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Investigating the Impact of Geopolitical Risks and Uncertainty Factors on Bitcoin

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Abstract

With the rise of cryptocurrencies and their appeal as alternative investment assets, this study, using daily and weekly data from early 2015 to late 2023, aims to analyze the influence of economic and geopolitical uncertainty factors on cryptocurrencies, particularly Bitcoin, and forecast their volatility using GARCH, EGARCH, and GJR-GARCH models. Our findings reveal that the Geopolitical Acts Index (GPAs), the U.S. Economic Policy Uncertainty Index (EPU), and the Volume of Bitcoin transactions exhibit a positive significant impact on its returns, whereas the Cryptocurrency Uncertainty Index (UCRY), S&P 500, and Volatility Index (VIX) demonstrate a negative one. Furthermore, by decomposing geopolitical turbulence into Geopolitical Risks (GPRs) and Threats (GPTs), these variables were found to be less significant compared to Geopolitical Acts. Finally, the asymmetry analysis (leverage effects) reflects on how negative shocks exhibit a greater influence than positive ones on Bitcoin returns, indicating that adverse news in the media tends to impact the cryptocurrency returns more profoundly. Our conclusions contribute to the existing literature by exploring the role that Bitcoin, and cryptocurrencies in general, play as investment assets, when taking into consideration the volatility they entail, especially following negative shocks in an economy.

Keywords

GARCH Modeling, Asymmetric Volatility, Geopolitical Risks, Economic Policy Uncertainty, Bitcoin Returns

1. Introduction

Understanding global financial markets relies heavily on staying abreast of economic and geopolitical developments, as they wield significant influence on the former (Alam et al., 2023; Demir & Danisman, 2021; Dhoha et al., 2024; Fang et al., 2019; Golitsis et al., 2022; Mitsas et al., 2022). Building upon this perspective, along with the rising importance of cryptocurrencies and their spillovers to financial markets (Demiralay & Golitsis, 2021; Mensi et al., 2023; Nam, 2023; Uzonwanne, 2021), there is value in investigating the effects of economic, geopolitical, and uncertainty factors on cryptocurrencies, and particularly Bitcoin.

Bitcoin's preeminent status among cryptocurrencies is distinguished by several key factors. Its first-mover advantage, largest market capitalization, decentralized nature, limited supply, brand recognition, and network effect collectively contribute to its prominence (Abdollahi et al., 2022; Jain, 2024; Park et al., 2020). Bitcoin's dominance as the top digital currency is reinforced by its unmatched security, scarcity, and widespread acceptance. Meanwhile, central banks are still exploring Central Bank Digital Currencies (CBDCs), but their introduction is still pending; the implementation and adoption of CBDCs hinge on factors like technological readiness, regulations, and public acceptance (Norges Bank, 2018; Ozili, 2022). Hence, the examination of Bitcoin's response to different uncertainties is of great interest.

The Bitcoin hedging hypothesis through the impacts of Economic Policy Uncertainty (EPU) and Geopolitical Risk Index (GPR) and their joint effect on Bitcoin's return and volatility (Nouir & Hamida, 2023; Panagiotidis et al., 2019) and other sources of uncertainty—indicatively of trade policy uncertainty—to Bitcoin returns (Gozgor et al., 2019) have been studied thoroughly in the literature. What still seems as under-investigated though, is an extensive coverage of the individual and joint effects of EPU and GPR, along with other Uncertainty factors, including the Cryptocurrency Uncertainty Index (UCRY) and the Chicago Board Options Exchange Volatility Index (VIX).

The main research questions we set to answer are the following. To what extent do the Uncertainty Indexes impact the volatility of Bitcoin returns, and how well can the GARCH model capture and predict this impact? How does the Geopolitical Risk Index influence the conditional volatility of Bitcoin returns, and what asymmetries exist in its impact on positive and negative shocks? What is the relationship between the CBOE VIX Index and Bitcoin returns, and how does this relationship vary under different economic conditions, as evidenced by various GARCH models, including an E-GARCH and a GJR-GARCH? Finally, can the Cryptocurrency Uncertainty Index be identified as a significant predictor of Bitcoin volatility?

To the best of our knowledge, while literature exists in this field (Karaömer, 2022; Sin, 2023; Wei et al., 2023), there are still gaps warranting further exploration; subsequently, the focal variables, including the aforementioned indexes, which are reflective of economic policy uncertainty, geopolitical turbulence (including the additional distinction of Geopolitical Acts (GPAs), Risks (GPRs) and Threats (GPTs)), crypto-assets uncertainty (including both the Policy and the

Price index) and stock market volatility are not tested under this specific set up and for this time period. Additionally, we focus on asymmetrical spillovers on cryptocurrency returns, which bring new insights, and have certain implications for policy makers and various stakeholders. By capturing the negative shocks that exhibit a greater influence on Bitcoin, and the adverse news in the media that tends to impact Bitcoin returns more profoundly and asymmetrically than the good news, policymakers may need to consider implementing measures to mitigate the impact of such events to ensure market stability and investor and user confidence in the cryptocurrency and digital space. Moreover, the understanding of asymmetric impacts of various shocks could inform regulatory strategies aimed at managing market volatility and reducing cryptocurrencies-related and digital currencies-related systemic risk.

The purpose of this paper is twofold. First, we investigate the impacts of EPU, GPR, UCRY, and VIX, along with S&P 500 and the volume of Bitcoin, on Bitcoin returns and volatility, by using and comparing various GARCH models. Secondly, we concentrate on examining the asymmetric effects of both positive and negative shocks on the conditional volatility of Bitcoin returns over an extended period of time, encompassing the escalation of recent geopolitical tensions up to the present day, including the COVID-19 pandemic, the Russia-Ukraine war, political elections, and Cyber-attacks on cryptocurrency exchanges.

The structure of the paper is as follows: Section 2 offers a literature review, Section 3 introduces the data and outlines the empirical model, Sections 4 and 5 present the empirical analysis and discuss findings considering existing literature, and finally, Section 6 delves into policy implications and discusses the conclusions.

2. Literature Review

In the last few years, a new type of currency has appeared in global markets, the so-called cryptocurrency, which is a new form of exchange that exists and was created to overcome the challenges and uncertainty posed by other types of transactions as we knew them until then. According to Haq et al. (2023), uncertainty is one of the major concerns among investors and policymakers. With all the contingencies investors are facing, the future viability of an investment falls most of the time on the uncertainty of events happening in the future. Some of this uncertainty in the last few years can be attributed to the Russia-Ukraine confrontation, and the COVID-19 pandemic. These types of events are classified and quantified as causing a certain degree of uncertainty. According to Singh et al. (2022), the Russia-Ukraine confrontation has had an impact on financial markets. Both long and short-term perspectives identified a strong mutual dependence between EPU, GPR, and Bitcoin returns, showing that Bitcoin could be linked to future uncertainties in economies, thus presenting a risk in terms of the currency being used as a safe-haven investment. However, it is fair to assume that it can be used as a hedge to the EPU and GPR. Bouri et al. (2018a) observe financial stress indexes, suggesting that cryptocurrencies, in this case Bitcoin, exhibit a safe-haven property against Global Financial stress for approximately 60 days. Almeida and Gonçalves (2022) report that in a diversified portfolio, cryptocurrencies exhibit a diversification and safe-haven property, while Bouoiyour et al. (2019) report that Bitcoin serves as a safe-haven to short-term stock losses. Bouri and Gupta (2021) predict that the internet-based economic uncertainty-related queries index is statistically stronger than the measure of uncertainty derived from newspapers in predicting Bitcoin returns. This uncertainty was always correlated with the economy and with cryptocurrencies, meaning that whenever we delve into the economy of the world of financial assets, we need to have a clearer view of the future (Bouri & Gupta, 2021).

2.1. Bitcoin

In 2008, Satoshi Nakamoto, a person/group using this pseudonym to safeguard anonymity, introduced Bitcoin. Bitcoin was introduced as a digital currency with the goal of making all payments electronic and subsequently discarding all third parties involved in transactions involving currencies. Nakamoto (2008) defines an electronic coin as "a chain of digital signatures". Any individual that owns the currency transfers it to another one, thus, creating a special type of signature on the public key; the public key is considered the public record of the digital signatures within the coin, which are delivered in chronological order, meaning the last signatures will be in the last keys of the coin and then this signature is verified by someone that owns another coin. The record of these transactions is kept automatically by the blockchain[1].

Initially, Nakamoto (2008) introduced Bitcoin to the world putting into circulation approximately 50 Bitcoin. In this early phase, the hype was casual, meaning that only a few computer fanatics around the world knew about its existence. Fauzi et al. (2020) state that around 2010 a Japanese company had created a platform in which Bitcoin was trading using 20 coins changing hands at the price of 4.951 cents. At that point, the total volume of transactions was approximately 1 USD. Nobody expected the hype linked with Bitcoin to raise the price so significantly, which at the time of this writing is at around $61891.55 USD (16/04/2024). Demir et al. (2018) report that from November 15th, 2017, to December 15th, 2017, Bitcoin's market capitalization rose from $111 Billion to $278 Billion, taking the value from roughly $6744.50 up to $17047.28, thus increasing by more than 200%, exhibiting at that time one of the most notable performances ever seen for a financial instrument.

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[1] The name "Cryptocurrency" originates from "Cryptography", the process of coding information with the goal of hiding the message where it can only be read or comprehended by the person intended to read it (Fortinet, 2021). Cryptography is the founding base of this new type of financial asset, which means that for two parties that want to proceed with an online transaction, the use of cryptocurrencies eliminates the need for financial institutions to be part of the process, thus, concealing all the information of the transaction, with the payment trust being all on the Cryptography part. Nakamoto had developed Bitcoin by the end of 2010, which was then implemented in what most people suggest was the beginning of real transactions with Bitcoin.

Baur et al. (2018) sought to understand the intention relative to holding Bitcoin as an asset or as a cryptocurrency. Their study indicates that the users of Bitcoin are interested more in digital currencies as an alternative type of investment and not as currency. This currency could also be used as a safe haven asset, but there is the counterargument that excessive volatility leads to excessive future uncertainty. On the other hand, gold or silver can remove this uncertainty as they do not have as much volatility as Bitcoin. Kurihara and Fukushima (2018) state that there is a difference between short-term volatility and long-term volatility, while Conrad et al. (2018) finds that this volatility is closely linked with global economic activity. Based on Katsiampa et al. (2019), cryptocurrency price volatility is attributed to its own past shocks and past volatility, while there is evidence that shocks can also be transmitted between Bitcoin, Etherium, and Litecoin, the other two well-known cryptocurrencies. Bitcoin transaction data analysis reveals that the predominant use of Bitcoins is for speculation rather than serving as an alternative currency or a medium of exchange. Corbet et al. (2018) support cryptocurrencies as a new investment class with considerable interconnectedness and a connection to other assets, compared to shares and bonds. Balcilar et al. (2017) mention that the causality-in-quantiles test reveals that volume can predict returns, and in terms of periods it is shown that there is a correlation. This assumption though, does not fit in bull and bear markets, demonstrating that volume cannot predict volatility at any point.

2.2. Security Technology

The blockchain is considered to be one of the best digital ledgers and most sophisticated technology since the arrival of the Internet, maintaining all the information in a decentralized network, which is a notable and important part linked to the privacy status it offers (Zaghloul et al., 2020). This is a main differentiating factor when comparing digital currencies to all other currencies. Compared to the traditional methods of the so-called traditional banks, the encryption of data is considerably more sophisticated, and this data is integrated into the blockchain and maintained in store in a decentralized database where it enjoys privacy in accordance with the GDPR standards used in the more "traditional" institutions.

Due to the decentralized nature of the blockchain, it is easier to protect confidential information and eliminate the intermediation that exists in the information flow which is always present in any other institution. This issue of identity privacy is important based on the features of the cryptocurrency that protect the user's profile by decentralizing the information. Fauzi et al. (2020) show that the privacy of 40 percent of users has been revealed, since people trade cryptocurrencies via an exchange, e.g. Binance (which is an exchange of cryptocurrencies). The account of each individual is linked to a wallet, and after a transaction takes place with the name of the Binance account, this is effectively not anonymous anymore, and is connected in an indirect way to the wallet itself; therefore, the privacy effect is eradicated.

