financial crises, periods of extreme market volatility, or geopolitical uncertainties. Understanding how these cryptocurrencies behave under varying economic conditions is essential for assessing their true hedging effectiveness. Furthermore, while several studies such as Ali et al., 2024b; Jiang et al., 2021, have analyzed short-term hedging capabilities, the long-term stability and risk mitigation potential of green cryptocurrencies remain largely unexplored.

Another gap in the literature is the conflicting evidence on the role of economic policy uncertainty in influencing the hedging effectiveness of cryptocurrencies. Some studies from Wang et al., 2019 and Khan et al., 2021 suggest that Bitcoin can act as a hedge during periods of high economic uncertainty, whereas others Wu et al. (2019) argue that its effectiveness is weak. Similarly, research on green cryptocurrencies of Ul Haq et al. (2023) has shown weak or negative correlations with EPU across different regions, indicating the need for further investigation to determine whether these assets can consistently hedge against economic uncertainty.

Moreover, the impact of green cryptocurrencies on equity markets has been studied mostly at a broad level, with little attention given to regional or cross-market differences. While Ali et al. (2023) discuss the safe-haven properties of green cryptocurrencies at both regional and global levels, more research is needed to determine how their hedging effectiveness varies across different stock markets, such as developed and emerging markets. Understanding these regional differences could provide valuable insights for investors looking to mitigate their risk.

Finally, most existing research focuses on well-established cryptocurrencies such as Ripple, Stellar, and Bitcoin, while emerging green cryptocurrencies with potential safe-haven properties remain largely underrepresented. As the cryptocurrency market continues to evolve, it is crucial to examine the role of newer digital assets in portfolio risk management. Future studies should explore whether these emerging green cryptocurrencies can offer better hedging capabilities compared to their more established counterparts.

Addressing these gaps through empirical research and broader market analysis will enhance the understanding of the role of cryptocurrencies in financial risk management and improve the reliability of their use as hedging instruments.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter offers a comprehensive description of the research methods and data-gathering procedures utilized in this research, encompassing the data sources, variable descriptions, and a rationale of the methodology employed in this research.

3.1 Research Design

A research design forms the foundation of the research framework and is a detailed plan or blueprint that includes all the appropriate techniques and methodologies. This design offers a coherent and interlinked framework that is customized to fulfill the research objectives. As such, creating the research plan before beginning the data gathering stage is essential. A quantitative methodology is used in this study, with an emphasis on inferring conclusions from the data that is available.

This study mainly explores the hedging ability across green and non-green cryptocurrencies with US stock along with the impact of EPU. Moreover, it also explores the hedging capability of green and non-green cryptocurrencies while adding OVX as the controllable independent variable. All data employed in this study are of the secondary type and daily frequency. A time period of 3 May 2021 to 31 December 2024 was used. Research conclusions are far more generalizable when secondary data is used. In this manner, quantitative approaches, which frequently depend on such data, offer obvious advantages. These methods are distinguished by their standardized protocols for gathering and analyzing data, which guarantee repeatable and trustworthy outcomes in a variety of circumstances. Quantitative research limits human interpretation and lowers the possibility of bias by depending on objective, numerical data, producing more unbiased and trustworthy results. These techniques also provide researchers more control over the variables, which reduces the possibility of competing theories and increases the reliability of the findings. The emphasis on accurate measurement and methodical nature of quantitative methods, thus, enhance the wider application and generalizability of study findings.

3.2 Variables & Data

3.2.1 Data Employed

The objective of this study, as outlined in Chapter 1, is to evaluate the hedging capabilities of non-green and green cryptocurrencies and examine how well the latter performs in the U.S. stock market. For this purpose, this study will be carried out employing the S&P 500 as well as the adjusted close prices of BTC, XCH, ADA, XNO, XLM, and ALGO. Aside from that, the OVX is the control variable. The data observations are conducted on a daily schedule, from March 3, 2021, to December 31, 2024, in order to acquire precise and trustworthy results to accomplish the research objectives. The chosen time period is not only according to the data availability of cryptocurrencies but also encompasses a number of significant worldwide events that are relevant to investors in major asset classes and cryptocurrencies, including the war between Russia and Ukraine, the Covid-19 pandemic, and Silicon Valley Bank's demise.

The financial website Yahoo Finance is the source of the cryptocurrencies' daily adjusted closing prices. Additionally, the OVX and the S&P 500 are gathered from the Investing.com website. From The Federal Reserve Bank of St. Louis to collect the EPU. The data sources and each variable's definition are shown in Table 3.2.1 below.

Table 3.2.1 Data Source and Variables

Variables	Measure	Description	Source
U.S. Stock Return	SNPR	Standard &Poor's 500 Index A stock market index that evaluates the market value of the 500 biggest-cap U.S. listed firms.	Investing.com (2024)
Non-green Cryptocurrency Return	BTCR	Bitcoin Price A cryptocurrency was introduced by Satoshi Nakamoto and launched in January 2009.	Yahoo Finance (2024)
Green Cryptocurrencies Return	XCHR	Chia Price A decentralized green cryptocurrency based on Proof of Space and Time consensus; it was initially released on 17 March 2021.	Yahoo Finance (2024)
	ADAR	Cardano Price A decentralized green cryptocurrency based on Proof-of-Stake consensus; it was launched in September 2017 following an Initial Coin Offering (ICO).	Yahoo Finance (2024)

	XNOR	NANO Price A decentralized green cryptocurrency initially released on 4 October 2015 based on Open Representative Voting (ORV) consensus.	Yahoo Finance (2024)
	XLMR	Stellar Price A decentralized green cryptocurrency officially launched in 2015, based on the Stellar Consensus Protocol consensus.	Yahoo Finance (2024)
	ALGOR	Algorand Price A decentralized green cryptocurrency based on the permissionless Pure Proof of Stake (PoS) blockchain protocol, launched in June 2019 through an initial coin offering (ICO).	Yahoo Finance (2024)
United States Economic Policy Uncertainty	EPU	A GDP-weighted mean of United States' EPU	Federal Reserve Bank of St. Louis (2024)
CBOE Crude Oil Volatility Index	OVX	An index represents the market's forecast of 30-day volatility in the price of crude oil in the United States.	Investing.com (2024)

3.2.2 Variables

3.2.2.1 Return of U.S. stock market

The S&P 500 index measures 500 of the biggest U.S. stocks based on their share value. Higher-value firms have larger weights and lower-value companies have a smaller position in the index since it is weighted by market capitalization, which is computed by multiplying the number of shares on the market by the share price (Zoll, 2013; Yousfi et al., 2021; Biktimirov & Xu, 2024). Due to the fact that the S&P 500's market capitalization comprises between 70% and 80% of the total U.S. stock market capitalization from a variety of sectors, it serves as a classification standard for the whole U.S. market and is often used as a benchmark for stock market performance. There are 11 sectors contained in S&P 500 including communication service, consumer discretionary, consumer discretionary, consumer staplers, energy, financials, health care, industrials, information technology, materials, real estate, utilities As a result, it accurately depicts the corporate economy in America. (Choi, 2021; Bossman et al., 2024; Rajendran et al., 2024).

