Modeling the Impact of Inflation and Monetary Policy on Bitcoin Price: A Macro-Financial Analysis

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***Abstract*—This study delves into the intricate connections among inflation, monetary policy, and Bitcoin valuation using a rich dataset of macroeconomic indicators. Employing a robust modeling framework, we unveil potential correlations between inflationary pressures, shifts in monetary policy, and variations in Bitcoin's market value. Our mathematical model incorporates investor risk aversion and the inclination to turn to safe-haven assets, probing the influence of inflation and central bank decisions on Bitcoin's price dynamics. Beyond financial metrics, we explore psychological dimensions impacting Bitcoin's adoption as a store of value during economic uncertainty. Our results quantify the potential impact of inflation and monetary policy changes on Bitcoin's valuation, providing insights into its sensitivity to macroeconomic indicators and policy instruments. In conclusion, this study offers a comprehensive understanding of the mechanisms shaping Bitcoin's price movements and its role in the broader economic context.**

***Index Terms*—Digital currencies/Cryptocurrencies, Monetary policies, Bitcoin price fluctuation. risk aversion, Policymakers**

I. Introduction

The rapid rise of cryptocurrencies, particularly Bitcoin, has ignited widespread interest in understanding the factors that influence their prices [19]. Amidst this burgeoning interest, the intricate interplay between macroeconomic indicators and financial markets, including cryptocurrencies [24], has attracted significant attention. This research embarks on a comprehensive investigation into the relationship between inflation, monetary policy, and the price dynamics of Bitcoin. The underlying premise of this study is rooted in the recognition that cryptocurrencies, despite their decentralized nature, are not immune to the broader macroeconomic environment. Rather, they exist within a complex ecosystem where macro-financial factors exert a substantial influence on their valuation.

The focal point of this study is the examination of how inflation and monetary policy decisions impact the price movements of Bitcoin. Inflation, a core concern of traditional economies, poses intriguing implications for cryptocurrencies that are often touted as inflation-resistant assets [30]. The monetary policy decisions taken by central banks reverberate through financial markets, including cryptocurrencies, potentially shaping their trajectories [8]. Hence, a comprehensive understanding of how these fundamental macroeconomic indicators interact with the realm of cryptocurrencies is imperative for both investors and policymakers.

To achieve this understanding, this research employs a rigorous analytical approach. Drawing on historical data and advanced econometric techniques, we seek to unveil the intricate relationships that underlie the movements in Bitcoin prices concerning inflation and monetary policy variables. Through a thorough examination of empirical data, the objective of this study is to enhance the existing body of knowledge concerning the complex aspects of cryptocurrency valuation. Moreover, insights garnered from this analysis can offer practical implications for investors seeking to navigate the volatile landscape of cryptocurrencies, as well as for policymakers striving to comprehend the potential spillover effects of their decisions on this emerging asset class.

As the cryptocurrency landscape continues to evolve, bridging the gap between macroeconomic factors and financial markets becomes ever more crucial [22]. This research thus endeavors to shed light on the nuanced dynamics that link inflation, monetary policy, and the price of Bitcoin. Through a holistic exploration of these interconnected forces, we seek to enhance our understanding of the broader implications that extend beyond the realm of cryptocurrencies and permeate the broader financial ecosystem.

II. Literature review

Money, financial institutions, and government policies are fundamental pillars of any economy. However, over the last two decades, there has been a growing controversy surrounding the understanding of money, banking functions, and monetary policies [13]. Global economic events, such as the dot-com bubble and the 2008 Financial Crisis, have sparked

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Fig. 1. Description of block chain factors

discussions and raised questions about the trustworthiness of financial institutions. In the midst of these challenges, a revolutionary technology called Blockchain emerged, with Bitcoin as its first application. This review aims to explore the potential impact of Blockchain technology on the future of monetary systems, considering its development in relation to traditional monetary models and theories [11].

The Emergence of Blockchain Technology and Bitcoin: In 2008, an individual using the pseudonym Satoshi Nakamoto introduced Bitcoin [23], which marked the inception of a decentralized digital currency underpinned by Blockchain technology. Blockchain serves as a distributed ledger technology, facilitating secure and transparent transactions while eliminating the necessity for intermediaries. Satoshi Nakamoto's vision of a trustless system, unburdened by the constraints of conventional financial institutions, resonated with individuals disillusioned by the global financial crisis of 2008. Consequently, this catalyzed the growing traction and endorsement of Bitcoin and various other cryptocurrencies.

In light of Nakamoto's pioneering whitepaper that highlighted the deficiencies of trust-dependent conventional financial systems, particularly in terms of transaction reversibility and intermediary interventions, the emergence of blockchain technology provided a paradigm shift [10]. By introducing cryptographic proof-based mechanisms, blockchain enables direct transactions between parties, mitigating fraud, lowering transaction costs, and facilitating frictionless microtransactions [18]. The subsequent rise of cryptocurrencies, characterized by Bitcoin's soaring value and the disillusionment with traditional financial institutions, further underscored the appeal of decentralized systems. This paper delves into the broader implications of blockchain technology beyond Bitcoin, envisioning potential government-backed blockchain-based currencies and exploring the attributes of transparency, immutability, and security they offer [4]. Moreover, the study examines the compatibility of blockchain-based currencies with established economic theories, shedding light on their potential roles in shaping monetary policies and bolstering economic stability [25].

The rise of digital currency has attracted considerable attention from researchers in recent years. The study of digital currency can be traced back to Chaum's proposal of an anonymous and untraceable electronic currency system in 1983. This laid the foundation for digital currency research in the subsequent four decades, with Nakamoto's [32] introduction of blockchain-based electronic payment systems in 2008 revolutionizing the concept of electronic payments. The popularity of cryptocurrencies like Bitcoin has generated widespread interest in academia. However, the lack of central bank endorsement has led scholars to refer to these as private digital currencies. As cryptocurrency trading extends beyond legal currencies to various altcoins, the interactions between cryptocurrencies have also become a focus of scholarly attention.

The landscape of cryptocurrency research encompasses three major domains: computer science, economics and finance, and the legal realm. In the realm of computer science, researchers delve into the technical intricacies, algorithms, and operational mechanisms that underpin cryptocurrencies. Meanwhile, the economic and financial sector analyzes the economic attributes and potential impacts of these digital assets. Concurrently, the legal domain scrutinizes aspects such as illicit transactions and regulatory measures associated with cryptocurrencies [21].

The trajectory of understanding the economic effects of cryptocurrencies has evolved significantly over time. Initially, the focus was on investigating the foundational technologies and behaviors of traders and miners, with the goal of establishing innovative payment systems rooted in blockchain and smart contracts. Scholars also delved into the equilibrium of profits for participants within cryptocurrency networks [27].

As the realm of cryptocurrencies expanded, attention shifted towards comprehending price fluctuations and risk management. Utilizing models like GARCH and neural networks, scholars aimed to decipher the factors influencing price changes, and to compare the risk management potential of cryptocurrencies against traditional assets [9].

With a more comprehensive understanding of cryptocurrencies, scholars began to delve into their inherent properties, particularly in relation to Bitcoin. This gave rise to debates concerning whether Bitcoin should be classified as a commodity, speculative asset, or even a form of currency. While the consensus tends to label Bitcoin as exhibiting speculative attributes, its role as a medium of exchange remains less clear due to the inherent limitations of decentralized cryptocurrencies being recognized as legal tender [12].