2.3. Cost of Transaction

The characteristics of decentralization and deregulation are factors that help the low-cost process associated with cryptocurrencies, where verifications are made by the network itself (Tsang & Yang, 2021). In addition to that, the common methods of payment using fiat currencies have flaws. Fauzi et al. (2020) mention that debit and credit cards have flaws, namely the automatic payment of interest related to the payment when this payment fails (default); debt is another factor related to costs, and nowadays the ease of credit is a great source of income for retail banks, and they sometimes take advantage of the lack of knowledge of the final consumer.

Although Bitcoin's volatility can be considerably high compared to traditionally used currencies, it can operate 24 hours a day, 7 days a week, throughout the year. In traditional systems, much of the information is omitted or even ignored. Using cryptocurrencies as a payment method could make things easier, with this new era of information being the key to many transactions.

2.4. High Return

Historically, Bitcoin is a volatile currency, which leads investors to make returns that are often above average. Although its characteristics were originally designed to be used as a currency, it is often used for speculative purposes, or even as a risk reduction instrument. Singh et al. (2022) found that Bitcoin can be used as a hedging tool against Global Economic Policy Uncertainty (GEPU) and EPU as well. Baek and Elbeck (2014) mention that higher speculation regarding the value of Bitcoin is mainly due to buyers' and sellers' expectations of the market. Interestingly, when verifying a transaction with Bitcoin the user is paid a small percentage of the value of the currency, which increases the number of coins in circulation on the market. On the other hand, Nekhili and Sultan (2022) found that conventional assets can hedge excessive swings in Bitcoin. Those who had been holding Bitcoin in its early days of introduction, may have raked in, and materialized profits of between 1000 to 10,000 percent on the principal they had invested.

2.5. Difficulties and Challenges

To this day, many people do not feel at ease to put their trust in cryptocurrencies. Another considerable difficulty was identified by Glaser et al. (2014), who found that Bitcoin users perceive it as an investment asset and not as currency used for transactions, therefore, lack of knowledge regarding the real use of Bitcoin and the true system behind it can pose significant challenges. Fauzi et al. (2020) identify the following as themes for challenge and improvement: Law, Electric Bills, Crashes and Bubbles, and Attacks on Networks, and Volatility among others.

2.6. Law

With the emergence of new currencies, and compared to traditional currencies, regulation is a huge challenge (Cappai, 2023; Cumming et al., 2019). In conventional currency systems, central banks function as regulatory bodies, formulating legislation to counteract instances of fraud and bribery. This proactive approach enhances the safety and fluidity of these currencies, rendering them more trustworthy and easily exchangeable. Regulatory laws established by central banks undergo continuous refinement aligned with overarching, long-term goals. Thus, by scrutinizing strategies aimed at bolstering the robustness of tangible currencies, insights can be gleaned for the evolution of digital currencies. Emphasizing stability and reliability in this evolution paves the way for their widespread adoption and utilization in the future (Hacker & Thomale, 2018). Finally, the characteristic of anonymity of cryptocurrencies gives rise to perceptions that they can be used to plan criminal acts and fraudulent transactions (Dupuis et al., 2021).

2.7. Electricity Cost

The difficulty related to electricity cost is mostly associated with cryptocurrency mining, which is one of the key parts of the process when it comes to Bitcoin. This process requires the high use of electricity, making the process of mining Bitcoin very costly. As a highly digital process, it requires a high amount of energy to be produced, thus having a considerable environmental impact. Duan et al. (2023) distinguish cryptocurrencies into two categories Clean and Dirty. Dirty is categorized on a Proof-of-Work basis, where they identify those that are considered to have a large ecological footprint due to the large energy expenditure for their production, and for this Proof-of-Work concept, they are put to work on a physical computer that consumes a significant amount of energy, thus leading to a larger ecological footprint. Whereas, Clean is categorized on a Proof-of-Stacking basis, namely on a more ecological basis where stacking is done without the need for a physical base to be mined or stacked, thus, lowering energy consumption.

2.8. Crashes and Bubbles

Another problem related to the operation of markets is the fluctuations of the business cycle with its crashes and bubbles. The devaluation of Bitcoin is a factor that becomes a persistent threat to the stability of this cryptocurrency. In the event of extreme volatility, investors are faced with significant difficulties, making fear a determinant in this asset's market. Volatility certainly creates uncertainty in the market and thus weakens the market. Klein et al. (2018) chose to investigate and compare Bitcoin and gold and found that they could not be more different. Bouri et al. (2018b) indicate that the possibility to predict Bitcoin price movements based on price information from the aggregate commodity index and gold prices can happen depending on the data collected and the period. When looking at the increased volatility in the market, investors look to the future with uncertainty, whether this same devaluation will happen in the future or whether it will not happen at all, thus, turning certainty and belief in this asset into uncertainty about future profitability.

Cheah and Fry (2015) demonstrate that Bitcoin experienced speculative bubbles, while Corbet et al. (2020) studied the spillover effects of cryptocurrencies related to FOMC (Federal Open Markets Committee) announcements, to verify whether there are effects related to FOMC events/announcements. Since these cryptocurrencies are focused on being an innovative new method of payment, the FOMC announcements affect these currencies, and this can be linked to the crashes and the bubble effects.

2.9. Attacks on Network

Despite the strong security that encryption brings to Bitcoin, cyber-attacks are a factor that can jeopardize the security aspect and trust in cryptocurrencies. Corbet et al. (2019) state that the report by Ernst & Young estimates that almost 10% of all ICO proceeds are stolen by hackers, while the lack of regulation and the private nature of these transactions are difficulties that can be linked to the complexity of the network and the entire system. Therefore, the resolution and continuous improvement of these threats are points that effectively become crucial for the effective improvement of this cryptocurrency.

2.10. Economic Policy Uncertainty (United States) (EPU)

Uncertainty is one of the major concerns of policymakers and investors. In 2016, Scott R. Baker, Nicholas Bloom, and Steven J. Davis, developed a new index, the Economic Policy Uncertainty index, which was based on news search in newspapers. The index is based on the search of news in the top 10 newspapers in the U.S.[2]

There are three types of underlying components in this analysis. The first and most adaptable component is the quantification of the words in the newspapers with the coverage of the news; the second part is the identification of the words. The oblivious difficulty of this news search referred to the raw data from the number of newspapers having large volume across time, therefore it was scaled down to standardize each monthly newspaper-level series to unit standard deviation from 1985 to 2009 and then average across by month. Finally, the data was normalized to a mean of 100 from the same period mentioned before.

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[2] Namely, USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal. These newspapers were accounted to understand and research the frequency of words such as: “economic” or “economy”; “uncertain”, or “uncertainty”; and one or more of “Congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation”, or “White House”.

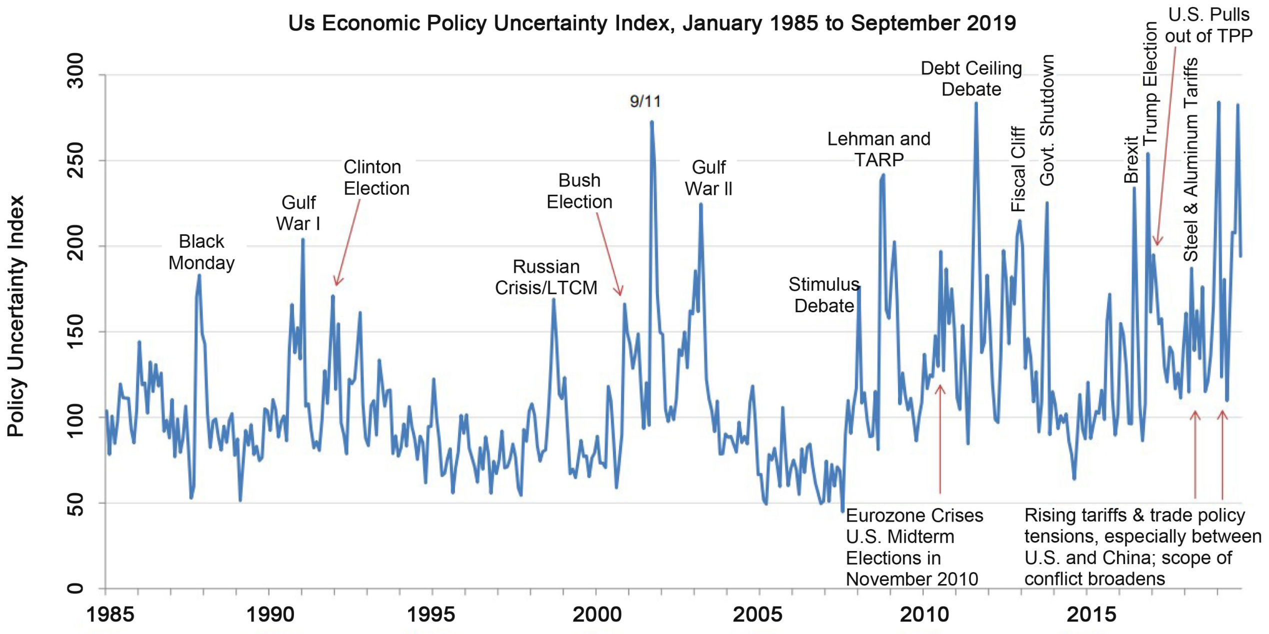

Figure 1. Economic policy uncertainty index. Source: Baker, Bloom, and Davis (2016). Note: Figure and values are extended according to https://www.policyuncertainty.com/.

Figure 1 shows spikes in the graph that stand out while presenting the main events that fuelled global uncertainty when examining the Policy Uncertainty Index. Many researchers have found evidence of interaction between the EPU and cryptocurrencies (Haq et al., 2021, 2023; Phan et al., 2021; Yen & Cheng, 2021). Phan et al. (2021) found that when the EPU increases, financial stability decreases by around 2.66% and 7.26%. Yen and Cheng (2021), related EPU and cryptocurrency volatility, to verify their connection and predictability, and to verify that the changes in the EPU of China predict the volatility of cryptocurrencies. On the other hand, the changes in the EPU of the U.S., Japan, and Korea, do not produce any type of correlation with the volatility of these currencies; moreover, they show that the changes in Chinese EPU have a negative effect on Bitcoin. Haq et al. (2021) add to the strand of literature that points out that although there is a mixed relationship between cryptocurrencies and EPU in all countries, the applicability of risk strategies to mitigate uncertainty must be adjusted from country to country, and the values are heterogeneous. Haq et al. (2023) investigated the dynamics during the COVID-19 pandemic and found that EPU in the U.S. is the strongest in transmitting volatility, revealing a relationship between the EPU and market volatility, while Yen et al. (2023) found empirical evidence that the change in Global EPU can have a dependency effect on Bitcoin, adding that when the GEPU increases, this dependency tends to be stronger. Mokni (2021) investigated the causes between EPU and Bitcoin volatility at the intermediate and high quantiles. Overall, it seems that when the EPU increases, it causes the returns of Bitcoin to increase too. On the other hand, when EPU decreases, Bitcoin's volatility increases too. Akyildirim et al. (2020) indicate that cryptocurrencies and financial market stress have a positive intercorrelation, which varies over time. Finally, Demir et al. (2018) studied the relationship between EPU and Bitcoin returns, using data for the 2010-2017 period. These authors conclude that there is indeed a correlation between these two factors, thus, the related Bitcoin returns are negatively associated with EPU. This inverse movement could turn Bitcoin to an asset of choice for combating economic uncertainty, in terms of hedging against periods of increased turbulence.

2.11. Geopolitical Risk Index (GPR)

Developed by Dario Caldara and Matteo Lamoriello in an effort to understand global risks, the Geopolitical Risk Index was created and developed based on the number of newspaper articles discussing the subjects of geopolitical events and risks. Electronic text research was made in archives of 11 newspapers[3].

The search was done in groups with a word search that included terms such as "Geopolitical Threats", "Nuclear Threats", "War Threats", "Terrorist Threats", "War Acts", and "Terrorist Acts". Each of these categories has also specific search terms. The normalized data was set to an average of 100, and then the variance was accounted for the instability of the geopolitical risk or put differently, the higher level of risk. To better organise and differentiate the terms, other indexes were created such as the Geopolitical Threats Index (GPTs) and the Geopolitical Acts Index (GPAs), with the goal of understanding if these events were caused in way of threats that did not materialize, or if the threats materialized into acts of terrorism or another type of event.