3.2.2.1.1 Return of S&P 500

Since the S&P 500 index measures the performance of 500 largest-cap companies in the U.S. stock market. The U.S. stock market return will be calculated using the S&P 500 daily return in this study to perform empirical investigation. During every trading day, from 0930 to 1630 (GMT-4) the index value will be recorded.

By using the daily adjusted close price of the S&P 500 index, the log returns of the U.S. stock market has been computed as follows:

$$SNPR = ln\,(\frac{SNP_t}{SNP_{t-1}})$$

The adjusted close price of market's index (SNP_t) is recorded at each trading day. SNP_{t-1} is the adjusted close price that was recorded on the previous trading day. A bullish signal occurs when it is a positive in the S&P 500 (SNPR) return for that particular day. In contrast, a bearish signal is when the return is negative.

3.2.2.2 Return of Cryptocurrencies

By decentralized system in cryptocurrency, its value depends on the market forces of supply and demand, unlike the traditional currencies that are backed by the government or central bank. Furthermore, the trust from users will reflect supply and demand of cryptocurrency. The amount of Bitcoin that may be traded is strictly restricted to 21,000,000 BTC. This scarcity which is similar to the oil and gold that have limited available resources has always driven up demand. Besides, the higher the trust led to a higher demand of cryptocurrency and higher the intrinsic value of cryptocurrency at the end. In simple words, the price of cryptocurrency rises when the demand increases. Conversely, the price goes down when there is a reduction in demand (Hossain, 2021). The demand of Bitcoin will be directly affected by the economic events such as changes in the price of stocks and bonds, as well as global events like the COVID-19 pandemic and war between Russia and Ukraine (Chen et al., 2020; Wang et al. 2020). Nonetheless, the speculative nature of the crypto market creates the potential of price bubbles and high volatility. Bitcoin has zero fundamental value as its value is based on the perceived value, which reflects broader scholarly and public worries on the long-term sustainability of Bitcoin. (Cheah & Fry, 2015). Since Bitcoin is the largest market cap in the cryptocurrency market, therefore, there are several studies using Bitcoin's return to represent the crypto market's return (Symitsi & Chalvatzis, 2019; Omole & Enke, 2024).

3.2.2.2.1 Return of Bitcoin (BTC)

The daily return of Bitcoin will be calculated by using its daily price. There is a similar formula used in the calculation of the return of the stock market in United States. The formula for the calculation of daily return is shown as follows:

$$BTCR = ln\left(\frac{BTC_t}{BTC_{t-1}}\right)$$

Where BTC_t is the adjusted closing price that is recorded every day, BTC_{t-1} is the adjusted close price on the previous day. Bitcoin's price is quoted in the format of exchange rate, a common quote for Bitcoin is BTC/USD which represents that the US dollar is the quoted currency. For instance, when the BTC/USD is 60,000, there is 60,000 USD to exchange with 1 BTC (Nagula & Alexakis, 2022).

Some researchers argue that the crypto market cap is not solely contributed by Bitcoin (BTC) but also the Ethereum (ETH) which hold the majority of market capitalization (Vujičić et al, 2018; Amsyar, 2020; Wu et al., 2021; Shahzad, 2024). Notwithstanding, ETH is taking a greener path which pivoted from proof-of-work (PoW) system to proof-of-stake (PoS) system, called Ethereum Merge (Hedera, n.d.). The carbon emission has been slashed by 99.992% after the merge in September 2022 (Spence, 2022). Bitcoin significantly represents the non-green cryptocurrency in this study as it still remains its PoW system in the mining process. The volatility of bitcoin prices fluctuates over time and clusters. The volatility of cryptocurrency prices is positively associated and varies over time. The features of BTC are chaotic. The price of cryptocurrencies is inherently unpredictable over the long run. Cryptocurrency price fluctuations have chaotic features and defy the widely accepted random walk model (Tong et al. 2022).

3.2.2.2.2 Return of Green Cryptocurrencies Portfolio

The technique to figure out the daily return of GCs using the daily adjusted close price of the five GCs chosen is the same as that used to compute the return of Bitcoin. The GCs' daily log return computation is displayed as follows:

$$GCR = \frac{ln\left(\frac{ADA_t}{\text{ADA}}\right)+ln\left(\frac{ALGO_t}{ALGO_{t-1}}\right)+ln\left(\frac{XCH_t}{XCH_{t-1}}\right)+ln\left(\frac{XLM_t}{XLM_{t-1}}\right)+ln\,(\frac{XNO_t}{XNO_{t-1}})}{5}$$

Where ADA_t, $ALGO_t$, XCH_t , XLM_t, XNO_t are the adjusted closing prices, which are recorded at the time period, ADA_{t-1}, $ALGO_{t-1}$, XCH_{t-1}, XLM_{t-1}, XNO_{t-1} are the adjusted close prices at the previous day. The value of those GCs is stated using a format akin to that of currency exchange rates; it is always in movement and is determined by the price in relation to the US dollar (USD).

Due to their distinct features, environmental sustainability, and the absence of research on their hedging potential and response to EPU, ADA, ALGO, XCH, XLM, and XNO have been selected as green cryptocurrencies in this study. ADA, a crucial blockchain, stands out for its early adoption of the PoS consensus, using significantly less energy than Bitcoin's PoW, and positioning itself as a key topic in hedges against discussions (F. Ali et al., 2024; Foroutan & Lahmiri, 2024; Haq et al., 2022; Husain et al., 2023; Pham et al., 2022). Despite little scholarly investigation, Algo maintains its position as one of the most talked-about green cryptocurrencies, asserts complete carbon neutrality, and has teamed up with Climate Trade to strengthen environmental responsibility (Francis, 2021; Iberdrola, 2023).XCH was chosen because, despite its declining market size, it is still one of the most environmentally friendly cryptocurrencies, designed for low energy consumption (Francis, 2021; CryptoNews, 2024; TRG Datacenters, 2024). XLM is renowned for its dedication to sustainability and financial inclusivity, using the Stellar Consensus Protocol (SCP) to end mining and drastically cut energy use (Dunne, 2024; Francis, 2021; Iberdrola, 2023). Last but not least, when compared to standard high-energy cryptocurrencies, XNO, an early eco-friendly cryptocurrency, allows for quick and fee-free transactions and is essential for comprehending the effects on the environment and the economy (Pham et al., 2022; Ren & Lucey, 2022; Husain et al., 2023). These five GCs offer a solid basis for assessing their potential for financial market disruptions, environmental impact, and hedging efficacy.

3.2.2.3 Economic Policy Uncertainty

This study will use daily U.S EPU to measure the effect of the U.S EPU on the hedging capabilities of cryptocurrencies in the U.S. stock market. Economy Policy Uncertainty is defined as a risk that is related to undefined government policies and regulatory framework in near future. (Al-Thaqeb & Algharabali, 2019). In 2016, Professor Baker, Professor Bloom, Mr. Davis, and their research team has formulated an index based on the frequency of newspaper articles, normally known as newspaper-based approach. This EPU can be available for several countries or regions. They also randomly choose 12000 articles from US. newspaper and conduct the more widen audit study on it. (Baker et al., 2016).