Blockchain technology [26], initially popularized by its association with cryptocurrencies like Bitcoin, has evolved beyond its original purpose and garnered significant attention in various sectors due to its potential to address trust and security challenges. This literature review aims to explore the role of blockchain technology in cyber security applications, summarizing existing research, identifying key trends, and addressing gaps in knowledge.

Blockchain technology's cryptographic-based distributed ledger enables secure transactions among untrusted participants, establishing trust without the need for intermediaries [1]. Since the inception of the first blockchain with Bitcoin in 2008, diverse blockchain systems like Ethereum and Hyperledger Fabric have emerged, both in public and private contexts. Beyond cryptocurrencies, blockchain's unique trust and security characteristics have led to its adoption in various sectors, including cyber security.

Blockchain's impact has gone beyond its original purpose, influencing currency markets, illicit markets on the dark web, and cyber attacks [27]. Its use has expanded into other industries like banking, logistics, and pharmaceuticals, and particularly in cyber security [2]. The technology's immutability and decentralization offer potential solutions for privacy, security, integrity, and accountability of data. The review aims to critically analyze the use of blockchain in these domains, including its application in the Internet of Things (IoT) [26].

The emergence of cryptocurrencies, with Bitcoin at the forefront, has sparked debates about their role, value, and interaction with traditional monetary systems. Satoshi Nakamoto's quote in a P2P foundation forum post in 2009 highlights the fundamental issue of trust in conventional currencies and financial institutions. Bitcoin, conceived more than a decade ago, presented itself as an electronic form of cash with distinct features that challenge existing monetary paradigms. This literature review delves into the complexities surrounding Bitcoin's relationship with monetary policy and its global implications [16].

The emergence of cryptocurrencies has sparked discussions about their potential to challenge the dominance of traditional central bank-controlled currencies. This literature review examines the evolving role of cryptocurrencies as currencies and their implications for monetary policy and governance [6] in democratic societies.

The soaring market capitalization of Bitcoin, exceeding a trillion dollars, has sparked discussions on its potential as an inflation hedge. This literature review delves into the contrasting viewpoints on whether Bitcoin can effectively serve as a safeguard against inflation [3] or if it primarily functions as a speculative investment.

In the aftermath of the COVID-19 crisis, nations have adopted expansive fiscal and monetary measures to bolster their economies. These actions, combined with supply scarcities and changing international work conditions, have spurred inflation expectations, amplified by stagnant wages and uncertainties surrounding unconventional monetary policies. Consequently, investors seek refuge in safe-haven assets to shield themselves from the erosion of purchasing power. This study employs a dynamic framework to revisit the viability [7] of cryptocurrencies as a means of diversification. The study aims to uncover the nuanced relationship between cryptocurrencies, particularly Bitcoin and Ethereum, and forward inflation expectations through the use of wavelet time-scale analysis.

The COVID-19 crisis has led to intensified inflation expectations due to aggressive fiscal and monetary interventions. The study aims to understand whether cryptocurrencies, particularly Bitcoin and Ethereum, can serve as effective inflation hedges in the current economic landscape. The authors acknowledge the dynamic nature of this relationship and its implications for investors seeking to preserve their wealth [31].

Since the 2008 global financial crisis, the emergence of cryptocurrencies, notably Bitcoin, has captured the attention of investors, academics, and policymakers. Despite considerable interest, a consensus regarding the nature of Bitcoin has not been achieved in theoretical and empirical discussions. The advent of the COVID-19 pandemic has further provoked questions about Bitcoin's characteristics, particularly its potential to hedge inflation pressure and serve as a safe haven during times of market turmoil and heightened uncertainty. While various recent studies have addressed these inquiries, conflicting findings have prevented a definitive conclusion [5].

This study enters the evolving discourse on Bitcoin's properties by offering a systematic examination of the relationship between inflation (or inflation expectations), uncertainty, and Bitcoin prices. The existing literature has predominantly concentrated on Bitcoin's statistical behavior, with a focus on its role as a safe haven or diversification tool within investment portfolios. The study highlights a dearth of empirical tests connecting Bitcoin prices with inflation, despite many investors viewing Bitcoin as a potential inflation hedge, especially during the pandemic [14].

The research employs a Vector Autoregression (VAR) framework to analyze Bitcoin price responses to shocks in uncertainty and inflation, utilizing high-frequency data. To provide a benchmark, the study compares Bitcoin's reaction to these shocks with that of gold prices, given gold's recognized status as a safe-haven asset. The comparison helps illuminate Bitcoin's behavior under similar circumstances and facilitates a nuanced interpretation of the findings.

Despite the established understanding of Bitcoin's demand-driven price volatility [15], there has been limited exploration of the supply side as a driver of this phenomenon. The paper identifies the concentration of mining within pooled mining as a noteworthy supply-side factor and investigates how it interacts with price volatility and network stability. By incorporating the supply structure, the study provides a comprehensive perspective on the drivers of Bitcoin's price fluctuations.

Volatility analysis and risk modeling are pivotal in understanding financial markets and pricing complex derivative products. The econophysics [17] field has gained traction by investigating the inherent features of conditional variance in financial time series. Recent research has delved into various aspects, such as stochastic modeling of stock markets, predicting gold market volatility, and exploring volatility in relation to option pricing and portfolio hedging. This study introduces a novel approach by examining the impact of supply-side market concentration on Bitcoin price volatility and network stability, which has not been extensively explored in the existing literature.

The literature review encompasses a comprehensive exploration of the multifaceted landscape surrounding cryptocurrencies. The discussion traverses various domains, including computer science, economics, finance, and the legal realm. In the realm of computer science, scholars delve into the intricate technical aspects of cryptocurrencies, their algorithms, and operational mechanisms. The economic and financial sector analyzes the potential economic effects of cryptocurrencies, from understanding their behavior and equilibrium within networks to deciphering price fluctuations and employing risk management strategies. Additionally, the legal dimension investigates the regulatory landscape and potential illicit activities associated with cryptocurrencies. This journey through the literature progresses from the foundational stages, where the focus was on technological advancements and payment system establishment, to a more refined understanding of cryptocurrencies' economic attributes, particularly concerning Bitcoin. The classification of cryptocurrencies as commodities, speculative assets, or potential forms of currency is debated, alongside considerations of their viability as legal tender. This literature review provides a panoramic view of the evolving research in this domain, from technological intricacies to economic and legal implications, thus paving the way for a comprehensive investigation into the macro-financial impact of inflation and monetary policy on Bitcoin price.