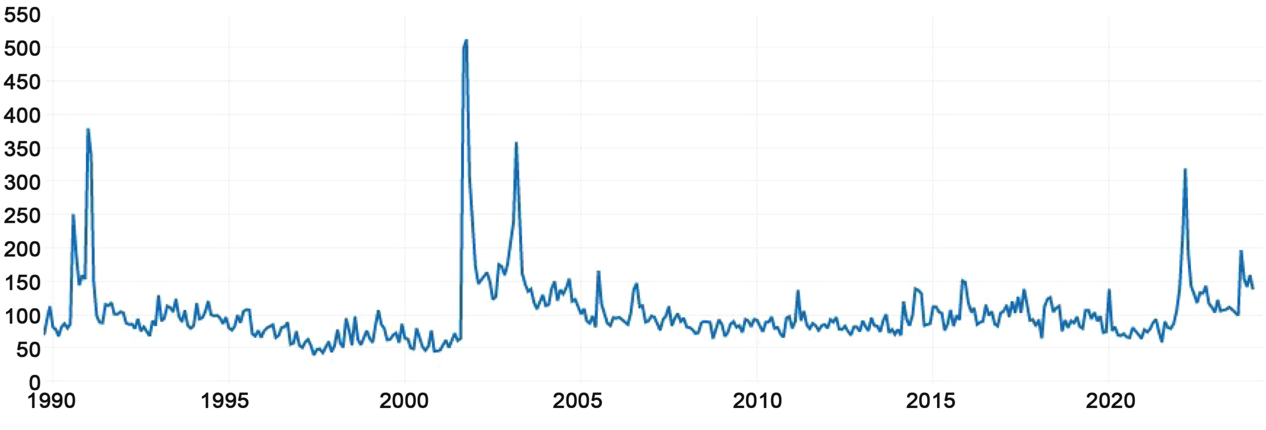

Figure 2. GPR index. Source: Caldara and Iacoviello (2022).

Comparing these events with the ones from EPU we can see that there might be an overlap between the two figures (**Figure 2**). The EPU presented previously is U.S. based, while the GPR index is inclusive of global events. Moving to the li-

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[3] The Boston Globe, the Chicago Tribune, the Daily Telegraph, the Financial Times, the Globe and Mail, the Guardian, the Los Angeles Times, the New York Times, the Times, the Wall Street Journal, and the Washington Post.

terature findings, Al Mamun et al. (2020) support that geopolitical risk, and global and US economic policy uncertainty are interconnected, but during unfavourable times with regards to economic conditions the values are more significant. Thus, the evidence of uncertainty not only comes with a fear attached to it, but it also brings a higher geopolitical risk to the table. Corbet et al. (2020) conclude that news relating to GDP, CPI, and Bitcoin returns do not have a statistically significant relationship, while Caldara and Iacoviello (2018) find that the exogenous changes in the GPR bring down economic activity and stock returns notably in the United States; meaning that even if an event is occurring in other parts of the world and not in the U.S., the latter's economy can still feel the pressure. Colon et al. (2021) support that even though cryptocurrencies react to the uncertainties of the markets, these uncertainties can have different manifestations depending on the type of uncertainty. Aysan et al. (2019) using the BSGVAR technique conclude that GPR has predictive power on both the returns and volatility of Bitcoin. Although by using the Ordinary Least Squares (OLS) estimations the values exhibit a slight change, price volatility is positively correlated and returns are negatively correlated in comparison to GPR, respectively. The latter finding implies that Bitcoin can be a useful tool to hedge Geopolitical Risks.

2.12. Cryptocurrency Uncertainty Index (UCRY)

With a novel approach based on the method used for the development of the Economic Policy Uncertainty index, Lucey et al. (2022) constructed the Cryptocurrency Uncertainty Index. As the name suggests the index aims to account for the future uncertainty that is related to the cryptocurrency world, posed as two indices, namely Policy Uncertainty and Price Uncertainty. Given that several types of uncertainty may have different impacts and predictive power on cryptocurrency markets, it is important to distinguish between policy, price uncertainty, and volatility. Price volatility measures the size of cryptocurrency returns' variations and can be measured using the standard deviation of logarithmic returns.

The related news in this index is drawn from the Lexis Nexis database, which includes news regarding major events from 2014 to 2020, namely the COVID-19 pandemic, political elections, and Cyber-attacks on cryptocurrency exchanges. Compared with the other similar indexes regarding uncertainty, it has a smaller range of observations, due to the different time frame of the cryptocurrency and of the related news. Therefore, this suggests that the index is not that volatile, although it could be useful in the future regarding the uncertainty of cryptocurrencies, portfolio diversification, and other decisions related to the uncertainty in the future of other assets. Elsayed et al. (2022) observe that cryptocurrency policy uncertainty can transmit some return spillovers to other assets.

2.13. CBOE Volatility Index (VIX)

Finally, we use the VIX, the Chicago Board Options Exchange Volatility Index.

In 1993, the CBOE introduced the CBOE Volatility Index® (VIX® Index). This was originally designed to measure the market prospect of a 30-day volatility implied by at-the-money S&P 100 index, but over time the index gained some importance and status than what was initially planned. Only later in 2003, CBOE collaborated with Goldman Sachs to update this index, so that the reflection of this index was more reflective of what has happening then. The new index is based on the S&P 500 index, uses the large and well-known index of U.S. companies, and estimates the expected volatility by aggregating the weighted prices of the S&P 500 Index over a series of spot prices. Using a portfolio of options and shares of the same asset as a base, the exposed volatility is calculated and thus transforms the VIX, from a slightly more abstract idea to a more practical application for use by investors and policymakers.

Overall, the index studies the implied volatility, by first calculating the implied volatility between the option prices of a certain asset, in this case the S&P 500, and then the weighted average. The calculations are then converted into a percentage. Chicago Board Option Exchange (2023) offers a stepwise explanation of the calculations for an easier understanding of this process. Haq et al. (2023) state that to understand uncertainty we have to start the analysis with a standard deviation of a risk measure, which can be captured by the CBOE VIX.

2.14. Cryptocurrencies and Uncertainty Indexes

To summarize, there are multiple analyses on relating cryptocurrencies with various indexes; using VIX and VSTOXX volatility indexes as a measure of the risk in the financial markets in the United States and Europe. Indicatively, Fang et al. (2020) studied the impact of the News-based Implied Volatility Index (NVIX) on cryptocurrency returns and concluded that NVIX is a better predictor of long-term volatility in selected cryptocurrencies than the Global Economic Policy Uncertainty Index (GEPU) of Davis (2016). Moreover, Dyhrberg (2016) supports that Bitcoin is a usable product for a hedging strategy against the stock market in general and it is a useful tool to diversify portfolios and to use as a risk management tool. Urquhart (2016) concludes that Bitcoin markets are not efficient, but they might be moving towards a direction of becoming efficient, while Nadarajah and Chu (2017) show that the hypothesis of the market being efficient is not valid. In accordance with this, Bariviera (2017) reports that daily returns of Bitcoin exhibited persistent inefficiency until 2014, but the market has become more informationally efficient since then; mostly due to the increase in Bitcoin miners that have helped the blockchain become a more established process. Finally, previous studies have examined various aspects of Bitcoin, such as its return volatility (Katsiampa, 2017), price clustering (Urquhart, 2017), and speculative bubbles (Cheah & Fry, 2015).

In relation to our applied methodology, Chi and Hao (2020) used several models to evaluate the impact of uncertainty, namely HIST, EMA, ARCH, GARCH, and EGARCH. Their analysis shows that the GARCH and EGARCH models perform much better than the others. Fang et al. (2020) used the GARCH to support that the uncertainty derived from the investor's perception is more important than the uncertainty indexes to predict cryptocurrency volatility, while Matic et al. (2023) used GARCH to understand the volatility in cryptocurrency options, finding that short-date options are less sensitive to volatility than longer-date options. Xia et al. (2023) scrutinized the impact of EPU and UCRY on Bitcoin, with the two uncertainty indexes revealing a significantly negative and positive effect on Bitcoin volatility. Katsiampa (2017) explored the optimal conditional heteroskedasticity to understand the best-fitted statistical model to identify the best approach and she ended up using mainly the AR-CGARCH Model to understand the longer variance of the Bitcoin data. Al-Yahyaee et al. (2019), using the standard GARCH, concluded that it is the best model among the five GARCH models to forecast Bitcoin and S&P 500 data, while Liang et al. (2020) used the GARCH-MIDAS to understand if the predictors chosen (VIX, GVZ, Google Trends, GEPU, and GPR) have any predicting power over Bitcoin, and found that the GVZ (CBOE gold ETF volatility index) has the strongest predicting power among the chosen predictors.

3. Data and Methodology

To investigate the influence of the Uncertainty and Volatility factors on Bitcoin, we use the Economic Policy Uncertainty Index (EPU), the Geopolitical Risk Index (GPR), along with Threats (GPTs) and Acts (GPAs), the Cryptocurrency Uncertainty index (UCRY), both Policy and Price Index, S&P 500, and the VIX. These measures of uncertainty in the economy are to be modelled, once the GARCH mean and variance equations are introduced.

The GARCH(1, 1) model entails estimating both the conditional mean and variance models concurrently. This approach allows for the integration of heteroskedasticity into the process, accommodating various structures of conditional variance, and the simultaneous estimation of multiple parameters (Bollerslev, 1986)[4]. To thoroughly investigate the relationship between Bitcoin returns, volatility, and the geopolitical risks index, along with the rest of the aforementioned indexes, this study employed three separate mean and variance equations (GARCH, GJR-GARCH, and EGARCH; the mean equation is common for all three models).

The following models were applied:

$$\begin{aligned} R_t &= C + x_1 EPU_t + x_2 GPR_t + x_3 GPA_t + x_4 GPT_t + x_5 SP500_t \\ &\quad + x_6 UCRY_t + x_7 UCRYP_t + x_8 VIX_t + x_9 VOLBTC_t + \varepsilon_t \end{aligned} \quad \text{(mean equation)} \quad (1)$$

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 \quad \text{(GARCH variance equation)} \quad (2)$$

where parameters must suffice the non-negativity constraints, $\omega > 0$, $\alpha, \beta \geq 0$.

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[4] The lag order (1, 1) is deemed adequate for capturing the nature of volatility clustering (Brooks, 2019; Pan & Chen, 2014).

In the mean equation, R_t represents the dependent variable, indicating the logarithmic daily Bitcoin return at time period t; the formula used to calculate returns is $R_t = \ln(P_t/P_{t-1}) * 100$, where t ranges from 1 to T, and P_t represents the closing price of the Bitcoin in day t. The independent variables are located on the right side of the equation, with GPR_t, GPT_t, and GPA_t denoting the measurements of geopolitical risks, threats, and acts indices, respectively. Additionally, EPU_t represents economic and policy uncertainty, $UCRY$ is the Cryptocurrency Policy Uncertainty index, while the Cryptocurrency Price Uncertainty is denoted as $UCRYP_t$; CBOE VIX, denoted as VIX, represents volatility, $SP500$ is Standard and Poor's 500, and Volume of Bitcoin ($VOLBTC$) are the final variables, totalling 10 variables overall. Finally, C denotes the constant, and ε_t represents the error term.

In the variance equation, h_t represents the conditional variance, and ω stands for the constant term, while the parameters α and β capture the ARCH and GARCH effects, respectively. The α coefficient measures how volatility reacts to market shocks, whereas β assesses the impact of new shocks on volatility, indicating the persistence of volatility in the series. A high β value suggests persistent volatility (Alom et al., 2012). Moreover, a high α value indicates a less responsive volatility to market movements. If the sum of these coefficients approaches one, it suggests that any shock would lead to a permanent change in future values, implying long memory or persistent shocks in the conditional variance. Additionally, it is important to note that the GARCH(1, 1) process is considered stable when the condition $\alpha + \beta < 1$ is met (Pan & Chen, 2014).

The GJR-GARCH(1, 1) model, introduced by Glosten et al. (1993), is an extension of the standard GARCH model, incorporating an extra term to account for asymmetries. The following equation captures the conditional variance:

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad \text{(GJR-GARCH variance equation)} \qquad (3)$$

The variable I_{t-1} functions as a binary indicator, a dummy variable in practice, assuming a value of one when $\varepsilon_{t-1} < 0$, and zero otherwise. It is important to highlight that γ identifies any asymmetric effects present in the data, while ensuring non-negativity constraints, such as $\omega > 0$, $\alpha > 0$, $\beta \geq 0$, and $\alpha + \gamma \geq 0$, as outlined indicatively by Saltik et al. (2016).