At first, they use 10 leading newspapers to initiate a monthly US. EPU index. They search each digital newspaper and obtain the numbers of article in monthly that contain following keywords: ‘economy’, ‘uncertainty’; policy terms as ‘congress’, ‘White House’, ‘deficit’, ‘Federal Reserves’, ‘legislation’, ‘regulation’ or ‘white house’ and variants such as ‘uncertainties’, ‘the Fed’ and ‘regulatory’. In addition, the index in daily count computed with the Newsbank news aggregator that cover around 1500 newspaper in U.S. This index provides reliability and high frequency alternatives to this study since it correlates with the monthly index at 0.85 (Baker et al., 2016).

Next, the journal articles have compared the differences between VIX and EPU in the theoretical term and its graph movement. In theory and findings, the VIX reacts more on the uncertainty event on equities and financial markets while the EPU is more on the policy uncertainty such as the war, presidential election and political issues on government budgets that affect the return. Until now, the application of EPU index has been widened in the research studies to measure the impact of uncertainty. There are more than 2,500 times cited in studies published in the last three years (Al-Thaqeb & Algharabali, 2019).

3.2.2.4 Control Variable

Referring to the study by Arouri et al. (2016), a relationship between stock return and EPU can reflect a simple “proxy effect”. In order to boost the internal validity, as well as obtain the reliable and unbiased result, this study would add on the one control variable (OVX), to avoid the EPU become an only proxy of the economic variables to affect the stock return.

3.2.2.4.1 Chicago Board Option Exchange (CBOE) Crude Oil Volatility Index (OVX)

The Chicago Board Options Exchange (CBOE) developed the OVX, a measure was developed to assess the market's expectation of future volatility in the 30-day price of crude oil using the implied volatility of options on the United States Oil Fund (USO) in May 2007. It is an intriguing uncertainty index for investors, policy makers, and researchers because it provides an intraday measurement of investors' uncertainty over changes in crude oil prices in the future. OVX is widely used in the volatility forecasting of various markets, such as the equity markets for clean energy, the stock markets in China, the price of Bitcoin, and so forth. As opposed to other volatility indicators, which base their estimates on models, OVX is a market-determined indicator of volatility, much like the stock market's implied volatility index (VIX) (Becker et al., 2009; Çelik et al., 2022; Degiannakis & Filis, 2022; Fernandez-Perez et al., 2023; Ji & Fan, 2016; Lu et al., 2020; Wagner and Szimayer, 2004). The OVX bases its calculations on option pricing from the USO Fund. The OVX formula as follows:

Formula:

$$OVX = 100 \times \sqrt{\frac{2}{T}\sum_{i}\frac{\Delta K_i}{K_i^2}e^{RT}Q(K_i) - \frac{1}{T}(\frac{F}{K_0} - 1)^{2}}$$

Where T refer to time of expiration, K is the strike price of the i-th option, ΔK_i is the interval between strike price, R is the risk-free rate, $Q(K_i)$ is the mid-price of the option, F_0 is the crude oil of forward price, K_0 is the strike price closest to the forward price.

Owing to OVX plays a similar role to the VIX in the stock market in expressing investor sentiment and market volatility (Ji & Fan, 2016). It is useful in mitigating price risk, especially in industries such as clean energy and accurately assesses investor fret (Dutta, 2017; Ahmad et al., 2018). The recent studies have drawn attention to its importance in predicting stock market volatility and its connection to financial market conditions (Christoffersen and Pan, 2018; Fernandez-Perez et al., 2023). Also, the accuracy of forecasts is improved even in longer predictive periods of 5 and 20 days when OVX is added to the GARCH-type model, as Chen et al. verified (Lu et al., 2020). To account for this, the OVX is a useful tool for comprehending how the volatility of oil prices affects cryptocurrency hedging tactics, particularly in light of the uncertainties surrounding economic policy and enhances the GARCH model's result to become more accurate and trustworthy.

3.3 Empirical Model

This study develops an econometric model that takes into account the correlation between S&P 500 returns along with CCR, EPU, and OVX. Three explanatory variables and one explained variable are included in the study models.

Economic Function:

Inspired by Gan et al. (2023), this study proposes an econometric model that uses the return of the S&P 500 as a function of the return of the S&P 500 in the prior period, CCR, EPU, OVX, as well as CCR*EPU. Three explanatory variables and one explained variable make up this model.

$$SNPR = \int(CCR, EPU, OVX) \quad (3.3.1)$$

Where:

SNPR = Return on S&P 500

CCR = Return on Cryptocurrencies

EPU = Economic Policy Uncertainty

OVX = CBOE Crude Oil Volatility Index

Two distinct cryptocurrencies will have an impact on the SNPR as well as the interaction term that will have an impact on the CCR, so indirectly influencing the return of the S&P 500, as demonstrated in the base mode. As a result, this paper will contain two models in total. The two models will be BTC acting as the non-green cryptocurrency and GC acting as the green cryptocurrency portfolio, respectively, that impact the SNPR.

Econometric Model:

$$\begin{aligned} ln\,SNPR_t \; &= \alpha_0 + \alpha_2 ln\,SNPR_{t-1} + \alpha_2 ln\,CCR_t + \alpha_3 ln\,EPU_t \; + \; \alpha_4 ln\,OVX_t \\ &+ \alpha_5 ln\,(CCR_t \times EPU_t) + \varepsilon_t \qquad (3.3.2) \end{aligned}$$

Where:

SNPR = Return on S&P 500

CCR = Return on Cryptocurrencies

EPU = Economic Policy Uncertainty

OVX = CBOE Crude Oil Volatility Index

As shown in Equation (3.3.2), the $SNPR_t$ act as the explained variable in the model, and the explanatory variables are $SNPR_{t-1}$, CCR_t, EPU_t, OVX_t, $(CCR_t \times EPU_t)$ where CCR may be either GC or BTC. In addition, the time period (t), represents the daily data from 3 May 2021 until 31 December 2024. In this study, the chosen five GCs become a portfolio since BTC has more than half (61.6%) of the market cap and large trading volume, compared to these 5 green cryptocurrencies (CoinGecko, 2025). Thus, the study employs Bitcoin for non-GC portfolios and 5 GCs for GC portfolio to avoid the impact of these market cap and trading volume into the study.

Subsequently, α_0 denotes the S&P 500 return intercept, α_1 the estimated coefficient of the S&P 500 return in the preceding period, α_2 the estimated coefficient of the cryptocurrency return, α_3 the estimated coefficient of EPU, α_4 the estimated coefficient of OVX, as well as α_5 the indirect relationship between the cryptocurrency return and EPU. The model's error term is then represented by ε_t. (t-1) is the lag of one time period, and t is the time period.