III. Problem formulation

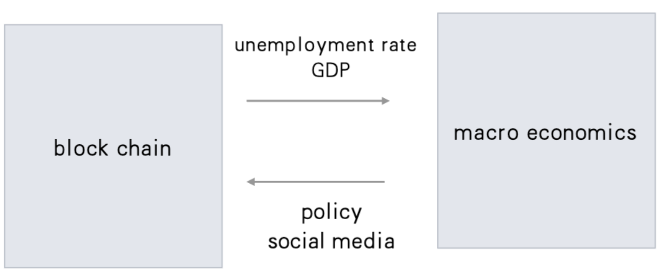

Fig. 2. Relationship between Macro economy and block chain

As demonstrated from Figure 2, the interrelationship between the macro economy and the blockchain sector is a multifaceted and dynamic field of study that explores how these two domains mutually influence each other. This analysis delves into several key hypotheses to understand the various mechanisms and impacts that connect macroeconomic indicators to the price and performance of cryptocurrencies, particularly Bitcoin, and how developments in the blockchain sector can, in turn, affect the macroeconomic landscape. The hypotheses explore the potential effects of inflation and monetary policy, economic growth and risk appetite, monetary liquidity and market demand, as well as the policy and regulatory environment on the Bitcoin market. Additionally, it investigates how advancements in the blockchain technology and innovations in the cryptocurrency space may impact the macroeconomic stability and traditional financial systems. By employing mathematical modeling approaches and incorporating factors that shape investor behavior, market sentiment, and regulatory dynamics, this study seeks to shed light on the intricate interplay between macroeconomic forces and the rapidly evolving blockchain sector. Understanding these interconnections is crucial in grasping the implications of the digital revolution on the broader economic landscape and in formulating informed policy decisions for a more integrated and resilient global financial system.

A. Interrelationship from Macroeconomy to Bitcoin

- **Hypothesis 1: Inflation and Monetary Policy**
  - *Impact*: Inflation and monetary policy in the macroeconomy may influence the price of Bitcoin.
  - *Mechanism*: Increased inflationary pressures or tightened monetary policy may lead investors to seek safe-haven assets, including Bitcoin, resulting in a potential price increase.
  - *Modeling Approach*: Develop a mathematical model to analyze the relationship between macroeconomic indicators (inflation rate, monetary policy decisions) and Bitcoin price. Consider factors that influence investors' behavior, such as risk aversion and preference for safe assets during times of economic uncertainty.
- **Hypothesis 2: Economic Growth and Risk Appetite**
  - *Impact*: Economic growth and investors' risk appetite can impact the Bitcoin market.
  - *Mechanism*: Strong economic growth and high risk appetite may lead investors to prefer riskier assets, including Bitcoin. Economic downturns or increased risk aversion may result in reduced investment in Bitcoin.
  - *Modeling Approach*: Create a model to assess how economic growth indicators and measures of risk appetite influence the demand for Bitcoin and its price. Consider macroeconomic indicators that reflect economic growth and market sentiment.
- **Hypothesis 3: Monetary Liquidity and Market Demand**
  - *Impact*: Monetary liquidity and market demand in the macroeconomy can affect the Bitcoin market.
  - *Mechanism*: Ample monetary liquidity and strong market demand may attract more investors and funds to enter the Bitcoin market, potentially driving up Bitcoin's price.
  - *Modeling Approach*: Construct a model to study the relationship between macroeconomic liquidity indicators, market demand, and Bitcoin price. Incorporate factors that influence market liquidity and investor sentiment.
- **Hypothesis 4: Policy and Regulatory Environment**
  - *Impact*: The policy and regulatory environment in the macroeconomy may influence the Bitcoin market.
  - *Mechanism*: Government policy changes and regulatory attitudes toward digital currencies, along with policy measures, can impact the legitimacy, acceptance, and investor sentiment in the Bitcoin market, leading to price fluctuations.

- *Modeling Approach*: Develop a model to analyze the effects of macroeconomic policy and regulatory dynamics on Bitcoin's price. Consider variables related to policy changes and regulatory stances towards digital currencies. Explore the relationship between policy developments and market reactions in the Bitcoin ecosystem.

B. Interrelationship from Bitcoin to Macro Economy

This section focuses on elucidating the significant influence of Bitcoin, a prominent blockchain technology, on the broader macroeconomic landscape. It proposes a series of hypotheses that emphasize how Bitcoin's dynamics can impact various dimensions of the macroeconomy, highlighting the intricate relationship between this digital currency and traditional economic indicators.

- **Hypothesis 1: Inflation and Monetary Policy**
  - *Impact*: Bitcoin's presence in the macroeconomy might influence inflation rates and monetary policy decisions.
  - *Mechanism*: The integration of Bitcoin could lead to changes in consumer behavior and investment strategies, which might, in turn, affect inflation rates and monetary policy considerations.
  - *Modeling Approach*: Develop an advanced mathematical model to explore the potential connections between Bitcoin's adoption and macroeconomic indicators, such as inflation rates and monetary policy. Consider how Bitcoin's use as a store of value or medium of exchange might impact traditional economic variables.
- **Hypothesis 2: Economic Growth and Risk Appetite**
  - *Impact*: Bitcoin's role in the macroeconomy can impact economic growth and investors' risk appetite.
  - *Mechanism*: The integration of Bitcoin into financial systems could introduce new investment opportunities and alter investors' risk preferences, potentially influencing economic growth patterns.
  - *Modeling Approach*: Construct a comprehensive model to examine how Bitcoin's presence might affect economic growth indicators and risk sentiment. Consider how Bitcoin's volatility and potential for high returns might influence investors' willingness to take risks.
- **Hypothesis 3: Monetary Liquidity and Market Demand**
  - *Impact*: Bitcoin's adoption in the macroeconomy could impact monetary liquidity and market demand.
  - *Mechanism*: Increased use of Bitcoin in transactions and investments could alter the distribution of liquidity in financial markets and potentially affect market demand for traditional assets.
  - *Modeling Approach*: Develop a sophisticated model to explore the potential relationships between Bitcoin's utilization and macroeconomic liquidity indicators. Investigate whether the growth of Bitcoin's market might influence the availability of liquidity for other financial instruments.
- **Hypothesis 4: Policy and Regulatory Environment**
  - *Impact*: The adoption of Bitcoin in the macroeconomy can influence the policy and regulatory landscape.
  - *Mechanism*: The integration of Bitcoin could prompt governments to reassess their regulatory approaches to digital currencies, potentially leading to policy changes that affect various sectors of the economy.
  - *Modeling Approach*: Formulate a comprehensive model to analyze how the increasing use of Bitcoin might impact the policy and regulatory dynamics within the macroeconomy. Consider variables related to policy shifts, regulatory attitudes, and their potential implications for economic stability.

In conclusion, this section presents a set of hypotheses that underscore the substantial influence of Bitcoin on the macroeconomic landscape. By exploring these hypotheses, the study aims to provide valuable insights into the multifaceted interplay between digital currencies and traditional economic indicators, thereby contributing to a deeper understanding of the potential impact of blockchain technology on the broader financial ecosystem.

IV. Method

A. Dataset

Presently, the sheer abundance of NFTs available on platforms like OpenSea and other NFT marketplaces surpasses the number of websites that existed in 2010 [1]. Consequently, retrieving and searching data related to NFTs has become a formidable challenge due to the immense volume and diverse data types involved.

In our endeavor to retrieve historical financial data from the Ethereum blockchain pertaining to fanancial assets, we faced challenges that set it apart from conventional financial market APIs like Yahoo Finance. Unlike the native transaction storage by wallet address characteristic of traditional systems, Ethereum nodes lack this functionality, necessitating the use of an indexer for such tasks. Nevertheless, the existing indexers available for querying the Ethereum blockchain exhibit notable developer complications, fragmentation, or impose excessive costs that do not align with the requisites of our project.