Moreover, while adverse events influence the conditional variance by $\alpha + \gamma$, positive news affects it by α alone. If $\gamma > 0$ and proves statistically significant, leverage effects are evident, indicating that negative shocks escalate volatility more than positive shocks of equivalent magnitude. Conversely, if γ is negative and statistically significant, positive shocks would impact volatility more than adverse shocks. In such instances, the model is deemed acceptable if the condition $\alpha + \gamma \geq 0$ is satisfied (Pilbeam & Langeland, 2014). For stability purposes, the condition $\alpha + \beta + \gamma/2 < 1$ must hold (Bampinas et al., 2018).

Nelson (1991) introduced the EGARCH(1, 1) model, offering an alternative asymmetric approach. Our study employs this variance equation as well:

$$\log\left(h_t\right)=\omega+\beta\log\left(h_{t-1}\right)+\alpha\left[\frac{\left|\varepsilon_{t-1}^{2}\right|}{\sqrt{h_{t-1}}}-\sqrt{\frac{2}{\pi}}\right]+\gamma\frac{\varepsilon_{t-1}^{2}}{\sqrt{h_{t-1}}}\quad \text{(EGARCH variance equation)} \quad (4)$$

The EGARCH model extends GARCH to account for volatility asymmetry, known as the leverage effect. The parameter γ captures this effect, where it must be statistically significant and negative ($-1 < \gamma < 0$). In this case, negative disturbances lead to a greater variance change than positive disturbances of the same magnitude, or differently, negative leverage indicates that high negative returns are followed by higher volatility growths than the positive ones. Conversely, if γ is positive and statistically significant, variance change is greater with positive disturbances. When γ equals zero, variance responds symmetrically to both negative and positive shocks. Lastly, employing the log form ensures that conditional variance remains positive even when parameters are negative (Zomorodian et al., 2016).

4. Data Analysis and Findings

To model the economic, uncertainty, and geopolitical influences on Bitcoin we have collected time series data from 02 January 2015 to 20 November 2023, using both daily and weekly observations; from the selected sample, only weekday data were considered, without including data for weekends, due to the lack of data for some of the indexes, namely, the VIX.

Most of our data come from the Federal Reserve Economic Data of St. Louis, such as Bitcoin price data, and Volume data (*Coinbase Bitcoin* (*CBBTCUSD*), *FRED*, *St. Louis Fed*, n.d.), Economic Policy Uncertainty Index for the Unites States (*Economic Policy Uncertainty Index for United States* (*USEPUINDXD*), *FRED*, *St. Louis Fed*, n.d.), for which daily observations were used; the SP500 was also used since it is the lead index of the US economy (*S&P* 500 (*SP*500), *FRED*, *St. Louis Fed*, n.d.). For the Country-Specific Geopolitical Risk Index (n.d.), the dataset was taken from Caldara's and Lamoriello's website, since the data is readily accessible, up to date, and listed per country. The database also includes the Geopolitical Threats and Geopolitical Acts. The Cryptocurrency Uncertainty Index data is drawn from the work of Lucey (*Cryptocurrency Uncertainty Index—Dataset*, *Brian M. Lucey*, n.d.), who created this index and presents it as weekly data; the variables UCRY Price Index and UCRY Policy Index were both used in our study. Finally, the Chicago Board Options Exchange data was taken from the FRED (*CBOE Volatility Index*: *VIX* (*VIXCLS*), *FRED*, *St. Louis Fed*, n.d.).

4.1. Diagnostic Tests

To capture volatility clustering, i.e. the tendency for periods of high volatility to be followed by periods of high volatility and vice versa, a common feature of financial time series data, we follow—as stated—the General Autoregressive Conditional Heteroskedasticity model (GARCH), and its extensions, which is a commonly used approach (Al-Yahyaee et al., 2019; Chi & Hao, 2020; Fang et al., 2020; Katsiampa, 2017; Liang et al., 2020; Matic et al., 2023; Xia et al., 2023). The GARCH is one of the most used modelling techniques that help in understanding and predicting the volatility of returns of a financial asset, which in this study is the Bitcoin return.

Prior to employing GARCH, we must first utilize the standardized residuals values and compute the Jarque-Bera statistic to test whether the standardized residuals exhibit a normal distribution. We then conduct a unit root test to determine the stationarity properties of the variables, confirming whether they are non-stationary or stationary. Finally, we run the conditional heteroskedasticity test to understand the presence of an ARCH process. Once these assumptions are validated, we can run the model.

4.2. Normality Test

In **Figure A1** (see **Appendix A**), we observe the histogram of residuals. We are under the null hypothesis (H_0) that residuals are normally distributed, while the alternative hypothesis (H_1) is that they are not normally distributed. Since probability (0.000) is lower than a 0.05 significance level, we reject the null hypothesis; this, as expected, provides evidence that residuals are not normally distributed.

4.3. Unit Root Testing

The unit root test allows us to investigate if the variables have a unit root or not, meaning if they are stationary or not in level. The null hypothesis associated with this test, to focus on the dependent variable, is that Bitcoin has a unit root, versus the alternative hypothesis that Bitcoin does not have a unit root, and therefore is stationary. **Figure A2**—BTC Unit Root Test (Constant) (see **Appendix B**) depicts the Augmented Dickey-Fuller test. We observe the probability value of 0.6902 according to which we cannot reject the null hypothesis, thus it is not stationary in level. Next, we conduct the test again but only by including the trend and intercept represented in **Figure A3**—BTC Unit Root Test (Trend and Intercept). The results are identical with the trend value being almost statistically significant at 0.0689, and the lagged value significant at 5% (0.0325); the ADF test has a probability value of 0.5231, indicating that the null hypothesis cannot be rejected, thus, leading us to not reject the existence of a unit root. Additionally, in **Figure A4**—BTC Unit Root Test (None), the test leads to a similar conclusion.

Since none of these tests demonstrates the stationarity of Bitcoin, we proceed with the first difference. Having taken the first difference, the probability value is lower than the 0.05 significance level, thus we reject the null hypothesis. However, the constant (C) is not significant (see **Figure A5**), and therefore we proceed with alternative ADF equations. In **Figure A6**, we see the ADF equation in first difference including a Trend and Intercept. The results are similar, rejecting the null hypothesis, and the constant again is statistically insignificant, which also holds for the trend (@TREND ("1/02/2015"). Therefore, Figure A7 presents the calculation of the Unit Root Test in first difference with neither constant nor linear trend. The p-value is now lower than the 0.05 significance level, and we can reject the null hypothesis of having a Unit Root, and thus provide strong statistical evidence that Bitcoin returns become stationary in their first difference[5].

4.4. Heteroskedasticity Testing

Proceeding to the Heteroskedasticity test, we initially use the ARCH Test (see **Appendix C**). As expected, the squared residuals are regressed on lagged squared residuals, including a constant, with the goal of understanding if the residuals are homoscedastic or not. Figure A8 (**Appendix C**) presents the results and according to the probability rule, with a significance level of 0.05, the null hypothesis is rejected, and thus residuals appear to be heteroskedastic, giving us grounds to proceed with GARCH modelling (see **Appendix D**).

4.5. GARCH, EGARCH and GJR-GARCH

We can subsequently proceed to GARCH models. According to the findings of GARCH(1, 1) (see Table 1), the estimated mean equation shows that the EPU, GPR Acts, SP500, UCRY Price Index, the volume of transaction in Bitcoin, and the VIX, are having a statistically significant impact on Bitcoin returns both at the 5% and 1% level of significance, while Geopolitical threats are statistically significant at the 10% level of significance. Moreover, it must be noted that the GPR, SP500, UCRY Price Index, and VIX have a negative coefficient, meaning that they are inversely related to Bitcoin returns. The variance equation is the following one:

$$h_t = 162.0198 + 0.573672 h_{t-1} + 0.361479 \varepsilon_{t-1}^2$$

where the constant, along with the GARCH and ARCH components, exhibits statistical significance. The ARCH component (α) measures the variance response to the market shock with a value of 0.361479, while the GARCH component (β), computes the impact of new shocks to the variance, and has a value of 0.573672. Considering that the estimated $\beta > \alpha$, the new shocks tend to impact the variance more than the existing shocks that gradually wear out, and therefore, the variance is considered persistent. Additionally, if $\alpha + \beta < 1$, $(0.36 + 0.57 = 0.93)$, we assume that the process is stable.

Transitioning to the GJR-GARCH model, an extension of GARCH, we direct our attention to the supplementary term, γ, aimed at accommodating asymmetrical effects. When examining the estimated mean equation, we obtain similar results in terms of statistical significance, and EPU, Geopolitical Acts, SP500,

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[5] To calculate the value of the first difference we assume "d_btc = d(btc)" or D_BTC = BTC − BTC (−1), meaning the first difference is the difference between the value in question and the previous value. Finally, for the given unit root findings (results are available upon request) we have transformed all variables on their first difference for the estimation of the volatility models.

UCRY price index, volume of transaction in Bitcoin, and VIX, are statistically significant at the 5% level of significance, while the Geopolitical threats are statistically significant at the 10% level of significance.

In terms of the variance equation, ω has a value of 161.8304, α has a value of 0.284176, γ has a value of 0.296315, and β is 0.561782, with all values being statistically significant; γ has a positive value and it is statistically significant too, meaning that there are leverage effects in the volatility process, thus, negative return-shocks cause larger variance.

$$h_t = 161.8304 + 0.561782 h_{t-1} + 0.284176 \varepsilon_{t-1}^2 + 0.296315 \varepsilon_{t-1}^2 I_{t-1}$$

If $\alpha + \gamma \geq 0$ (0.284176099732 + 0.296315360235 = 0.58049146) the model is admissible and reliable (Francq & Zakoian, 2019). To check for the conditional stationarity, we must check if $\alpha + \beta + \gamma/2 < 1$ (0.284176099732 + 0.56178163561 + (0.296315360235/2) = 0.99411541545) which holds and thus the stability condition is met.

Table 1. Bitcoin returns based on GARCH, EGARCH and GJR-GARCH.

	Bitcoin Return GARCH(1, 1)	**Bitcoin Return EGARCH(1, 1)**	**Bitcoin Return GJR-GARCH(1, 1)**
EPU	0.0293	0.0092	−0.0278
	[3.7857]***	[0.8913]	[−3.1628]***
GPR	−0.0772	0.0399	−0.1019
	[−1.1700]	[0.7945]	[−1.6545]*
GPA	0.0842	−0.0132	0.1161
	[2.7828]***	[−0.5845]	[4.0134]***
GPT	0.0611	−0.0264	0.0480
	[1.7370]*	[−0.9474]	[1.5150]
SP500	−0.0644	−0.0311	−0.0611
	[−6.3589]***	[−0.9854]	[−5.2392]***
UCRY	−0.2617	−0.5454	−0.2617
	[−0.0642]	[0.1306]	[0.0086]
UCRYP	−35.9190	1.3530	−33.3662
	[−5.6804]***	[0.1306]	[−6.3375]***
VIX	−0.9747	−0.3133	−0.9776
	[−2.6051]***	[−0.7551]	[−2.6468]***
VOL	0.0001	0.0001	0.0001
	[11.4461]***	[25.5750]***	[23.9522]***

Continued

C	4.0592	1.1720	2.2981
	[7.4673]*	[2.3552]**	[3.3384]***
Akaike Info Criterion	14.66754	13.73464	14.66062
Schwarz Info Criterion	14.70184	13.77158	14.69757
Log Likelihood	−15754.61	−14750.73	−15746.17

Note: These are the mean equations. The variance equations are reported in Table 2. The values in brackets are the z-stat values. *, ** and *** indicate statistical significance at the 0.10, 0.05 and 0.01 level, respectively. See Figures A9-A11 in **Appendix D** for detailed results.

Table 2. Results from the variance equation of GARCH, EGARCH and GJR-GARCH.