3.4 Estimation Methods

3.4.1 Ordinary Least Square (OLS) Model

$$SNPR_t = \alpha_0 + \alpha_1 CCR_t + \alpha_2 EPU_t + \alpha_3 OVX_t + \varepsilon_t$$

The basic as well as popular technique is called Ordinary Least Squares (OLS). OLS is an approach for evaluating the coefficients of linear regression equations, multiple linear regression in this case, which characterizes the correlation between dependent variable and independent variables. Since mistakes might occasionally be positive or negative and add up to almost a null value, it considers the sum of squared errors rather than the errors as they are. Additionally, the OLS technique aims to minimise the sum of square discrepancies between the observed as well as expected values while accounting for any multicollinearity issues. The best estimates using OLS regression will only be obtained if all of the assumptions are true which model is linear in the coefficients, no autocorrelation, no correlation between independent variables and error terms, independence in error terms homoscedasticity, normally distributed errors (Farahani, 2010).

With Lagged Dependent Variable (Dynamic Term):

$$SNPR_t = \alpha_0 + \alpha_1 SNPR_{t-1} + \alpha_2 CCR_t + \alpha_3 EPU_t + \alpha_4 OVX_t + \varepsilon_t$$

One of the OLS estimator's assumptions needs to be emphasized is the residual in one point that has no autocorrelation with any other point. However, this assumption will always be violated in the time series data. Either the political dynamic or the technical violation will reveal autocorrelation. Because this study employed time series data, the changing political environment may have an impact on the S&P 500's return. Therefore, in order to capture the mean of the political dynamic process and ride the model for autocorrelation, the lagged dependent variable is used in this study (Keele & Kelly, 2006).

Regression analysis has employed lagged dependent variables (LDVs) to obtain reliable estimates of the effects of independent variables (Wilkins, 2017). The inclusion of additional lags in data-generating processes yields more accurate parameter estimates and coefficient estimates for independent variables, compared to alternatives in previous research. It was evidenced by Wilkins (2017).

As evidenced by substantial prior research, volatility clustering is expected to be present in the financial data analysed in this study due to its nature. Because of this phenomenon, which is seen in asset classes such as commodities, stock returns, and currency rates, OLS regression's constant variance assumption has been called into question, which reduces its ability to capture time-varying volatility (Chen, 2024; Samuel, 2023). In order to deal with this, we transform to the GARCH method

(Bollerslev, 1986), which successfully captures heteroscedasticity by integrating estimates of current variance with historical volatility. This change guarantees a more realistic depiction of the dynamics of financial markets, enhancing risk assessment and volatility forecasts.

3.4.2 Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH)

An expansion of the autoregressive conditional heteroskedasticity model (ARCH) is the generalised autoregressive conditional heteroskedasticity model (GARCH), which was initially introduced by Bollerslev in 1986. It allows the conditional variance to vary over time based on previous errors while maintaining a constant unconditional variance. These models are commonly used in financial modeling to forecast the volatility of financial returns (Ampountolas, 2024). The state of serially autocorrelated variation across time is referred to as heteroskedasticity.

One nonlinear time series model that is frequently used to anticipate volatilities in financial and economic data is the GARCH model. The GARCH model has higher flexibility and efficiency in modeling volatility, particularly in financial time series where volatility clustering occurs frequently since conditional variance takes previous conditional variances as well as previous squared residuals into account (Rahman et al., 2023). The GARCH model is more frugal as it just requires one or a small number of parameters, Whereas the ARCH model would require an unlimited number of parameters to accomplish (Bollerslev, 1986). Similar to standard deviation, GARCH provides a measure of volatility that may be utilized in financial computations for choosing a portfolio, risk assessment, and derivative valuation. The model may be used, for instance, to figure out how likely it is that a big market crash will occur or how much risk should be managed for an asset portfolio.

GARCH (p, q) model, p is the autoregressive lags or ARCH terms appear in the equation, q referred to as the number of GARCH terms, indicates the quantity of moving average delays have been specified. For instance, GARCH $(1,1)$ indicates that the p and q are equal to one. It means that the squared residual return and variance of the previous period are higher than those of the present period. The GARCH (1,1) specification performed well in the majority of applied scenarios, as indicated by Bollerslev et al. (1994), and Sadorsky (2006) also showed that the GARCH (1,1) model fit crude oil volatility well (Wei et al., 2010).

After gathering the residual variance derived from the GARCH variance series, use the error variance to construct the weighted covariance matrix. Next, use FGLS to gauge the GARCH model coefficients using this matrix.

3.4.3 Feasible Generalized Least Square (FGLS)

$$\frac{SNPR_t}{GARCH} = \frac{\alpha_0}{GARCH} + \frac{\alpha_1}{GARCH} SNPR_{t-1} + \frac{\alpha_2}{GARCH} CCR_t + \frac{\alpha_3}{GARCH} EPU_t + \frac{\alpha_4}{GARCH} OVX_t + \frac{\varepsilon_t}{GARCH}$$

$$SNPR_t^* = \alpha_0^* + \alpha_1^* \, SNPR_{t-1} + \alpha_2^* \, CCR_t + \alpha_3^* \, EPU_t + \alpha_4^* \, OVX_t + \varepsilon_t^*$$

FGLS is an extension of the conventional OLS regression method proposed by Parks (1967). FGLS is a versatile and effective method for regression analysis with non-constant variances and correlated errors. It is a standardized approach that uses cross-section the covariances as parameters. This method allows for correlation and heteroscedasticity inside and between cross-section units. FGLS assumes heteroscedastic disturbances that are associated with panels, resulting in unbiased estimates through variance-covariance and standard errors. It tackles the issue of variable bias and autocorrelation. By taking the structure of the error terms in account, it provides more reliable parameter estimations. (Chen et. al, 2024; Faizulayev et al., 2022).

FGLS can estimate error variance in GARCH (1,1) for disturbances with non-constant variances. Furthermore, it might model error variance using other explanatory factors and lagged error variances. The predicted variance-covariance matrix of the errors is used to determine the weighted sum of squared residuals, which is then minimised by FGLS to determine the model parameters. Results from the estimations will be more accurate and efficient than those utilising the greatest likelihood technique (Eric, 2024).

3.4.4 Feasible Generalized Least Square (FGLS) with Interactive Term of Cryptocurrencies and EPU

$$\frac{SNPR_t}{W} = \frac{\alpha_0}{W} + \frac{\alpha_1}{W} SNPR_{t-1} + \frac{\alpha_2}{W} CCR_t + \frac{\alpha_3}{W} EPU_t + \frac{\alpha_4}{W} (CCR_t \times EPU_t) + \frac{\alpha_5}{W} OVX_t + \frac{\varepsilon_t}{W}$$

$$SNPR_t^* = \alpha_0^* + \alpha_1^* \, SNPR_{t-1} + \alpha_2^* \, CCR_t + \alpha_3^* \, EPU_t + \alpha_4^* \, (CCR_t \times EPU_t) + \alpha_5^* \, OVX_t + \varepsilon_t^*$$

This Feasible Generalized Least Squares (FGLS) model involving cryptocurrencies and Economic Policy Uncertainty (EPU), first estimates a simple regression to get initial parameter guesses. Then, use these initial results to model how the volatility of the errors changes over time, often using a GARCH model. This helps to understand how unpredictable or volatile the errors are. Next, adjust the data for this changing volatility by dividing it by the estimated volatility. Finally, re-run the regression with this adjusted data to get more accurate parameter estimates. This process helps to correct issues like changing error variability, leading to more reliable and precise results.