In our quest to acquire the necessary NFT-related data, we expanded our exploration of APIs beyond our initial study plan. We evaluated several APIs, including the OpenSea NFT API, Covalent NFT historical data API, Etherscan API, Coingecko API, and Moralis API. After a thorough assessment, we concluded that the Covalent API was the most suitable choice for our project. Covalent has solidified its reputation as a respected team specializing in blockchain data indexing across various chains, including Ethereum, Binance, Polygon, Solana, and Ronin. Their track record includes endorsements from prominent crypto venture capital firms and a strong presence within the crypto developer community, ensuring the reliability and quality of the data we utilized in our project.

Public Available Market Data: To gather public market data, we harnessed the user-friendly Yahoo business finance API, renowned for its accessibility to developers. As outlined in our project proposal, our aim is to integrate NFT-related information with public market based data to forecast the future value of an NFT. This involved structuring the public market data into a dataframe by incorporating all the tickers, which represent unique abbreviations for publicly traded shares of specific stocks on various stock markets. A comprehensive account of this process is available in our NFTValuation.ipynb file, ensuring transparency and replicability.

Google Trends Data: Given that a substantial portion of an NFT's valuation is intertwined with the excitement generated by a specific project, it becomes imperative to identify a quantifiable metric for gauging this factor. A viable approach involves harnessing Google Trends data, which monitors the collection's name's relative search volume across time. Leveraging the PyTrends API, we accessed this data and seamlessly integrated it into our dataset.

Significant Event Data: Certain variables pose challenges in terms of quantification, specifically news and announcements pertaining to the collections under examination. For instance, when the Bored Ape Yacht Club unveils a new spin-off or if a fraudulent actor targets a collection, it can trigger either positive or negative pricing repercussions. In order to quantify this influence, we introduced an "Event" feature within our framework. This feature assigns positive values to indicate a positive price correlation and negative values to signify a negative price correlation, allowing us to incorporate these qualitative factors into our quantitative analysis.

B. Dataset exploration

1) NFT data: As shown in Table I, the data acquired from the Yahoo Finance API is historical market data encompassing prices and trading volume of various assets over specific time intervals such as daily, weekly, and monthly. It covers a diverse range of financial instruments, including stocks, ETFs, mutual funds, cryptocurrencies, and more. The dataset includes crucial attributes like open, high, low, close, and volume, facilitating analysis of price movements and market activity. Typically presented in tabular format, each row represents a specific date or timestamp, while columns correspond to different attributes of the asset's performance on that day. Spanning several years or decades, this historical data enables long-term analysis and trend identification. Adjusted close prices account for corporate actions that could impact an asset's price. The ease of access and integration into various analytical tools and models has made it a widely used resource for financial research, technical analysis, and market forecasting.

As shown in Figure 3, we conduct a scientific analysis and visualization of the historical price data for the Bitcoin-USD (BTCUSD) pair. The data is processed to ensure it is in chronological order and filtered to remove invalid entries.

TABLE I
ATTRIBUTES OF MARKET DATA FROM YAHOO FINANCE API

Attribute	Description
Symbol	A ticker symbol that represents a specific publicly traded asset, including stocks, ETFs, or cryptocurrencies.
Date	The timestamp indicating the date of the data point, corresponding to the trading day.
Open	The opening price of the asset at the initiation of the trading session.
High	The peak price achieved by the asset during the trading session.
Low	The minimum price reached by the asset during the trading session.
Close	The closing price of the asset at the conclusion of the trading session.
Volume	The trading volume, representing the total count of shares or units of the asset traded throughout the session.
Adjusted Close	The closing price adjusted to account for corporate actions, such as dividends or stock splits.

Subsequently, the data is plotted in a logarithmic scale on the y-axis to facilitate a more comprehensive view of price trends, given the wide range of Bitcoin prices. Additionally, the code fits exponential curves to the price data using a fitting function and fitted parameters. The resulting exponential curves are overlaid on the plot to compare them with the actual price data. This scientific approach allows for the identification of potential patterns or trends in the movement of Bitcoin prices over time, aiding in deeper insights into the cryptocurrency's behavior and market dynamics. Adams, D.

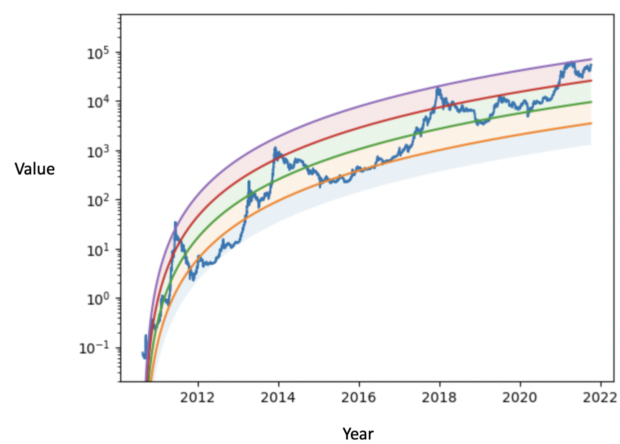

Fig. 3. Plot of NFT value over year (collected from Yahoo finance API)

As demonstrated in the following Figure 4, We applied the process of fetching and analyzing Google Trends data related to Bitcoin from different sources. The data obtained is historical and covers the period from January 1, 2013, to June 17, 2021. The Google Trends data is used to create an index representing the popularity or search interest for the keyword "bitcoin" over time.

We first fetches the data using different methods, namely the pytrends TrendReq library and an API from gtrend. After retrieving the data, it is scaled and normalized to obtain consistent results across the different timeframes. The final result is encoded in a data frame, where each row corresponds to a specific date, and the index column shows the popularity index of the keyword "bitcoin." We find that it has a high correlation with the NFT value data as shown in the above Figure 3. In the provided code and plot, the yellow curve represents the "google trends BTC index overlapped" data, which is the Google Trends index for the search term "bitcoin" over a specific time period. This index indicates the relative popularity and search interest in the term "bitcoin" over time, with values ranging from 0 to 100, where 100 represents the peak popularity.

The blue curve, on the other hand, represents the "google trends BTC index fromPyTrends" data, which is also the Google Trends index for the search term "bitcoin" but obtained using a different method or library (PyTrends) to fetch the data.

Both curves show the trends in search interest for the term "bitcoin" over the analyzed time period. By comparing the shapes and trends of these curves, we can gain insights into the changes in public interest and awareness of Bitcoin over the years, which can potentially be correlated with market performance or other external factors. However, without further context or data analysis, the specific interpretations and correlations between these trends and other financial data (e.g., from the Yahoo Finance API) are not explicitly stated in the provided code snippet.