GARCH(1, 1)	ω	α	β	
Bitcoin Returns	162.0198	0.3615	0.5737	
	[0.0000]***	[0.0000]***	[0.0000]***	
EGARCH(1, 1)	ω	α	β	γ
Bitcoin Returns	−0.117368	0.2333	0.9970	0.0601
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
GJR-GARCH(1, 1)	ω	α	β	γ
Bitcoin Returns	161.8304	0.2842	0.5618	0.2963
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***

Note: The values in brackets are the p values. *, ** and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

On the EGARCH mean equation, the constant and the volume of transactions in Bitcoin are statistically significant, meaning the volume of Bitcoin transactions drives its returns to the same direction. In the variance equation all terms are statistically significant, namely, ω = C(11), α = C(12), γ = C(13) and β = C(10). The estimated variance equation is the following:

$$\log\left(h_t\right) = -0.117368 + 0.996959\log\left(h_{t-1}\right) + 0.233332\left[\frac{\left|\varepsilon_{t-1}^2\right|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + 0.060146\frac{\varepsilon_{t-1}^2}{\sqrt{h_{t-1}}}$$

where the estimated β is greater than α, meaning the volatility is considered persistent, and the new shocks have a higher impact on the volatility of the returns. Moreover, γ = C(13) is statistically significant and is presented in a positive value of 0.060146. Therefore, it can be concluded that leverage effects exist according to this model. The positive value of gamma means that variance does not respond symmetrically to negative and positive shocks, and more specifically, it is greater with positive disturbances.

4.6. Diagnostics of GARCH, EGARCH and GJR-GARCH Models

To be able to verify the findings we must run various diagnostic tests. There is value to understand if the EGARCH model is well-specified, given that the mean equation has yielded less significant results compared to the other two models. Thus, an Autocorrelation test on the standardized squared residuals is applied, then an ARCH test on the residuals, and finally the Jarque-Bera normality test on the standardized residuals of the EGARCH model (results are available in **Appendix E**). According to the lowest Akaike (AIC) and Schwarz Criteria values, and the highest log-likelihood results, the best fitting model appears to be the EGARCH, followed by the GJR-GARCH with an AIC of 14.66062, and finally the GARCH with an AIC of 14.66754. However, all three models meet the related robustness criteria[6]. Given that gamma, which detects the variance asymmetries, is statistically significant, the extended GARCH models should be preferred over the standard one; and for the given mean equations, in terms of the statistical significance of the parameters, apart from the goodness of fit, if one model was to be preferred, we would choose the GJR-GARCH.

Figure A12 (**Appendix E**) presents the Autocorrelation test on the standardized squared residuals, under the null hypothesis (H_0), that there is no serial correlation, and the alternative one (H_1) that serial correlation exists. According to the probability rule, and the respective statistics, at the value of 2 lags, the null hypothesis cannot be rejected, meaning that there is no serial correlation on the squared residuals, and the values of the autocorrelation and partial autocorrelation are close to zero, which means that the model is robust. Moreover, in Figure A13 (**Appendix F**), we test for heteroskedasticity according to the ARCH model. The null hypothesis (H_0) is that there is no heteroskedasticity, and the alternative one (H_1) is the opposite. According to the probability rule, we see that the value is higher than the significance level of 5%, so we do not reject (H_0), and thus the EGARCH is robust as well.

Finally, in Figure A14 (**Appendix G**), the Jarque-Bera normality test for the standardized residuals of the EGARCH model is available. According to the histogram a sample negative skewness is evident, and according to the null hypothesis (H_0) that the residuals are normally distributed, as opposed to the alternative hypothesis (H_1) that the residuals are not, there is evidence that the standardized squared residuals are not normally distributed in the population.

5. Discussion of Results

With the rapid growth of Bitcoin and cryptocurrencies, it is important to under-

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[6] For brevity, the rest of the robustness related tests are available upon request (see **Appendix E** and **Appendix G**).

stand the influence that Uncertainty factors have on these types of assets. To do so, we have used GARCH, GJR-GARCH, and EGARCH to study, model, estimate, and predict volatility and understand the effects of these uncertainty indexes to Bitcoin returns. Apart from the previously presented and discussed statistically significant results, we can further underline the values of SP500, UCRY Price Index, and VIX under the GARCH, all of which have negative coefficients, revealing that these variables are negatively related to Bitcoin returns. On the other hand, we have found that EPU, Geopolitical Acts, and the volume of transactions in Bitcoin have a positive impact, which indicates that when these variables increase Bitcoin returns increase too, and vice-versa.

To reflect on the asymmetries in the GARCH modelling, we proceeded with a GJR-GARCH (and an EGARCH). The additional term (γ) detects the variance asymmetries and captures their positive or negative over-responsiveness of Bitcoin returns to shocks. In the respective estimated mean equation, we observe that EPU, Geopolitical Acts, SP500, UCRY Price index, volume of transaction in Bitcoin, and the VIX, are statistically significant at the 5% level of significance, and the Geopolitical threats are statistically significant at the 10% level of significance. In terms of the variance equation, ω, α, γ, and β are all statistically significant.

As γ bears a positive and statistically significant sign, it can be concluded that leverage effects exist and are properly captured through this model. Therefore, the volatility triggered by the negative returns is more pronounced than the positive return in the following period. In practice, this means that Bitcoin returns are over-responsive to negative shocks, in comparison to a positive shock of the same magnitude which will have a lower effect; suggesting that adverse news tends to affect the returns of Bitcoin more strongly than good news of equal magnitude.

Finally, moving to EGARCH, the previously reported leverage findings are further supported, confirming the presence of persistence and asymmetry in volatility. Thus, with γ being positive and statistically significant, the volatility of Bitcoin returns is positively correlated to the returns, and the volatility is affected by the leverage effect.

In conclusion, we can support with strong confidence that the uncertainty, volatility, and financial indexes, along with the volume of transactions, impact the future volatility of Bitcoin returns. In the GARCH and the GJR-GARCH models, we observed that the Cryptocurrency Uncertainty Price Index, EPU, Geopolitical Acts, VIX, SP500, and Bitcoin's volume are all statistically significant; moreover, the EPU, the GPR Acts and the volume of transactions have a positive coefficient, while the UCRY Price Index, VIX and SP500 have a negative coefficient, both under GARCH and GJR-GARCH; the only exception is the EPU, which bears a negative sign under the asymmetric model, which calls for further investigation and justifies our choice to model the returns using three models both for robustness and comparison purposes.

6. Conclusion

In this study, spanning from early 2015 to late 2023, we utilized GARCH, EGARCH, and GJR-GARCH models with daily and weekly data. Our analysis, among various uncertainty factors, prominently featured the Geopolitical Risk Index. By decomposing it into three distinct types, the Geopolitical Risks, the Geopolitical Acts, and the Geopolitical Threats, we investigate how these indexes influence the conditional volatility of Bitcoin returns. Even though the Geopolitical Threats and the Geopolitical Risks were found to be statistically significant at the 10% level of significance, in the GARCH Model and the GJR-GARCH model respectively, the Geopolitical Acts were found to be statistically significant at the 1% level of significance in both models. These findings support that in the period under study, the Geopolitical Acts variable was more important compared to Geopolitical Threats and Risks in driving the volatility of Bitcoin returns.

Moreover, as far as the leverage effects (asymmetric effects) are concerned, we managed to capture and model both via the GJR-GARCH and the EGARCH. The gamma values, which were statistically significant in these two models, provided evidence of their existence; meaning that Bitcoin returns are affected asymmetrically both to negative and positive shocks; specifically, according to the GJR-GARCH model, the asymmetrical impact of negative shocks on Bitcoin returns manifests a greater influence compared to positive shocks of equivalent size.

In both GARCH and GJR-GARCH models, we have also found statistically significant impact from the Cryptocurrency Uncertainty Price Index (UCRY), Economic Policy Uncertainty (EPU), Geopolitical Acts (GPAs), VIX, S&P 500, and Bitcoin's transaction volume to Bitcoin returns; with the latter emerging as the main finding, particularly under the EGARCH model. Notably, EPU, Geopolitical Acts, and Transaction Volume exhibit positive coefficients, while UCRY, VIX, and S&P 500 have negative coefficients in both models.

Policymakers should address the disproportionate impact of negative shocks on Bitcoin returns, along with adverse media effects, to maintain market stability and investor confidence, when and if needed. Finally, recognizing the asymmetrical influence of negative shocks can guide regulatory efforts to manage cryptocurrency market volatility and systemic risk more effectively.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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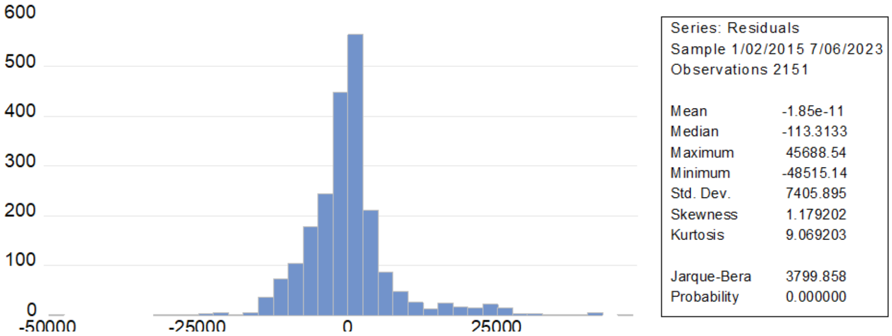
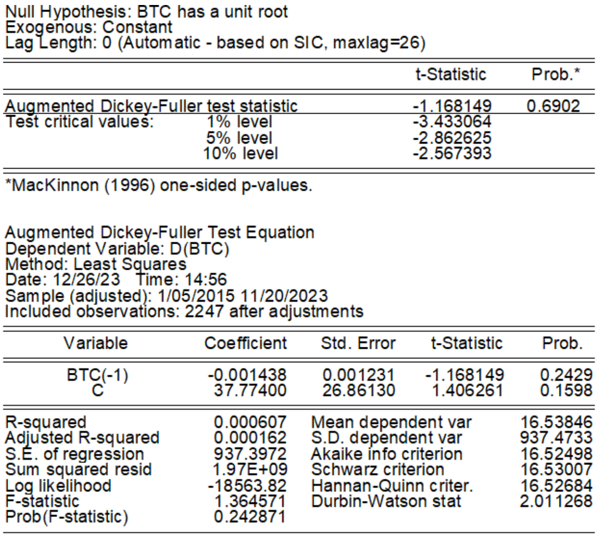
Appendix A



```
Series: Residuals
Sample 1/02/2015 7/06/2023
Observations 2151

Mean          -1.85e-11
Median        -113.3133
Maximum        45688.54
Minimum       -48515.14
Std. Dev.      7405.895
Skewness       1.179202
Kurtosis       9.069203

Jarque-Bera    3799.858
Probability    0.000000
```

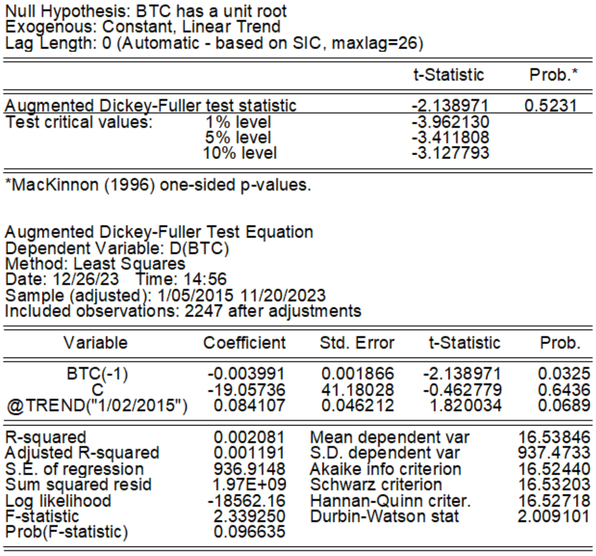
Figure A1. Histogram and normality test.