3.5 Diagnostic Tests

Problems with autocorrelation, heteroscedasticity, multicollinearity, and deviations of the error term from the normal distribution can all have an impact on the econometric models. As a result, four major tests must be we performed in order to confirm that the GARCH model (FGLS) specification is accurate, including the Jarque-Bera test, the Breusch-Godfrey LM test, the ARCH-LM test, and the Variance Inflation Factor test. In order to ensure the model is appropriate and accurate, several tests are vital.

3.5.1 Jarque-Bera test – Normality

Normality test is used to identify whether the dataset relies on a normal distribution which is the data clustered around the mean with bell-curve shape. In 1980, Carlos Jarque and Anil Bera recommended this Jarque Bera test to check whether the data is best fit with a normal distribution when analyzing the large samples (Khadka, 2023). In the Classical normal linear regression model (CNRLM), it is expected that the error term in the regression model must hold since the sample size is large. A normality distributed variable must consist of the zero-skewness coefficient and the value of kurtosis must be 3. This means that JB statistic is almost nearest to zero, the better of normality assumption would be made (Gujarati, 2015, pp. 145).

The null hypothesis identifies as:

H_0 = The error terms are normally distributed.

The equation to compute the Jarque-Bera test statistic:

$$JB = n(\frac{S^2}{6} + \frac{(K-3)^2}{24})$$

Where:
n= sample size

s= skewness

k= kurtosis

If the Jarque-Bera test statistic is more than the chi-squared critical value that is computed from the degree of freedom and alpha value, the null hypothesis is rejected. As a conclusion, the model does not meet the normality assumption of the error term (Gujarati, 2015, p.288).

3.5.2 Breusch-Godfrey LM-test – Autocorrelation

Autocorrelation, known as serial correlation, refers to the correlation between the error term in two periods. In the estimation of OLS assumption, each error term in the model is independent of each other. If the model has autocorrelation problem, the bias of coefficients' variance leads to t and f statistics tending to be higher or lower (Ullah, 2024). Breush and Godfrey have established a test that can detect the autocorrelation in the lagged value of dependent variables, higher-order autoregressive schemes, and moving average terms of error term (Wooldridge, 2019, p. 405).

To achieve no correlation of any order for error term, the null hypothesis (H0) identified as:

$$\rho_1 = \rho_2 = \rho_3 \ldots\ldots = 0$$

When the sample size is larger, the equation identifies as:

$$\text{LM} = (n - p)R^2$$

The n represents sample size and p equals to degree of freedom. If the chi-squared test statistic is more than the critical chi-squared value, the origin hypothesis is considered to be rejected. As a result, the correlation of error terms exists in the model.

3.5.3 ARCH Lagrange Multiplier (LM) Test – Autoregressive Conditional Heteroscedasticity

One of the Ordinary Least Square assumptions is that the error term consists of constant variance which is not heteroscedasticity. The presence of heteroscedasticity will cause the inaccuracy of the estimate of coefficient standard error and hard to access the actual value of the error term. An alternative test would be Lagrange Multiplier Test to detect the conditional heteroscedasticity on lagged residuals and regressors. (Studenmund & Johnson, 2017 p. 115, 390-391).

The null hypothesis considered as:

H_0: $\lambda_i = 0$, where i = 1, 2, 3 ….

The LM test equation devoted as:

$$\text{LM} = (n)(R^2)$$

The original hypothesis can only be rejected when the test statistic is larger than the chi-squared critical value. The conclusion made from the result indicates that there is heteroscedasticity problem in the model (Gujarati, 2015, p.288).

3.5.4 Variance Inflation Factor (VIF) Test - Multicollinearity

VIF measures the degree of multicollinearity in a multiple linear regression model. If the VIF values are more than 5 or 10, it indicates that the regression coefficient is poor due to multicollinearity. If one or more of the eigenvalues are small or close to zero and the subsequent condition number is big, this suggests multicollinearity (Daoud, 2017).

The calculation formula is as follows:

$$\text{VIF} = \frac{1}{Tol}$$

$$\text{Tol} = 1 - R^2$$

$$\text{VIF} = \frac{1}{1-R^2}$$

Tolerance values below 0.1 or close to 0, are often used as a rule of thumb to indicate serious multicollinearity issues. A high $R2$ or close to 1 implies that the other predictors explain a significant percentage of the predictor's variation. This suggests a high degree of multicollinearity, which yields a high VIF. If $R2$ is low or close to 0, it indicates that the predictor is generally independent from other predictors, resulting in a lower VIF (Cheng et. al, 2022).

3.6 Summary

This study framework has included secondary data and suitable methodology techniques to fulfill our research objectives. The outcomes of the data analysis would compare the hedging capabilities between green cryptocurrencies as Chia, Cardano, Nano, Stellar Lumens and Algorand; and non-green cryptocurrencies as Bitcoin to S&P 500 along the effect of EPU and OVX act as control variable in the return form. Our empirical model in the research would include OLS model, GARCH model and FGLS model to ensure that parameter estimates are reliable and consistent. Also, the study has included interactive terms of cryptocurrencies and EPU in return form for FGLS model to capture the hedging capabilities of both cryptocurrencies on S&P500 with along the effect of EPU. For diagnostic tests, this study would utilize the Jarque-Bera test, Bruesch-Godrey test, ARCH Lagrange Multiplier Test and VIF test to assess the normality, heteroscedasticity, autocorrelation between error term and multicollinearity problem in the model.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter illustrates the outcomes of employing the methodologies outlined in Chapter 3. This chapter comprises the unit root test, FGLS methodology, and diagnostic checking to guarantee that the results models employed are reliable and accurate. Furthermore, the research provides a summary of the chapter prior to its conclusion.

4.1 Unit Root Test

For each parameter in the analysis, the unit root test is performed first using the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests. The existence of stationarity in data is evaluated through the unit root tests. The specific variable is stationary and lacks a unit root when the null hypothesis is rejected. The results of the PP and ADF tests at both level forms for every variable are summarized in Table 4.1.1, which also takes into account the intercept and trend. Throughout the investigation, the PP and ADF tests are used to do the unit root test for each variable, which are S&P 500, Bitcoin, Green Cryptocurrencies returns, EPU, and OVX at both levels, accounting for the intercept and trend. The outcomes are displayed in the following tables.