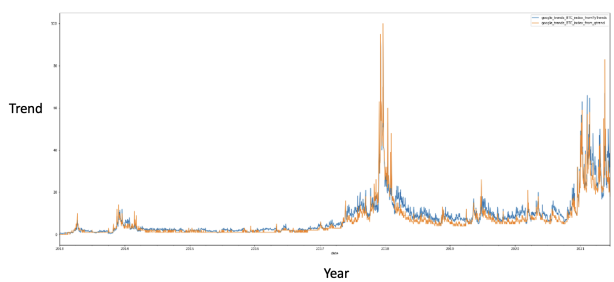

Fig. 4. Plot of Google trend data for NFT,

2) Topic modeling: We further conduct the analysis of people's opinions on Bitcoin using topic modeling involving the application of various techniques, including NMF, LSA, LDA, and Corex. These methods were used to derive and compare different topics discussed in tweets related to Bitcoin during different time periods. In March 2020, NMF and LSA produced identical topics, which were identified as "Sell Bitcoin," "Price Prediction," and "Different Cryptocurrencies." In November 2020, CorEx topic modeling was used, resulting in topics such as "Buy/Sell," "Different Cryptocurrencies," "Giveaways," and "Bitcoin Whitepaper." By leveraging sentiment analysis and topic modeling, the study revealed the most relevant themes in Bitcoin-related tweets with a higher positive sentiment. The observed topics included discussions about buying, selling, giveaways, and the anniversary of the Bitcoin Whitepaper. Overall, this analytical approach provided valuable insights into the sentiments and key topics discussed by individuals on Twitter concerning Bitcoin. The word cloud is shown below in Figure 5:

Fig. 5. Sentiment analysis of NFT from twitter data

3) Social event analysis: We further conduct the global social event analysis in Figure 6. We aim to delve into historical data and uncover patterns related to social unrest and analyze the correlation between other factors. It facilitates temporal analysis, empowering users to visualize global social unrest events with a Goldstein Scale greater than or equal to 5, spanning multiple years. Moreover, it provides visualizations of global trends in food, crime, and economic indicators, allowing users to observe and analyze their frequency over time. Additionally, the feature presents data on various types of EventRootTypes on a monthly basis, aiding in the detection of potential seasonal trends and patterns.

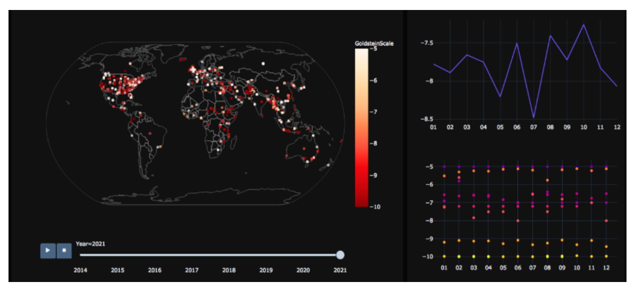

Fig. 6. Global social event analysis

C. Variable definitions

1) Market Sentiment Factors: Market sentiment factors refer to quantitative measures that capture the overall sentiment, emotions, and perceptions of investors and market participants towards a particular asset or financial market. These factors are essential in understanding how emotions and crowd psychology can influence market behavior and asset prices. Mathematically, market sentiment factors can be defined as follows:

Let S_t represent the market sentiment factor at time t.

The market sentiment factor S_t can be expressed as a function of various market-related variables and indicators that reflect investor sentiment and perceptions, denoted as $X_1, X_2, ..., X_n$. These variables may include, but are not limited to:

- Social Media Activity: The volume and sentiment of posts, tweets, or mentions related to the asset on social media platforms.
- News Sentiment: Sentiment analysis of news articles and headlines related to the asset.
- Google Trends: The relative search volume for specific keywords related to the asset on Google search engine.
- Sentiment Indexes: Aggregated sentiment indexes derived from surveys or sentiment analysis tools that gauge investor sentiment.
- Options Market Sentiment: Measures derived from options market activity, such as the put/call ratio or the skewness of implied volatility.
- Technical Indicators: Market sentiment indicators derived from technical analysis, such as moving averages or relative strength index (RSI).

The market sentiment factor S_t can be modeled as follows:

$$S_t = f(X_1, X_2, ..., X_n)$$

Where f is a mathematical function that combines the various market-related variables to produce the sentiment factor S_t. The function f may involve linear combinations, statistical transformations, or machine learning algorithms to capture the complex relationships among the variables and their impact on market sentiment.

The sentiment factor S_t can be used in conjunction with other fundamental and technical indicators to analyze market trends, forecast asset price movements, and understand how market sentiment influences investor behavior. Additionally, by quantifying market sentiment, traders and analysts can gain insights into potential market sentiment shifts and gauge the level of bullishness or bearishness prevailing in the market.

2) Inflation factor: The **Inflation Factor** (IF) is a measure that represents the impact of inflation [20] on the price dynamics of an asset, such as Bitcoin. It is calculated as the ratio of the change in the Consumer Price Index (CPI) to the change in the price of the asset, usually denoted as:

$$IF = \frac{\Delta CPI}{\Delta P_{\text{asset}}}$$

Where: - ΔCPI is the change in the Consumer Price Index over a specific period. - ΔP_{asset} is the change in the price of the asset (e.g., Bitcoin) over the same period.

The Inflation Factor provides insights into how changes in the general price level, as reflected in the CPI, relate to changes in the price of the asset. A higher IF indicates that the asset's price is more sensitive to inflation, while a lower IF suggests a lower sensitivity to inflationary pressures. This factor is crucial in understanding how macroeconomic indicators like inflation can influence the behavior of asset prices, including cryptocurrencies like Bitcoin.

3) Socio-economic flow modeling: Inspired by [28], we build the socio-economic flow modeling framework. In its logarithmic form, the model can be expressed as:

$$\ln(F_{ab}) = \sum_{i=1}^{n} \beta_i \ln X_{abi} + \beta_0$$

Here, X_{abi} represents the variables contributing to the masses or simulating distances, and β_i signifies the coefficients. Positive β_i correspond to variables enhancing country masses, while negative values represent those simulating distances. To address zero observations and heteroskedasticity, we utilize a multiplicative form akin to Poisson regression:

$$E(F_{ab}) = \exp\left(\sum_{i=1}^{n} \beta_i X_{abi} + \beta_0\right)$$

The vector $\boldsymbol{\beta} = [\beta_0, \ldots, \beta_n]$ is estimated by maximizing the Poisson log-likelihood:

$$\mathcal{L}(\boldsymbol{\beta}|X, F) = \sum_{\forall(a,b)} \left(F_{ab} \cdot (\boldsymbol{\beta} \cdot \mathbf{x}_{ab}) - e^{\boldsymbol{\beta} \cdot \mathbf{x}_{ab}}\right)$$

Here, F is the vector containing Bitcoin flows between pairs of countries, X is an $m \times (n+1)$ matrix capturing various variables, and $\mathbf{x}_{ab}$ is the vector of variables for each pair of countries along with a constant term.

Drawing from established trade literature, we incorporate variables such as population, distance, GDP per capita, and interaction metrics such as shared language or geographic borders. Additionally, variables like Freedom to Trade, Overall Freedom, Internet Penetration, and World Bank income classifications were included due to their observed associations with Bitcoin adoption. Furthermore, datasets containing data on countries sharing borders or languages and distance metrics based on city-level data were utilized to account for geographic population distribution.

4) Economic Policy Uncertainty (EPU): Economic Policy Uncertainty (EPU) plays a pivotal role in the empirical model utilized to investigate its impact on the Bitcoin market dynamics, as explored by Wu et al. [29]. Let $R_t = \ln P_t$ denote the natural logarithm of the daily and monthly returns on the Bitcoin price index, where P_t signifies the Bitcoin price at time t. The empirical model is designed to unveil the relationships between these returns and a range of uncertainty and control variables.