Appendix B



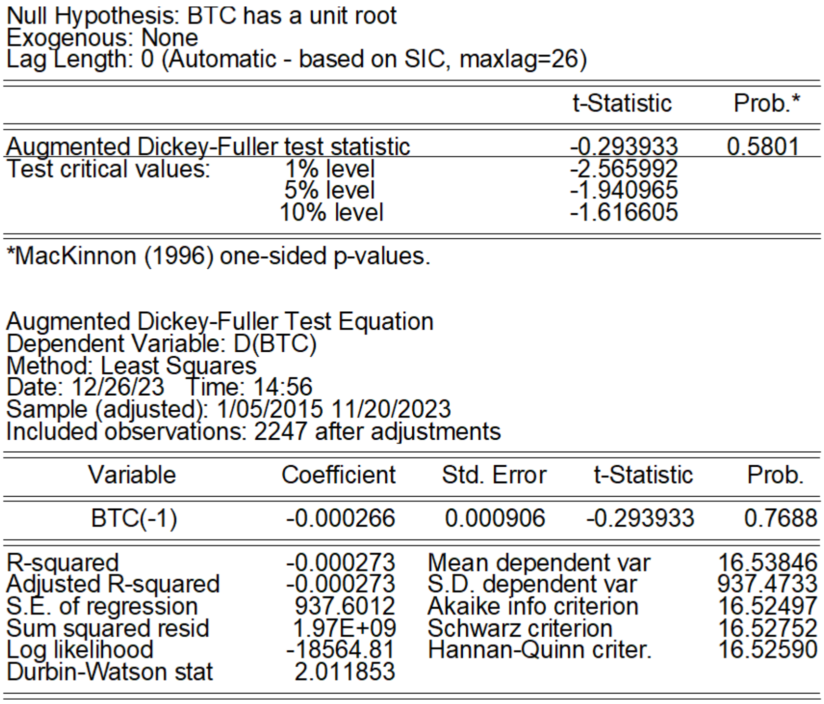
```
Null Hypothesis: BTC has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=26)

                                              t-Statistic   Prob.*

Augmented Dickey-Fuller test statistic        -1.168149    0.6902
Test critical values:      1% level           -3.433064
                           5% level           -2.862625
                           10% level          -2.567393

*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC)
Method: Least Squares
Date: 12/26/23   Time: 14:56
Sample (adjusted): 1/05/2015 11/20/2023
Included observations: 2247 after adjustments

        Variable      Coefficient   Std. Error   t-Statistic   Prob.

        BTC(-1)       -0.001438     0.001231     -1.168149     0.2429
           C           37.77400     26.86130      1.406261     0.1598

R-squared             0.000607    Mean dependent var      16.53846
Adjusted R-squared    0.000162    S.D. dependent var      937.4733
S.E. of regression    937.3972    Akaike info criterion   16.52498
Sum squared resid     1.97E+09    Schwarz criterion       16.53007
Log likelihood       -18563.82    Hannan-Quinn criter.    16.52684
F-statistic           1.364571    Durbin-Watson stat      2.011268
Prob(F-statistic)     0.242871
```

Figure A2. BTC unit root test (Constant).



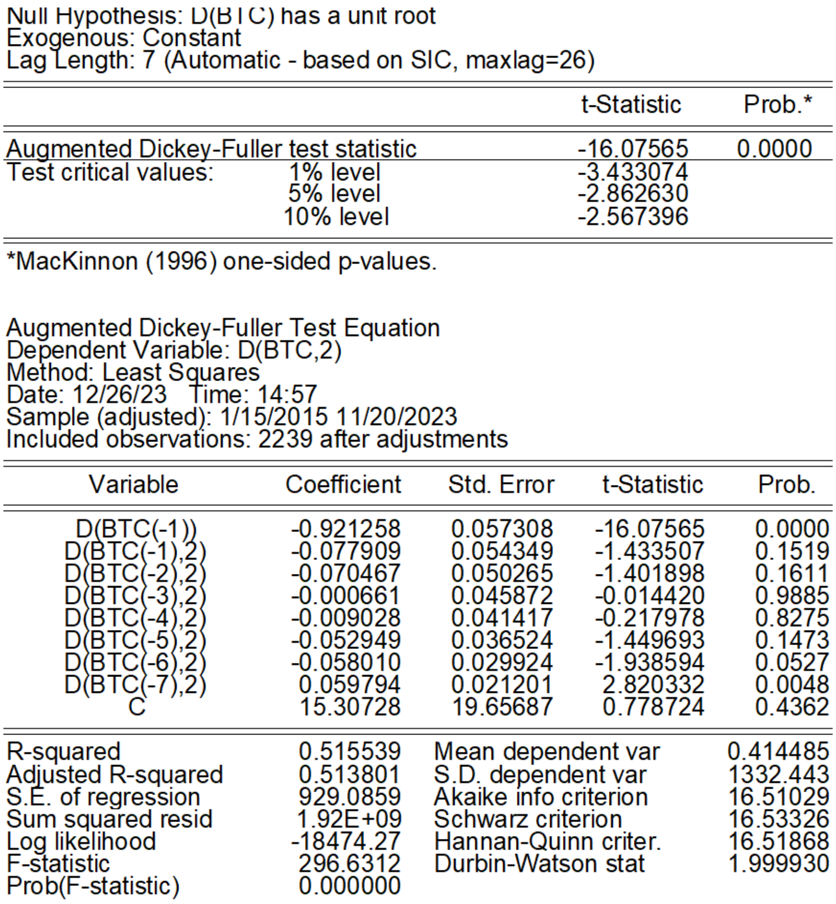
```
Null Hypothesis: BTC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=26)

                                              t-Statistic   Prob.*

Augmented Dickey-Fuller test statistic        -2.138971    0.5231
Test critical values:      1% level           -3.962130
                           5% level           -3.411808
                           10% level          -3.127793

*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC)
Method: Least Squares
Date: 12/26/23   Time: 14:56
Sample (adjusted): 1/05/2015 11/20/2023
Included observations: 2247 after adjustments

        Variable       Coefficient   Std. Error   t-Statistic   Prob.

        BTC(-1)        -0.003991     0.001866     -2.138971     0.0325
           C           -19.05736     41.18028     -0.462779     0.6436
@TREND("1/02/2015")     0.084107     0.046212      1.820034     0.0689

R-squared             0.002081    Mean dependent var      16.53846
Adjusted R-squared    0.001191    S.D. dependent var      937.4733
S.E. of regression    936.9148    Akaike info criterion   16.52440
Sum squared resid     1.97E+09    Schwarz criterion       16.53203
Log likelihood       -18562.16    Hannan-Quinn criter.    16.52718
F-statistic           2.339250    Durbin-Watson stat      2.009101
Prob(F-statistic)     0.096635
```

Figure A3. BTC unit root test (trend and intercept).



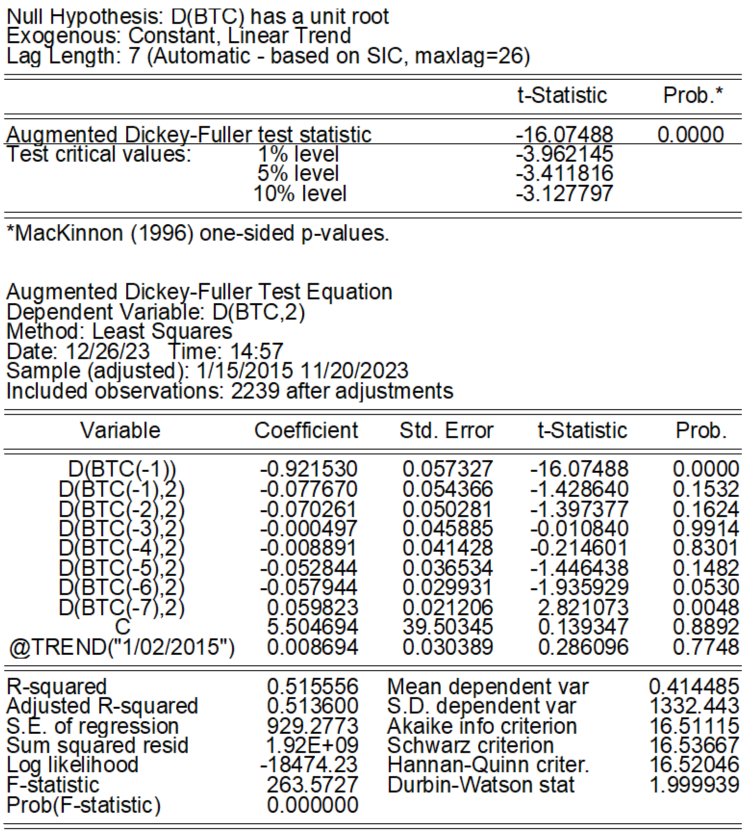
```
Null Hypothesis: BTC has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=26)

                                                t-Statistic    Prob.*

Augmented Dickey-Fuller test statistic           -0.293933    0.5801
Test critical values:        1% level            -2.565992
                             5% level            -1.940965
                             10% level           -1.616605

*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC)
Method: Least Squares
Date: 12/26/23   Time: 14:56
Sample (adjusted): 1/05/2015 11/20/2023
Included observations: 2247 after adjustments

      Variable         Coefficient    Std. Error    t-Statistic    Prob.

      BTC(-1)          -0.000266      0.000906      -0.293933      0.7688

R-squared              -0.000273    Mean dependent var         16.53846
Adjusted R-squared     -0.000273    S.D. dependent var         937.4733
S.E. of regression      937.6012    Akaike info criterion      16.52497
Sum squared resid       1.97E+09    Schwarz criterion          16.52752
Log likelihood         -18564.81    Hannan-Quinn criter.       16.52590
Durbin-Watson stat      2.011853
```

Figure A4. BTC unit root test (None).



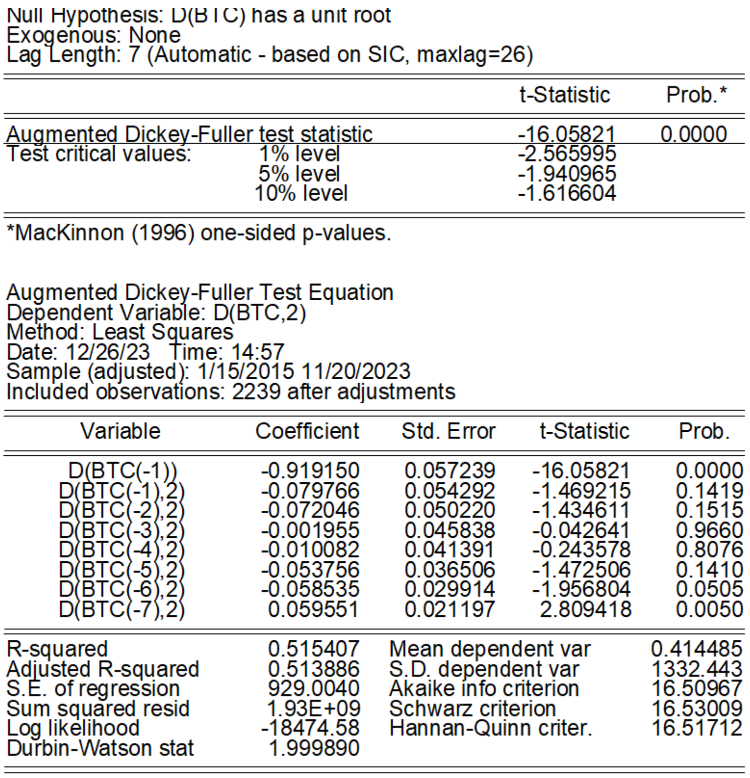
```
Null Hypothesis: D(BTC) has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=26)

                                                t-Statistic    Prob.*

Augmented Dickey-Fuller test statistic           -16.07565    0.0000
Test critical values:        1% level            -3.433074
                             5% level            -2.862630
                             10% level           -2.567396

*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC,2)
Method: Least Squares
Date: 12/26/23   Time: 14:57
Sample (adjusted): 1/15/2015 11/20/2023
Included observations: 2239 after adjustments

      Variable         Coefficient    Std. Error    t-Statistic    Prob.

     D(BTC(-1))        -0.921258      0.057308      -16.07565      0.0000
    D(BTC(-1),2)       -0.077909      0.054349      -1.433507      0.1519
    D(BTC(-2),2)       -0.070467      0.050265      -1.401898      0.1611
    D(BTC(-3),2)       -0.000661      0.045872      -0.014420      0.9885
    D(BTC(-4),2)       -0.009028      0.041417      -0.217978      0.8275
    D(BTC(-5),2)       -0.052949      0.036524      -1.449693      0.1473
    D(BTC(-6),2)       -0.058010      0.029924      -1.938594      0.0527
    D(BTC(-7),2)        0.059794      0.021201       2.820332      0.0048
         C              15.30728      19.65687       0.778724      0.4362

R-squared               0.515539    Mean dependent var         0.414485
Adjusted R-squared      0.513801    S.D. dependent var         1332.443
S.E. of regression      929.0859    Akaike info criterion      16.51029
Sum squared resid       1.92E+09    Schwarz criterion          16.53326
Log likelihood         -18474.27    Hannan-Quinn criter.       16.51868
F-statistic             296.6312    Durbin-Watson stat         1.999930
Prob(F-statistic)       0.000000
```