Table 4.1.1 PP and ADF Tests' Results

Variables	Phillips-Perron (PP) Test		Augmented Dickey-Fuller (ADF) Test	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
	Level	Level	Level	Level
S & P 500	-36.71539***	-36.73049***	-36.67809***	-36.68766***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BTC	-37.86240***	-37.95794***	-37.88732***	-37.97315***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
XCH	-37.16156***	-37.19997***	-37.16867***	-37.20375***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ADA	-35.69836***	-35.69559***	-35.69774***	-35.69479***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
XLM	-41.47440***	-41.64560***	-9.893565***	-10.04448***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ALGO	-37.00235***	-37.06057***	-36.89657***	-36.93117***

	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NANO	-37.72051***	-37.82384***	-29.70623***	-29.74323***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EPU	-93.29593***	-102.5242***	-24.80003***	-25.08296***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
OVX	-39.16717***	-39.16225***	-38.23602***	-38.22512***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*Notes: At the significance levels of 10%, 5%, and 1%, respectively, *, **, and *** indicate rejection of the null hypothesis. P-values are shown by figures in parentheses. The Schwarz Information Criterion (SIC) is used to determine the lag length for the ADF test, taking into account a maximum number of lags. The Bartlett kernel method's Neway-West bandwidth determines the bandwidth choice for the PP test. Using the Bartlett kernel approach, the PP test is dependent on Neway-West Bandwidth.*

According to the findings of the PP and ADF tests, the rejection of the null hypothesis occurs at the significance level of 1% for all variables at the level form. When taking into account both the intercept and the trend, the p-values have not exceeded all the significance levels, leading to this rejection. There is no unit root and the variables are stationary as well as all of them are I(0) regressors when taking into account of the intercepts. In time series analysis, the results of the PP and ADF tests show that all variables are exhibit stationarity and offer greater accurate estimations of the regression parameters. Furthermore, it may contribute to an improvement in the overall performance of the model as reflected by model evaluation metrics.

4.2 GARCH Model

The following equation (4.2.1) was developed in Chapter 3. By examining the hedging capabilities of green and non-green cryptocurrencies towards the US stock market while accounting for economic policy, this equation seeks to accomplish the objectives of this study.

$$\boldsymbol{SNPR_t^* = \alpha_0^* + \alpha_1^*\, SNPR_{t-1} + \alpha_2^*\, CCR_t + \alpha_3^*\, EPU_t + \alpha_4^*\,(CCR_t)(EPU_t) + \alpha_5^*\, OVX_t + \varepsilon_t^*} \quad \textbf{(4.2.1)}$$

The estimation findings of Models I and II in the GARCH model, which aims to determine whether there is a short-term link between all of the variables of interest, are shown in Table 4.3.1.

4.3 FGLS Model

Table 4.3.1 FGLS Method's Results

Explained Variable: S & P 500		
	GC	BTC
	i	ii
S & P 500 (-1)	-0.020055	0.005081
	(0.4631)	(0.8474)

CCR	-0.002061**	0.102405
	(0.0254)	(0.1809)
EPU	-0.001733**	-0.000041
	(0.0276)	(0.9996)
CCR × EPU	0.001816**	0.0000348
	(0.0265)	(0.9996)
OVX	-0.023199***	-0.017022***
	(0.0000)	(0.0000)
C	1.045251***	0.909565***
	(0.0000)	(0.0000)
Adjusted R^2	0.099741	0.176158

*Notes: At the significance levels of 10%, 5%, and 1%, respectively, *, **, and *** indicate rejection of the null hypothesis. P-values are shown by figures in parentheses. CCR is measured with GC (XCH, ADA, XLM, ALGO, NANO) and BTC, respectively. The implication of the adjusted R-squared is different from standard cases, as it is generated under FGLS estimation with GARCH variance.*

The FGLS approach's estimated results, which reveal key findings regarding the relationship between the return of the S&P 500 as well as green cryptocurrencies, and Bitcoin (BTC), are displayed in Table 4.3.1. First, model (i) presents an insignificant but negative coefficient (-0.020055) for the S&P 500's lagged return, with a p-value of

0.4631, more than the significance levels of 10%. This suggests that there is not adequate statistical support to make the conclusion that the S&P 500's return is influenced by the return of the day before. Likewise, model (ii) offers a p-value of 0.8474 with a positive however insignificant estimate (0.005081), supporting the finding that the past return of the S&P 500 does not significantly predict future returns. The results reveal that of the S&P 500 is mostly influenced by latest information rather than past patterns.

For GCs, model (i) displays the statistically significant negative coefficient of -0.002061 at the 5% and 10% significance levels (p-value = 0.0254) when considering the effect of GCs on the return of the S&P 500. It demonstrates that on average, when the GC's return increases by 1%, the S&P 500's return will decrease by 0.002061%, ceteris paribus. According to the finding, a modest decrease in the return of the S&P 500 is linked to a rise in the return of the GCs. This highlights the GCs' potential hedging capability against the changes in the US stock market. Rather, they may show some inverse movement, which could suggest a flight-to-safety behaviour in which investors switch from equities to GCs during uncertain periods. This finding coincides with Ali et al. (2023), Ali et al. (2024a), and Bouri et al. (2020a), who proved that GC could serve as a hedge to lower the risk and the expected shortfall.

Nevertheless, at the 5% level of significance (p-value = 0.0276), EPU exhibits a noteworthy negative coefficient (-0.001733) for Model (i). This implies that the return of the S&P 500 is adversely affected by greater economic uncertainty, which is in line with earlier studies that connected rising uncertainty to equity market declines. Model (i)'s interaction term (CCR × EPU) is positive as well as significant (0.001816, p-value = 0.0265), suggesting that although GC return has a negative influence on the S&P 500, this effect is lessened in situations where EPU is high. This result suggests a possible conditional relationship, whereby the impact of GCs on the stock market is less noticeable when uncertainty is high. The efficiency of GC's hedging under increased EPU may have weakened for some reasons. The reality that GCs have less liquidity as well as market maturity than more conventional asset classes like gold or perhaps BTC could be one reason. GC demand may drop during times of increased uncertainty as investors may become less willing to take risks and instead favour established assets. Furthermore, investor hesitancy may be increased by regulatory concerns about environmental regulations and the larger cryptocurrency market, which would further restrict GC's capacity to serve as a trustworthy hedge. These results are consistent with those of Ul Haq et al. (2023) and Yatie (2022), who contend that weakly either negative or positive correlations between GCs and EPU indicate a more regionally specific or mixed safe-haven effect.

In contrast, the return of BTC in Model (ii) is positive but not statistically significant (0.102405, p-value = 0.1809), indicating that there is no relationship between the S&P 500's return and BTC return. In other words, the BTC does not have the hedging capability against the S&P 500, which aligns with Bouri et al. (2017), Gil-Alana et al (2020), Tiwari et al (2019), Hao et al. (2021) and Kristjanpoller et al. (2020), who contend that BTC cannot act as a hedge against U.S. stock market. In term of EPU, it shows a negative coefficient (-0.000041) with a p-value of 0.9996, indicating that, when taking Bitcoin into account, EPU has no statistically significant impact on S&P 500 returns. Similarly, the interaction term (CCR×EPU) is likewise insignificant (p-value = 0.9996), suggesting that the relationship between BTC's return and the S&P 500 return is no effect by fluctuations in varying EPU.