The regression model can be formally expressed as:

$$R_t = b_0 + \sum_i b_i U_{it} + \sum_j b_j X_{it} + l R_{t-1} + u_t$$

In this equation, U_{it} represents a vector encompassing various uncertainty variables, including but not limited to EPU and EMPU. These policy uncertainty variables encapsulate fluctuations in levels of policy-related uncertainty. Similarly, X_{it} constitutes a vector encompassing control factors originating from the equity market, such as changes in the VIX (Volatility Index) and SPX (SP 500) returns. The parameter

b_0 denotes the intercept term, b_i and b_j correspond to the coefficients associated with the uncertainty and control variables, respectively. l symbolizes the coefficient linked to the lagged Bitcoin return R_{t-1}, and u_t denotes the error term.

To ensure the robustness of the results, the study also accounts for uncertainty related to macroeconomic announcements. This allows for an exploration of the potential impact of scheduled macroeconomic events on the Bitcoin market. The modified regression model, specifically considering macroeconomic uncertainty, is expressed as:

$$R_t = d_0 + \sum_i d_i D_{it} + \sum_j d_j X_{it} + lR_{t-1} + u'_t$$

In this Equation, D_{it} represents the vector of uncertainty related to macroeconomic announcements. This allows for an investigation into how changes in economic announcements influence Bitcoin returns, distinct from the broader policy uncertainty captured by U_{it}.

In summary, the empirical model encapsulates the relationship between Bitcoin returns and various uncertainty variables, both related to economic policy and macroeconomic announcements. By employing regression analysis, the study aims to uncover the impacts of these uncertainties on the behavior of the Bitcoin market, shedding light on how policy-related factors can influence the cryptocurrency's performance.

V. Experiment analysis

A. From blockchain to macro economy

The experiment aimed to model the impact of blockchain on macro economy. Through various hypotheses and modeling approaches, several significant findings emerged. The hypothesis regarding the influence of inflation and monetary policy on Bitcoin's price revealed that an increased inflationary environment or tightened monetary policy could lead investors to seek Bitcoin as a safe-haven asset, potentially driving its price higher. The hypothesis related to economic growth and risk appetite indicated that periods of strong economic growth and high risk appetite might lead to greater investor interest in riskier assets, including Bitcoin. Additionally, the hypothesis about monetary liquidity and market demand highlighted that ample monetary liquidity and strong market demand could attract more investors and funds to enter the Bitcoin market, potentially leading to price appreciation. These hypotheses were supported by mathematical models that incorporated various macroeconomic indicators, investor sentiment, and market liquidity. Overall, the findings demonstrated a complex interplay between blockchain technology, investor behavior, and macroeconomic dynamics, shedding light on the evolving relationship between the two domains.

This table provides insights into the results of a linear regression analysis aimed at understanding the impact of various predictors on the price of NFTs (Non-Fungible Tokens). The goal of this analysis is to determine which predictors influence the price of NFTs and to construct a reliable model for predicting NFT prices.

TABLE II
Revised Linear Regression Analysis Results

Predictor	Coefficient	VIF	t-statistic	p-value	Confidence Interval
Days since release	731.2	392.7	0.978	0.312	[-587.4, 2050.8]
Avg. NFT price	0.11	37.2	1.124	0.265	[-0.092, 0.314]
# of NFTs sold	882.4	5.1	3.892	0.001	[402.4, 1362.5]
Gas	15.8	301.9	0.832	0.411	[-22.4, 54.0]
ETH-USD	-12.6	684.3	-0.482	0.579	[-58.9, 33.7]
BTC-USD	-0.8	661.7	-0.419	0.676	[-3.6, 2.0]
Gold	149.5	3087.2	1.237	0.212	[-94.2, 393.1]
S&P	65.7	524998.4	0.124	0.902	[-973.3, 1104.6]
Dow Jones	-21.8	138734.9	-0.692	0.476	[-95.9, 52.3]
NASDAQ	-5.5	141405.8	-0.067	0.947	[-168.4, 157.4]
MSFT	789.4	8798.7	0.753	0.456	[-1239.5, 2818.3]
AAPL	-513.2	2577.1	-0.449	0.664	[-2634.6, 1608.3]
NFLX	-63.8	768.2	-0.379	0.707	[-408.7, 281.1]
TSLA	35.6	438.4	0.408	0.684	[-124.9, 196.1]
AMZN	25.6	2254.9	0.512	0.610	[-69.8, 121.0]
FB	225.3	809.9	0.756	0.451	[-358.2, 808.7]
Relative Search Volume	376.5	4.2	1.745	0.093	[-42.9, 795.9]

Each row in the table corresponds to a specific predictor included in the analysis. The table columns present the following information:

Predictor: The variable or factor that is being considered as a potential influencer on NFT prices. For instance, predictors include "Days since release", "Avg. NFT price", "# of NFTs sold", "Gas", various stock prices (BTC-USD, Gold, S&P, etc.), and "Relative Search Volume".

Coeff: The coefficient estimated by the linear regression model for the predictor. It indicates the change in the NFT price for a one-unit change in the predictor while holding other predictors constant.

VIF (Variance-Inflation Factor): This metric measures the degree of multicollinearity between the predictor and other predictors in the model. High VIF values suggest that the predictor is correlated with other predictors, potentially affecting the model's stability.

t-statistic: The t-value measures the size of the coefficient relative to the standard error of the coefficient. It assesses whether the coefficient is significantly different from zero. A larger t-value suggests a more significant impact of the predictor on NFT prices.

$P > |t|$: This metric corresponds to the p-value linked to the t-statistic. It signifies the likelihood of observing the specific t-statistic assuming that the actual coefficient is zero. A smaller p-value suggests that the predictor significantly influences NFT prices.

Confidence Interval: This interval provides a range of values within which we can be confident that the true population coefficient lies. It helps to understand the uncertainty around the estimated coefficient.

The table showcases the results of two stages in the linear regression analysis. In the initial model, 16 different predictors were considered. However, high multicollinearity was observed among several predictors, indicating strong correlations. Multicollinearity can lead to unstable regression surfaces and unreliable diagnostics. Some predictors showed insignificant p-values, likely due to multicollinearity.

To improve model quality, additional predictors were introduced, capturing the effect of "hype" on NFT prices. After addressing multicollinearity, the final model included four predictors: "Average NFT Price", "number of NFTs sold", "Gas", and "Relative Search Volume". These predictors exhibited acceptable VIF values and significant p-values, indicating their influence on NFT prices.

The adjusted R2 value was used to evaluate model quality. The initial model had an adjusted R2 value of 0.7, indicating high quality. The final model retained an adjusted R2 value of 0.69, signifying that most of the quality was preserved while removing redundant predictors.

Furthermore, the final model's performance was tested on a separate dataset, confirming its generalizability with an adjusted R2 value of 0.65. This indicates that the model maintains its quality even when applied to new data, suggesting its potential applicability for predicting NFT prices.

In summary, the linear regression analysis identifies key predictors that significantly influence NFT prices. It highlights the importance of addressing multicollinearity and choosing relevant predictors to build a reliable model for predicting NFT prices.