Figure A5. BTC unit root test in 1st difference (Constant).



```
Null Hypothesis: D(BTC) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 7 (Automatic - based on SIC, maxlag=26)
==========================================================================
                                                 t-Statistic    Prob.*
==========================================================================
Augmented Dickey-Fuller test statistic            -16.07488     0.0000
Test critical values:       1% level              -3.962145
                            5% level              -3.411816
                            10% level             -3.127797
==========================================================================
*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC,2)
Method: Least Squares
Date: 12/26/23   Time: 14:57
Sample (adjusted): 1/15/2015 11/20/2023
Included observations: 2239 after adjustments
==========================================================================
      Variable           Coefficient   Std. Error   t-Statistic    Prob.
==========================================================================
      D(BTC(-1))          -0.921530     0.057327    -16.07488     0.0000
     D(BTC(-1),2)         -0.077670     0.054366    -1.428640     0.1532
     D(BTC(-2),2)         -0.070261     0.050281    -1.397377     0.1624
     D(BTC(-3),2)         -0.000497     0.045885    -0.010840     0.9914
     D(BTC(-4),2)         -0.008891     0.041428    -0.214601     0.8301
     D(BTC(-5),2)         -0.052844     0.036534    -1.446438     0.1482
     D(BTC(-6),2)         -0.057944     0.029931    -1.935929     0.0530
     D(BTC(-7),2)          0.059823     0.021206     2.821073     0.0048
           C               5.504694     39.50345     0.139347     0.8892
@TREND("1/02/2015")        0.008694     0.030389     0.286096     0.7748
==========================================================================
R-squared                  0.515556   Mean dependent var        0.414485
Adjusted R-squared         0.513600   S.D. dependent var        1332.443
S.E. of regression         929.2773   Akaike info criterion     16.51115
Sum squared resid          1.92E+09   Schwarz criterion         16.53667
Log likelihood            -18474.23   Hannan-Quinn criter.      16.52046
F-statistic                263.5727   Durbin-Watson stat        1.999939
Prob(F-statistic)          0.000000
==========================================================================
```

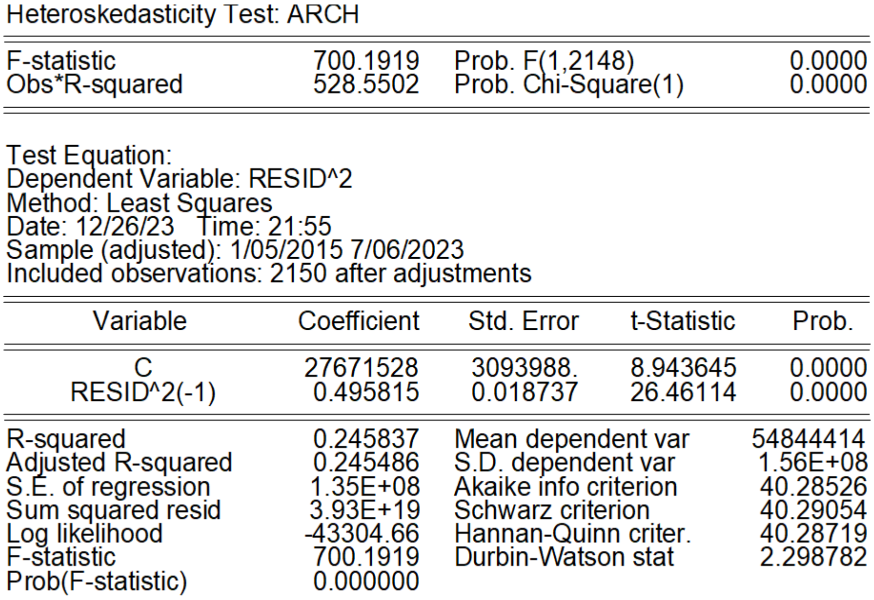
Figure A6. BTC unit root test in 1st difference (trend and intercept).



```
Null Hypothesis: D(BTC) has a unit root
Exogenous: None
Lag Length: 7 (Automatic - based on SIC, maxlag=26)
==========================================================================
                                                 t-Statistic    Prob.*
==========================================================================
Augmented Dickey-Fuller test statistic            -16.05821     0.0000
Test critical values:       1% level              -2.565995
                            5% level              -1.940965
                            10% level             -1.616604
==========================================================================
*MacKinnon (1996) one-sided p-values.


Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BTC,2)
Method: Least Squares
Date: 12/26/23   Time: 14:57
Sample (adjusted): 1/15/2015 11/20/2023
Included observations: 2239 after adjustments
==========================================================================
      Variable           Coefficient   Std. Error   t-Statistic    Prob.
==========================================================================
      D(BTC(-1))          -0.919150     0.057239    -16.05821     0.0000
     D(BTC(-1),2)         -0.079766     0.054292    -1.469215     0.1419
     D(BTC(-2),2)         -0.072046     0.050220    -1.434611     0.1515
     D(BTC(-3),2)         -0.001955     0.045838    -0.042641     0.9660
     D(BTC(-4),2)         -0.010082     0.041391    -0.243578     0.8076
     D(BTC(-5),2)         -0.053756     0.036506    -1.472506     0.1410
     D(BTC(-6),2)         -0.058535     0.029914    -1.956804     0.0505
     D(BTC(-7),2)          0.059551     0.021197     2.809418     0.0050
==========================================================================
R-squared                  0.515407   Mean dependent var        0.414485
Adjusted R-squared         0.513886   S.D. dependent var        1332.443
S.E. of regression         929.0040   Akaike info criterion     16.50967
Sum squared resid          1.93E+09   Schwarz criterion         16.53009
Log likelihood            -18474.58   Hannan-Quinn criter.      16.51712
Durbin-Watson stat         1.999890
==========================================================================
```

Figure A7. BTC unit root test in 1st difference (None).

Appendix C

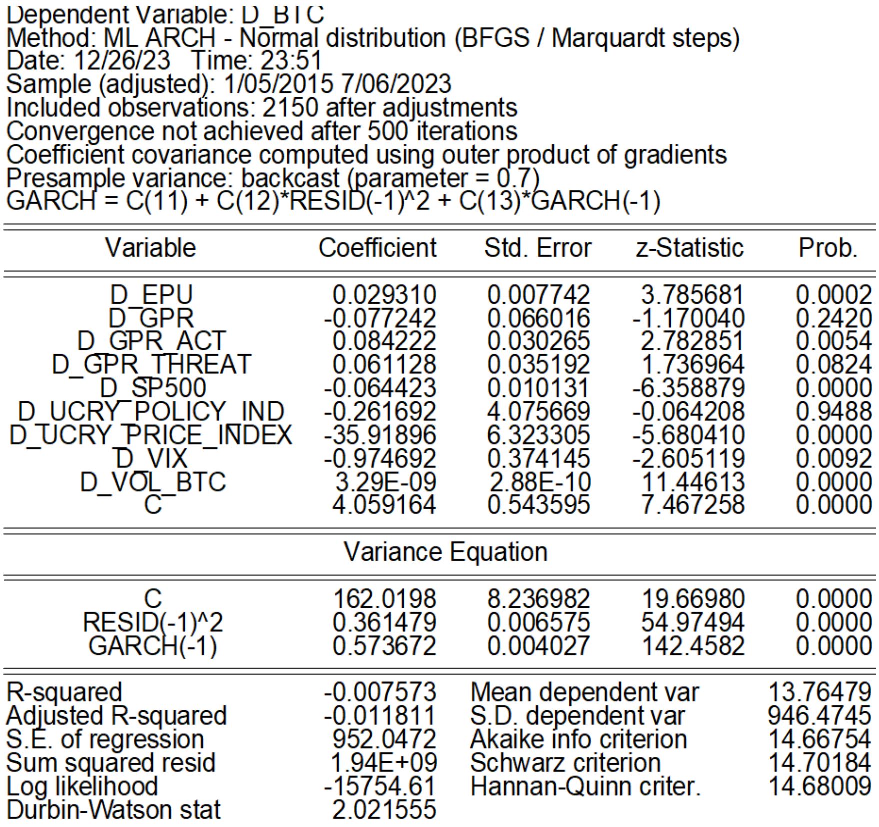


```
Heteroskedasticity Test: ARCH

F-statistic            700.1919    Prob. F(1,2148)          0.0000
Obs*R-squared          528.5502    Prob. Chi-Square(1)      0.0000


Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/26/23   Time: 21:55
Sample (adjusted): 1/05/2015 7/06/2023
Included observations: 2150 after adjustments

       Variable        Coefficient   Std. Error   t-Statistic    Prob.

          C             27671528     3093988.     8.943645      0.0000
      RESID^2(-1)       0.495815     0.018737     26.46114      0.0000

R-squared              0.245837    Mean dependent var      54844414
Adjusted R-squared     0.245486    S.D. dependent var      1.56E+08
S.E. of regression     1.35E+08    Akaike info criterion   40.28526
Sum squared resid      3.93E+19    Schwarz criterion       40.29054
Log likelihood        -43304.66    Hannan-Quinn criter.    40.28719
F-statistic            700.1919    Durbin-Watson stat      2.298782
Prob(F-statistic)      0.000000
```

Figure A8. Heteroskedasticity test.

Appendix D

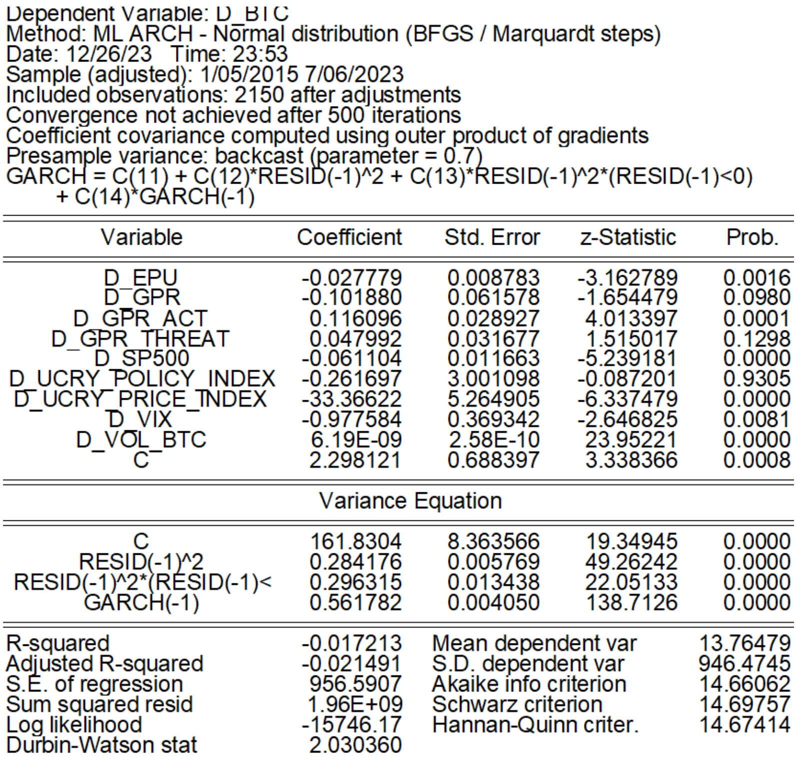
GARCH



```
Dependent Variable: D_BTC
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/26/23   Time: 23:51
Sample (adjusted): 1/05/2015 7/06/2023
Included observations: 2150 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*GARCH(-1)

         Variable            Coefficient   Std. Error   z-Statistic    Prob.

          D_EPU               0.029310     0.007742     3.785681      0.0002
          D_GPR              -0.077242     0.066016    -1.170040      0.2420
        D_GPR_ACT             0.084222     0.030265     2.782851      0.0054
       D_GPR_THREAT           0.061128     0.035192     1.736964      0.0824
         D_SP500             -0.064423     0.010131    -6.358879      0.0000
    D_UCRY_POLICY_IND        -0.261692     4.075669    -0.064208      0.9488
   D_UCRY_PRICE_INDEX        -35.91896     6.323305    -5.680410      0.0000
          D_VIX              -0.974692     0.374145    -2.605119      0.0092
        D_VOL_BTC             3.29E-09     2.88E-10     11.44613      0.0000
            C                 4.059164     0.543595     7.467258      0.0000

                               Variance Equation

            C                 162.0198     8.236982     19.66980      0.0000
       RESID(-1)^2            0.361479     0.006575     54.97494      0.0000
        GARCH(-1)             0.573672     0.004027     142.4582      0.0000

R-squared                    -0.007573    Mean dependent var      13.76479
Adjusted R-squared           -0.011811    S.D. dependent var      946.4745
S.E. of regression            952.0472    Akaike info criterion   14.66754
Sum squared resid             1.94E+09    Schwarz criterion       14.70184
Log likelihood               -15754.61    Hannan-Quinn criter.    14.68009
Durbin-Watson stat            2.021555
```