Several important distinctions between BTC and GC account for the lack of a discernible EPU effect on BTC. BTC is less vulnerable to short-term EPU than GC since it has a larger institutional adoption and stronger market liquidity. Unlike GC, which is still in its infancy, BTC has long been acknowledged as a store of value, and the emotion of the global market influences its price more so than the unpredictability of domestic legislation. Furthermore, because BTC is a decentralised global asset, its value is more affected by monetary policies, institutional demand, and global economic conditions than by the unpredictability of national economic policies. EPU, on the other hand, mostly measures uncertainty at the national level, which might not be very important for BTC's international investor base. Some studies contend that BTC might serve as a hedge against economic uncertainty, including Yu (2019), Paule-Vianez et al. (2020) and Shaikh (2020). These studies are contradicted by the results of Model (ii), which imply that BTC does not always act as a trustworthy hedge against EPU.

In both models, the S&P 500 return is strongly and negatively impacted by the OVX index, which gauges the volatility of the oil market. The OVX coefficients, which are significant at the 1% level (p-value = 0.0000), are specifically -0.023199 (Model i) and -0.017022 (Model ii), indicating that when the OVX increases by 1%, the S&P 500's return will decrease by 0.023199% and 0.017022%, respectively. This supports the majority of research on the detrimental effects of energy market swings on equity performance by confirming that rising oil price volatility causes drops in the US stock market.

4.4 Diagnostic Checking

4.4.1 Normality

Table 4.5.1.1 Normality Test's Results

	GC	BTC
	i	ii

Jarque-Bera	2045.934***	153.3420***
	(0.0000)	(0.0000)

*Notes: At the significance levels of 10%, 5%, and 1%, respectively, *, **, and *** indicate rejection of the null hypothesis. P-values are shown by figures in parentheses with lag length of 12.*

Tables 4.4.1.1 show the result for normality of the data by using Jarque-Bera test in JB test statistic and p-value with lag length of 12. Jarque-Bera test statistic that computed by kurtosis and skewness as BTC and GC are 2045.934 and 153.342 respectively. For p-value approach, the probability value larger than significant value as 0.01, 0.05 and 0.1 considered as the normality assumption of data is hold. The p-value of BTC and GC are 0.000, smaller than 0.01, 0.05 and 0.1 significant level. This means that the null hypothesis is rejected, and both model data is not normally distributed. However, the size of data sample is sufficient to conduct the study. As quite similar cases with the research (Haq et al., 2023), the null hypothesis for normality assumption is rejected since the probability value is smaller than 1% significance level.

4.4.2 Breusch-Godfrey LM-test – Autocorrelation

Table 4.4.2.1 Breusch-Godfrey LM Test's Results

	GC	BTC
	i	ii

Breusch-Godfrey	99.7586***	72.96294***
	(0.0000)	(0.0000)

*Notes: At the significance levels of 10%, 5%, and 1%, respectively, *, **, and *** indicate rejection of the null hypothesis. P-values are shown by figures in parentheses with lag length of 12.*

Table 4.4.2.1 show the Breusch-Godfrey Lagrange Multiplier Test for GC and BTC model. This test of GC and BTC model has chi-square test statistic and the p-value of test statistic. From p-value of both model, there has sufficient evident that GC and BTC reject the null hypothesis since the p-value of both model is smaller than significant level in 1%.

4.4.3 Autoregressive Conditional Heteroskedasticity

Table 4.4.3.1 ARCH LM Test's Results

	GC	BTC
	i	ii
ARCH	91.64802***	58.31046***
	(0.0000)	(0.0000)

*Notes: At the significance levels of 10%, 5%, and 1%, respectively, *, **, and *** indicate rejection of the null hypothesis. P-values are shown by figures in parentheses with lag length of 12.*

Table 4.4.3.1 has revealed the result of ARCH LM test with the chi-squared test statistic and their p-value with lag length of 12. For p-value approach, the probability value of test statistic is smaller than significant level, mean that the heteroscedasticity in the model exist. As result, GC and BTC model's p-value is smaller than significant level in 1%. This means that the origin hypothesis is rejected, and both models have ARCH effect.

4.4.4 Variance Inflation Factor (VIF) Test - Multicollinearity

Table 4.4.4.1 Results of VIF Test

	R^2	VIF
BTC	0.026143	1.026845
GC	0.015014	1.015243
EPU	0.001987	1.001991
OVX	0.012366	1.012521

Based on Table 4.4.4.1, the Variance Inflation Factor tests the correlation between these independent variables. The VIF of BTC, GC, EPU, and OVX are 1.0268, 1.0152, 1.001 and 1.01 respectively. Also, another way to determine the multicollinearity problem is R-squared. If the r-squared below 0.9, there is no perfect collinearity in the model. These R-squared of these independent variables as BTC, GC, EPU, and OVX are 0.026143, 0.015014, 0.001987 and 0.012366 respectively. From these VIF and R-squared of independent variables, there is no multicollinearity problem.

4.5 Chapter Summary

In a nutshell, the stationarity of the variables utilised in this research was investigated using the unit root test. Each of the variables are stable at their level form, according to the results. This guarantees that the regression analysis that follows will be reliable. Additionally, the ability of Bitcoin and green cryptocurrencies to hedge against the stock market in United States was examined employing the GARCH model. According to the estimation results, BTC had no noticeable effect on the S&P 500 return, but green cryptocurrencies had a notable one. Furthermore, the S&P 500 return showed strong correlations with both EPU and OVX, indicating the impact of volatile oil markets and uncertain economic policy on market performance. Both heteroscedasticity and autocorrelation were detected for the diagnostic tests. Because the Newey-West HAC standard errors offer resilience against heteroscedasticity and autocorrelation, the Newey-West Heteroskedasticity and Autocorrelation Consistent (HAC) approach was used to address these problems (Newey & West, 1987). Finally, the results provide significant fresh findings about the relationship between stock market returns, market uncertainty, and cryptocurrencies. Chapter 5 will offer the empirical findings and additional discussions.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 Introduction

The final chapter will significantly deliberate the conclusion of this research according to the overall result and findings stated in the previous chapter. Sections 5.1 and 5.2 will provide the primary findings and implications of this study respectively. In the incoming sub-chapter, Section 5.3 discusses the restrictions of this research as well as Section 5.4 offers recommendations for future research.

5.1 Discussion on Major Findings

This study is a preliminary endeavor to examine the hedging capabilities between Bitcoin and Green Cryptocurrencies against the S&P 500 with taking into account the influence of Economic Policy Uncertainty. Meanwhile, the OLS and FGLS methodologies is being employed, including unit root testing and diagnostic testing.