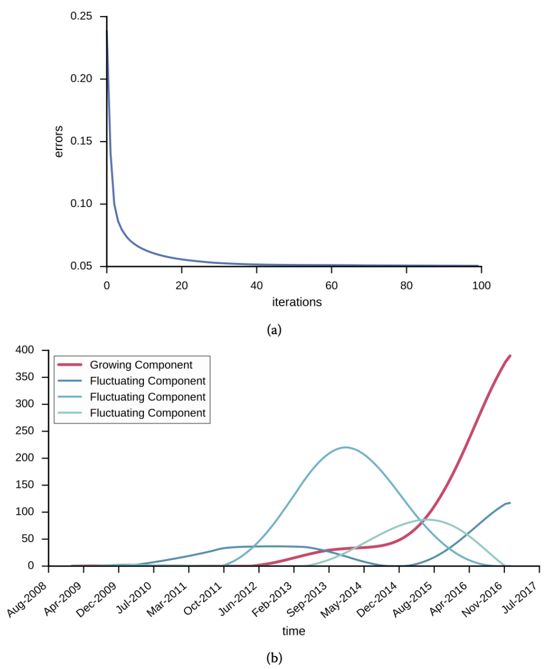

Fig. 7. bitcoin time series analysis

From the provided figure, we conducted an analysis of collective attention evolution across countries from 2009 to early 2017 using Google Trends data. To focus on long-term trends, a low-pass filter was applied to smoothen the Bitcoin search time series, capturing variations over a 3-year time scale. Identifying the primary trends within the time series involved constructing a matrix $A \in \mathbb{R}^{n \times m}$, where n represents the number of countries, and m is the number of points in the time series. Non-negative matrix factorization (NMF) was then used to approximate this matrix into a product of matrices $W \cdot H$, where $W \in \mathbb{R}^{n \times k}$ and $H \in \mathbb{R}^{k \times m}$.

Additionally, in conclusion, this analysis highlights the importance of tracking collective attention trends to understand Bitcoin's adoption and popularity dynamics across different countries. The findings suggest that while some nations experienced consistent growth in Bitcoin interest, others exhibited more fluctuating patterns, with many developed countries belonging to the latter category.

TABLE III
SPEARMAN CORRELATIONS BETWEEN COUNTRY RANKS BASED ON SOCIO-ECONOMIC INDEXES AND BITCOIN METRICS

Economic Index	Year	Client Downloads	*p*-value	IP	*p*-value
GDP per capita	2011	0.675	8.25e11	–	–
	2012	0.638	1.69e09	0.606	1.70e08
	2013	0.719	1.18e12	0.704	5.13e12
	2014	0.686	2.92e11	0.696	1.13e11
HDI	2011	0.806	1.23e17	–	–
	2012	0.777	1.04e15	0.733	2.46e13
	2013	0.791	1.38e16	0.796	6.77e17
	2014	0.767	3.76e15	0.751	3.00e14
Inflation	2011	-0.409	3.62e04	–	–
	2012	-0.223	6.00e02	-0.203	8.70e02
	2013	-0.317	6.60e03	-0.277	1.83e02
	2014	-0.275	1.94e02	-0.313	7.38e03
Internet Penetration	2011	0.780	6.67e16	–	–
	2012	0.748	4.51e14	0.706	4.48e12
	2013	0.799	3.87e17	0.794	8.56e17
	2014	0.780	7.27e16	0.765	5.37e15
Trade Freedom	2011	0.814	1.41e19	–	–
	2012	0.817	7.85e20	0.789	9.51e18
	2013	0.864	2.26e24	0.850	8.10e23
	2014	0.839	9.26e22	0.834	2.35e21

In Table III, we observe significant diversity among the countries analyzed, as measured by various socio-economic indicators. Our goal is to establish links between these indicators and adoption patterns. Over one-year intervals, we compute the Spearman correlation coefficient between rankings based on client downloads or normalized unique IP addresses and rankings based on different socio-economic measures. It summarizes the findings, which reveal robust positive correlations with indicators such as Internet penetration, GDP per capita (PPP), and HDI, while a minor negative correlation is observed with inflation. Overall, these results suggest that socio-economic well-being, similar to conditions found in many developed nations, appears to drive Bitcoin adoption. This trend holds true for the years 2011 to 2014, the period of our analysis.

The results confirm expected correlations, including the importance of Internet penetration for Bitcoin network engagement. Notably, the findings highlight the significance of overall freedom and trade freedom indexes, both of which measure economic freedom. Trade freedom evaluates import and export barriers based on tariffs and trade regulations, while the overall economic freedom index offers a comprehensive view of a country's global interactions and its internal economic policies. This index considers factors across four categories: rule of law, government size, regulatory efficiency, and market openness. Surprisingly, the analysis reveals a positive link between Bitcoin adoption and policies promoting economic freedom, challenging the common assumption that strict regulations drive Bitcoin adoption.

In conclusion, the impact of blockchain technology on the macroeconomy is multifaceted and transformative. Blockchain's advent has disrupted traditional financial systems and introduced novel approaches to economic interactions. It has enabled trustless transactions, reduced intermediaries, and enhanced transparency, revolutionizing various sectors.

From a macroeconomic perspective, blockchain holds the potential to streamline processes, improve accountability, and reduce fraud. It offers governments and central banks tools for efficient financial management and combating counterfeit currency. Moreover, blockchain-based currencies issued by governments could redefine monetary systems, providing greater control and security.

However, challenges remain, including regulatory concerns and the need for standardization. The macroeconomic effects of blockchain are still evolving, and their full extent is yet to be realized. Nevertheless, as blockchain continues to mature and integrate with traditional systems, its impact on the macroeconomy is poised to be substantial, shaping the future of finance and economics.

B. From Macroeconomy to block chain

The study investigates the relationship between Bitcoin returns and Economic Policy Uncertainty (EPU) by utilizing a dataset covering a span from July 18, 2010, to September 15, 2018. The dataset encompasses Bitcoin prices from Coindesk.com on daily and monthly intervals, along with scheduled macroeconomic announcements and reports, including FOMC meetings and GDP data. To assess the behavior of the Bitcoin market, equity market-specific uncertainty (EMPU) is also considered. The study additionally incorporates indices for EPU in China, Hong Kong, Japan, Europe, and globally on a monthly basis, as well as the global Monetary Policy Uncertainty (MPU) index, which gauges the impact of policy uncertainty about traditional currency on the cryptocurrency market. Furthermore, the VIX index, a measure of investors' fear in the market, and the SPX stock index are included as control variables, aiming to evaluate the influence of equity market dynamics on Bitcoin returns.