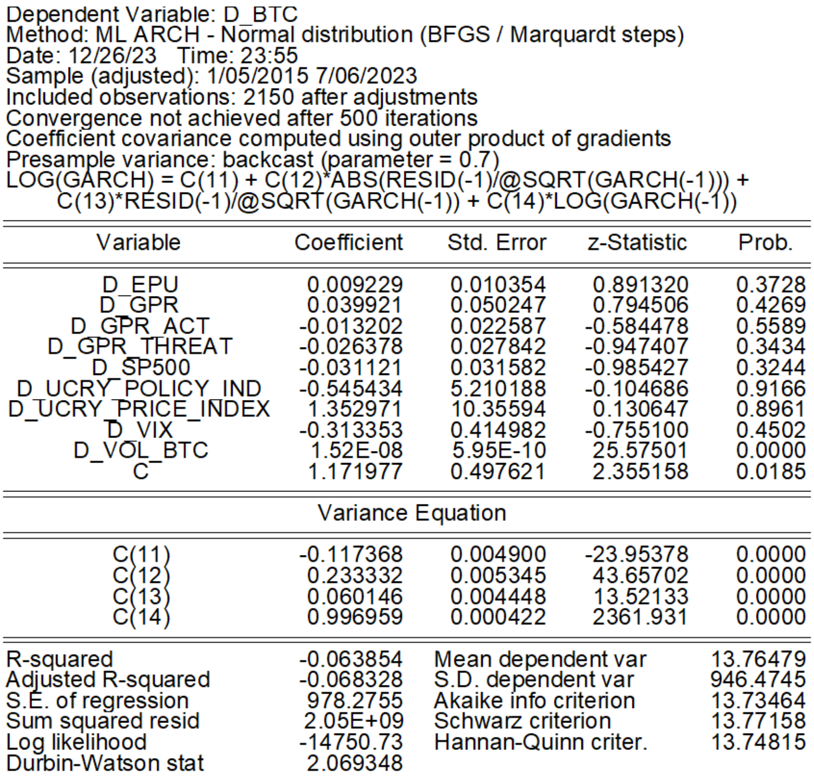
Figure A9. GARCH test.

GJR-GARCH



```
Dependent Variable: D_BTC
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/26/23   Time: 23:53
Sample (adjusted): 1/05/2015 7/06/2023
Included observations: 2150 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*RESID(-1)^2*(RESID(-1)<0)
        + C(14)*GARCH(-1)

        Variable            Coefficient   Std. Error   z-Statistic    Prob.

          D_EPU              -0.027779    0.008783    -3.162789     0.0016
          D_GPR              -0.101880    0.061578    -1.654479     0.0980
        D_GPR_ACT             0.116096    0.028927     4.013397     0.0001
      D_GPR_THREAT            0.047992    0.031677     1.515017     0.1298
         D_SP500             -0.061104    0.011663    -5.239181     0.0000
  D_UCRY_POLICY_INDEX        -0.261697    3.001098    -0.087201     0.9305
   D_UCRY_PRICE_INDEX        -33.36622    5.264905    -6.337479     0.0000
          D_VIX              -0.977584    0.369342    -2.646825     0.0081
        D_VOL_BTC             6.19E-09    2.58E-10     23.95221     0.0000
            C                 2.298121    0.688397     3.338366     0.0008

                          Variance Equation

            C                 161.8304    8.363566     19.34945     0.0000
        RESID(-1)^2           0.284176    0.005769     49.26242     0.0000
  RESID(-1)^2*(RESID(-1)<     0.296315    0.013438     22.05133     0.0000
        GARCH(-1)             0.561782    0.004050     138.7126     0.0000

R-squared                    -0.017213   Mean dependent var       13.76479
Adjusted R-squared           -0.021491   S.D. dependent var       946.4745
S.E. of regression            956.5907   Akaike info criterion    14.66062
Sum squared resid             1.96E+09   Schwarz criterion        14.69757
Log likelihood               -15746.17   Hannan-Quinn criter.     14.67414
Durbin-Watson stat            2.030360
```

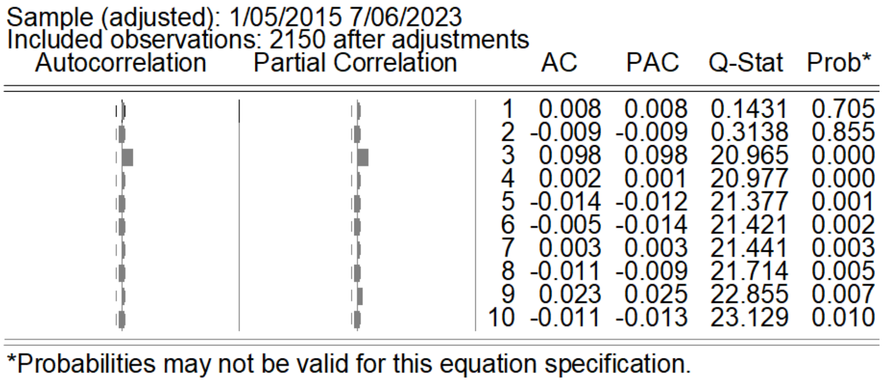
Figure A10. GJR-GARCH.



```
Dependent Variable: D_BTC
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/26/23   Time: 23:55
Sample (adjusted): 1/05/2015 7/06/2023
Included observations: 2150 after adjustments
Convergence not achieved after 500 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(11) + C(12)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
        C(13)*RESID(-1)/@SQRT(GARCH(-1)) + C(14)*LOG(GARCH(-1))

        Variable            Coefficient   Std. Error   z-Statistic    Prob.

          D_EPU               0.009229    0.010354     0.891320     0.3728
          D_GPR               0.039921    0.050247     0.794506     0.4269
        D_GPR_ACT            -0.013202    0.022587    -0.584478     0.5589
      D_GPR_THREAT           -0.026378    0.027842    -0.947407     0.3434
         D_SP500             -0.031121    0.031582    -0.985427     0.3244
    D_UCRY_POLICY_IND        -0.545434    5.210188    -0.104686     0.9166
   D_UCRY_PRICE_INDEX         1.352971    10.35594     0.130647     0.8961
          D_VIX              -0.313353    0.414982    -0.755100     0.4502
        D_VOL_BTC             1.52E-08    5.95E-10     25.57501     0.0000
            C                 1.171977    0.497621     2.355158     0.0185

                          Variance Equation

          C(11)              -0.117368    0.004900    -23.95378     0.0000
          C(12)               0.233332    0.005345     43.65702     0.0000
          C(13)               0.060146    0.004448     13.52133     0.0000
          C(14)               0.996959    0.000422     2361.931     0.0000

R-squared                    -0.063854   Mean dependent var       13.76479
Adjusted R-squared           -0.068328   S.D. dependent var       946.4745
S.E. of regression            978.2755   Akaike info criterion    13.73464
Sum squared resid             2.05E+09   Schwarz criterion        13.77158
Log likelihood               -14750.73   Hannan-Quinn criter.     13.74815
Durbin-Watson stat            2.069348
```

Figure A11. EGARCH.

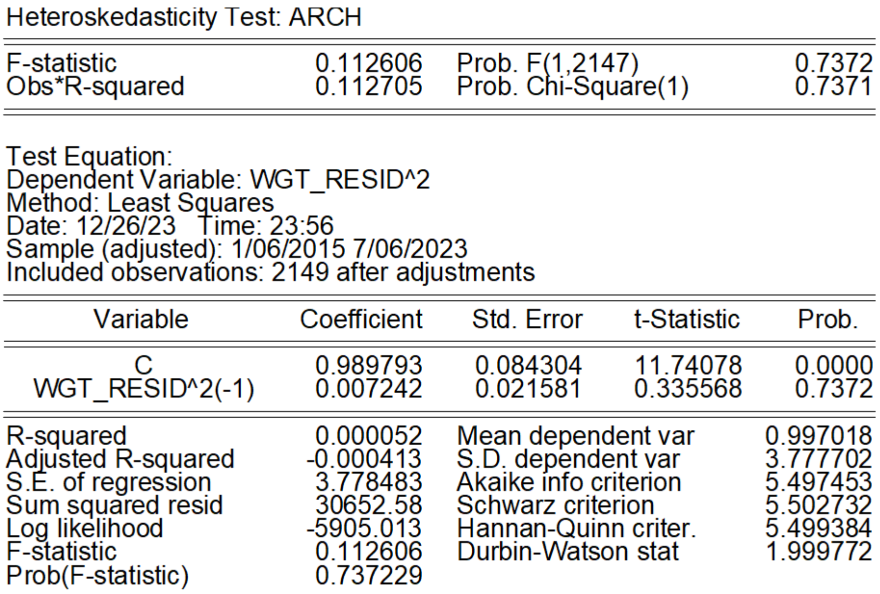
Appendix E



```
Sample (adjusted): 1/05/2015 7/06/2023
Included observations: 2150 after adjustments
   Autocorrelation    Partial Correlation         AC     PAC    Q-Stat  Prob*

                                             1  0.008   0.008  0.1431  0.705
                                             2 -0.009  -0.009  0.3138  0.855
                                             3  0.098   0.098  20.965  0.000
                                             4  0.002   0.001  20.977  0.000
                                             5 -0.014  -0.012  21.377  0.001
                                             6 -0.005  -0.014  21.421  0.002
                                             7  0.003   0.003  21.441  0.003
                                             8 -0.011  -0.009  21.714  0.005
                                             9  0.023   0.025  22.855  0.007
                                            10 -0.011  -0.013  23.129  0.010

*Probabilities may not be valid for this equation specification.
```

Figure A12. Autocorrelation test (EGARCH).

Appendix F



```
Heteroskedasticity Test: ARCH

F-statistic            0.112606    Prob. F(1,2147)          0.7372
Obs*R-squared          0.112705    Prob. Chi-Square(1)      0.7371


Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/26/23   Time: 23:56
Sample (adjusted): 1/06/2015 7/06/2023
Included observations: 2149 after adjustments

        Variable        Coefficient   Std. Error   t-Statistic    Prob.

           C             0.989793     0.084304     11.74078      0.0000
    WGT_RESID^2(-1)      0.007242     0.021581     0.335568      0.7372

R-squared               0.000052    Mean dependent var      0.997018
Adjusted R-squared     -0.000413    S.D. dependent var      3.777702
S.E. of regression      3.778483    Akaike info criterion   5.497453
Sum squared resid       30652.58    Schwarz criterion       5.502732
Log likelihood         -5905.013    Hannan-Quinn criter.    5.499384
F-statistic             0.112606    Durbin-Watson stat      1.999772
Prob(F-statistic)       0.737229
```

Figure A13. Heteroskedasticity test (EGARCH).

Appendix G

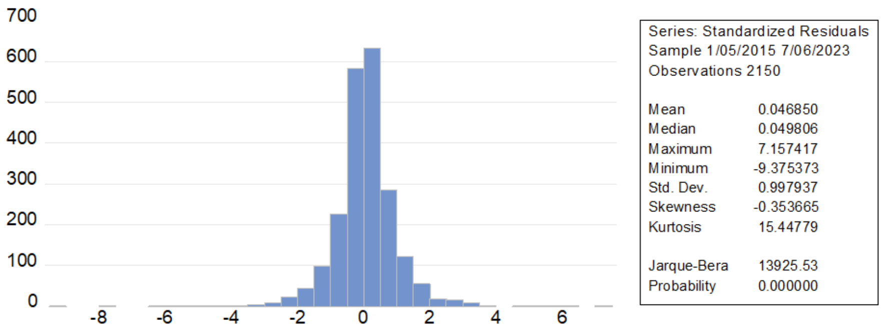


Figure A14. Histogram and normality test (EGARCH).