Through the application of FGLS method, the result from model I shown the coefficient in negative sign and significant, which indicating the return of green cryptocurrencies and return of U.S. stock market is in a negative relationship. At the same time, EPU was significant and negative correlated with the return of U.S. stock market. This result indicating the relationship between return of U.S. stock market and EPU were adverse. The interactive term (CCR*EPU) has shown a positive relationship and significant. This means the increase in a unit of the EPU may cause the weaken in hedging capability of green cryptocurrencies. The empirical findings of this study are aligned with the findings in Bouri et al. (2020a), Ali e al. (2024a), Jiang et. al (2021) and Ul Haq et al. (2023), which shows that green cryptocurrencies and the U.S. stock market are negatively correlated, it indicating green cryptocurrencies are a safe haven asset or hedging instrument in lowered the portfolio risk. Based on Simran & Sharma (2023) and Aftab et al. (2023), the study highlighted that the hedging capability of green cryptocurrency exists at certain level of EPU. Hence, the results comprehend the green cryptocurrencies serve as a hedging tool to mitigate the risk on U.S. equity market return. However, its hedging power influenced by the EPU, it can only be used as a hedging tool during period of specific economy policy uncertainty. (Bouri et al., 2020a, Ali et al., 2024, Jiang et al., 2021, Ul Haq et al., 2023)

In opposition, the result in model II exhibited it was insignificant and positive sign. This revealed that there is positive correlation among BTC's return and U.S. stock market return, showing both returns have a co-movement. Additionally, the interactive term (CCR*EPU) showed a positive coefficient and not significant. Thus, it is to be said BTC has no hedging ability towards the U.S. stock market and the rise in EPU may strengthen co-movement between BTC and U.S. stock market. Since the results are insignificant, indicating that BTC has no hedging capability in this study.

To sum up, there is different hedging capability between BTC and green cryptocurrencies, which green able to provide hedging power towards U.S. stock market return, but not for BTC. According to Ali et al. (2024a), the study found that the correlation of equity indices with green cryptocurrency are more diverse than the correlation of equity indices with another non-green cryptocurrency. Likewise, the EPU has an effect on green cryptocurrencies' hedging ability. Hedging capability of green cryptocurrencies can be weaken when the increase in EPU, which implies it may loss its hedging capability towards U.S. stock market. Conversely, the decrease in EPU will strengthen its hedging capability, due to the inverse relationship between EPU and green cryptocurrencies.

Refer to previous part, the control variable of OVX was denotes a negative coefficient and significant on return of U.S. stock market return in both model I and II. The result found a negative correlation between the OVX and return of U.S. equity market. These outcomes are in accordance with the results from past studies, including Dutta (2017) and Ahmad et al. (2021). While Bašta and Molnár (2018) and López et al. (2022) were found that OVX and U.S. stock market has a co-movement in long run.

5.2 Implication of Study

As previously mentioned, this study has filled the gap by investigating the hedging capabilities between BTC and green cryptocurrencies as well as the impact of EPU on their hedging effectiveness. There are several consequences that result from the main findings of this study. First and foremost, the return of green cryptocurrencies and U.S. stock market is negative correlated. The outcome of this study provides valuable knowledge which there are differences in hedging capabilities for these two categories of cryptocurrencies and the hedging capability is affected by economic policy uncertainty.

For the Investors and fund managers, the findings of this study can assist them in selecting hedging tools. There are various factors that investors must consider when making an investment decision, risk is one of the cornerstones. On the other words, the risk tolerance is different between every investor, who is risk taker investor seeking for the higher rewards from investment at higher risk, while risk adverse investor looking for an investment at minimum risk. Generally, investors always desired to make an investment which has optimal returns while at acceptable risk. Therefore, green cryptocurrencies can be a risk management tool in hedge against the risk from equity market. Additionally, GCs is better risk management tools for the investors who are more concerned on the environmental issue. Nevertheless, the changes in EPU might be taken into consideration. In period of rising EPU, selecting green cryptocurrency as a hedging tool are withhold recommendation. Investors are suggested to choose alternative assets that able to provide protection and risk mitigation.

As from the findings in this study, which observed that green cryptocurrencies can be a risk management tool, while Bitcoin has no hedging power against the U.S. stock market. The fund managers advise distributing green cryptocurrencies in a portfolio to protect against risk, the weight can be adjusted based on the intended returns. Over and beyond that, utilizing GCs can help reduce environmental challenges as well as hedge against the risk from stock market. Nonetheless, this recommendation is not valid when there is a rise in EPU. Consequently, fund managers might consider substitutive assets that provide protection to the portfolio.

Based on empirical results of this study, the correlation between the United State stock market, non-green cryptocurrency, and green cryptocurrencies can be thoroughly understood by future researchers. Further, they can also comprehend how the EPU will affect the hedging capabilities of both green and non-green cryptocurrencies. On top of that, this study delivers some valuable insights and guidance for future researchers who possess an interest in a logical expansion of this field of study.

Last but not least, throughout the present study, there is an inverse correlation between green cryptocurrencies and stock market in U.S. during a certain of economic policy uncertainty. Green cryptocurrencies may be recognized as an alternative financial product that might serve as hedging tool. Policymakers such as Securities and Exchange Commission should strengthen the supervision and make adjustment in the policies and regulations of the cryptocurrency market to maintain financial market stability as well as promoting eco-friendly financial products. The study concluded that EPU has an impact on the effectiveness of hedging. This suggests that increased regulatory openness and stability might improve the effectiveness of green cryptocurrency hedging power. Policymakers should be cautious that frequent or confusing policy changes might undermine investor confidence in these assets. Stable and transparent economic policies such as fiscal, monetary and regulatory are required to promote the growth and trustworthiness of green financial tools such as green cryptocurrencies.

5.3 Limitation of Study

The study limitations that were mentioned in the previous paragraph will be reviewed in this paragraph. Finding the research's shortcomings is crucial for researchers to build on their findings and find better strategies to address or broaden these limitations in subsequent investigations.

One of the main limitations of this study is that it not applicable to other countries' markets, the hedging effectiveness of green and non-green cryptocurrencies may differ depending on the economic policies, market structures, and investor behaviours of different countries. Additionally, the study uses the S&P 500 as the only benchmark for stock market performance, which may not accurately reflect the dynamics of other major indices such as the FTSE 100 (UK), DAX 40 (Germany), or Nikkei 225 (Japan). Hence, the conclusions may not hold in economies with different financial systems, regulatory environments, and risk factors.

Besides, the lack of historical data on green cryptocurrencies is one of the main limitations. In contrast to well-known cryptocurrencies like Bitcoin, green cryptocurrencies tend to be newer, have a smaller market capitalization, and have less trading history. Researchers' capacity to examine patterns and evaluate the effectiveness of hedging in various economic scenarios is limited by the lack of long-term data. It becomes challenging to make firm judgements on their function in financial markets in the absence of adequate historical data.

5.4 Recommendation for Future Study

Future research should incorporate other international financial markets in order to overcome this constraint and broaden the investigation beyond the U.S. market. Scholars might investigate in a variety of economies with different market structures, monetary policies, and regulatory frameworks. To determine whether the observed correlations between cryptocurrencies and stock markets hold true across various financial systems, future research should also look into employing a wider range of stock market indices, such as the FTSE 100 (UK), DAX 40 (Germany), Nikkei 225 (Japan), and other region-specific benchmarks. A more thorough grasp of the ways in which economic conditions impact bitcoin hedging capabilities would be possible through a comparative examination of several marketplaces.

Extending data availability is one of the most important areas for improvement. Given the relatively short trading history of green cryptocurrencies, researchers should focus on gathering and collecting longer periods of historical data in future. Additionally, other sources of information, like on-chain data, trading sentiment, and liquidity measures, to supplement traditional price and volume metrics. Expanding data sources will improve the accuracy of hedging analyses and enable more accurate evaluations.

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