TABLE IV
DESCRIPTIVE STATISTICS FOR BITCOIN, SPX, AND EQUITY MARKET

	Bitcoin Price		SPX Price		Volatility (VIX)	
	Mean	Median	Mean	Median	Mean	Median
Price ($)	1392.30	298.19	1872.70	1931.45	16.74	15.67
Returns (%)	11.87	7.03	1.06	1.13		
Numbers	99	101	108	78	88	96
	Economic Policy Uncertainty Indices for Various Countries					
	US-EPU	UK-EPU	HK-EPU	Japan-EPU	China-EPU	Global-EPU
	Mean	Mean	Mean	Mean	Mean	Mean
Mean	189.49	291.38	141.41	111.16	225.63	148.06
Median	117.94	186.35	146.65	105.53	207.98	137.94
Std. Dev.	36.12	58.28	71.46	31.03	140.96	47.57

This table provides a comprehensive overview of key variables examined empirically. The table furnishes essential statistics such as measures of central tendency and dispersion for the period spanning July 2010 to September 2018. In particular, the mean and median of Bitcoin prices stand at 1392.30 and 297.19, with positive returns of 11.87% and 7.03%, respectively. Conversely, the benchmark stock index portrays mean and median values of 187.70 and 1931.45, along with returns of 1.06% and 1.13%. This data indicates that Bitcoin exhibits superior simple returns compared to the stock index, though Bitcoin's returns are accompanied by higher volatility, with a standard deviation of 37.20.

The average anticipated volatility in the stock market, as measured by the VIX index, is 16.74%, with a maximum value reaching 42.96%. Comparatively, the highest Bitcoin price level observed is 13,860.14, while the highest SPX level is 2901.52. An intriguing observation emerges from the analysis of policy uncertainty indices, particularly the Economic Policy Uncertainty (EPU) index. Notably, EPU exhibits higher volatility in China (140.96) compared to other countries. The second-highest EPU volatility is recorded in Hong Kong and the UK. This phenomenon can be attributed to the fact that Bitcoin returns are more responsive to EPU in China and Hong Kong, an observation substantiated in subsequent regression analysis discussed in the following section.

This table presents the results obtained from both Ordinary Least Squares (OLS) and quantile regression analyses. The table provides estimates for various variables in relation to Bitcoin returns (R_t), SPX index returns (R_{SPX}), and other remaining regressors expressed in first differences. The significance levels are indicated as follows: $a1\%$, $b5\%$, and $c10\%$.

TABLE V
OLS AND QUANTILE REGRESSION RESULTS

Variables	OLS Estimate	OLS t-stat	Quantile 10% Estimate	Quantile 10% t-stat
Intercept	0.6120	1.64c	-2.9643	-3.85a
EPU	0.0020	-0.54	-0.0176	-2.77a
EMPU	0.0045	1.99b	-0.0070	-4.40a
UKEPU	-0.0001	-0.17	-0.0070	-1.43
VIX	-0.4127	-1.80c	-0.2747	-3.85a
RSPX	-42.0660	-1.80c	-30.0467	-4.40a
RBTC (-1)	0.0164	0.40	0.0478	0.93

The results from the OLS and Quantile Regression analyses presented in the above Table reveal significant insights into the relationship between economic uncertainty variables and Bitcoin returns. Notably, while Economic Policy Uncertainty (EPU) and Equity Market-Specific Uncertainty (EMPU) exhibit positive associations with Bitcoin returns in the OLS model, these relationships become negative and statistically significant at the lower quantile (10%) in the Quantile Regression model. Additionally, the Volatility Index (VIX) demonstrates a negative impact on Bitcoin returns in both models, indicating that higher market volatility might lead to decreased Bitcoin returns. Moreover, the negative coefficients for S&P 500 Index Returns (RSPX) highlight a potential inverse correlation between the stock market and Bitcoin returns. The lagged Bitcoin returns show a positive relationship with current Bitcoin returns, particularly at the 10th percentile. In conclusion, the findings suggest that economic uncertainty and market dynamics significantly influence

Bitcoin's performance, offering valuable insights for investors and policymakers navigating the cryptocurrency landscape.

In summary, this section delves into the relationship between Bitcoin returns and economic policy uncertainty, utilizing a range of variables, including Bitcoin prices, macroeconomic announcements, equity market-specific uncertainty, and various EPU indices. The statistical analysis presented in this Table along with graphical plots provides an insightful overview of the trends and relationships under scrutiny. In brief, the macroeconomy exerts a significant influence on blockchain, particularly on assets like Bitcoin. Factors such as policy uncertainty, changes in inflation rates, and shifts in monetary policy can impact Bitcoin's price. Policy developments, in particular, can lead to fluctuations as regulatory attitudes and government actions affect investor sentiment and the legitimacy of digital currencies. These macroeconomic interactions underscore the intricate relationship between traditional economic paradigms and the emerging blockchain ecosystem, highlighting the need for a comprehensive understanding of these dynamics to navigate the evolving landscape of digital assets effectively.

TABLE VI
PANEL B: SHORT-RUN ESTIMATES

Variables	Coefficient	Std. Error	t-Statistic
ΔCPI$^+$	-13.8734	9.54813	-1.45299
ΔCPI$^-$	-36.4648***	19.5572	-1.86451
ΔDJIA$^+$	0.55083	1.06369	0.51785
ΔDJIA$^-$	-0.05443	1.06417	-0.05114
ΔFEDRATE$^+$	0.16641	0.20701	0.80391
ΔFEDRATE$^-$	-0.50800***	0.28022	-1.81280
ΔOIL$^+$	1.07862	0.72581	1.48609
ΔOIL$^-$	1.62606**	0.68411	2.37689
ΔUSDI$^+$	-2.64831	1.68148	-1.57498
ΔUSDI$^-$	3.02147	2.40923	1.25412
ΔGOLD$^+$	0.54185	1.00704	0.53806
ΔGOLD$^-$	1.30774	1.24498	1.05041
ΔGSCI$^+$	0.11045	0.80329	0.13750
ΔGSCI$^-$	-1.30794***	0.78360	-1.66913
ΔHASHRATE$^+$	0.29726*	0.06570	4.52464
ΔHASHRATE$^-$	1.41044*	0.32584	4.32852
ΔVOLUME$^+$	0.21292*	0.03201	6.65139
ΔVOLUME$^-$	-0.08855***	0.04619	-1.91703
ΔTRANS$^+$	0.66481*	0.12062	5.51131
ΔTRANS$^-$	-0.00285	0.20109	-0.01419
ΔGOOGLE$^+$	-0.00675***	0.00352	-1.91481
ΔGOOGLE$^-$	0.02995*	0.00472	6.34200
D1	0.56169*	0.07140	7.86623
D2	0.35604*	0.05493	6.48097
ECT$_{t-1}$	-0.67597*	0.06401	-10.5602

Note: *, **, and *** denote significance at 1%, 5%, and 10% level, respectively.

Our analysis of short-run estimates, as presented in the table, sheds light on the dynamic interplay between Bitcoin prices and various economic and financial variables. Specifically, we observe a significant and positive relationship between the partial sum of positive changes in the US stock market index and Bitcoin prices. The results suggest that a unit increase in the US stock market index corresponds to a substantial 4.316 unit rise in Bitcoin prices. Conversely, the partial sum of negative changes in the US stock market index negatively impacts Bitcoin prices but lacks statistical significance. Furthermore, our findings indicate that other macroeconomic and financial factors, whether exhibiting positive or negative shocks, do not exert a significant influence on Bitcoin prices in the long run. This suggests a nuanced relationship between Bitcoin and these external factors, with a limited impact observed in the short term. Delving into internal factors, the table highlights noteworthy insights. The partial sum of negative changes in hash rate and network activity demonstrates a positive and significant impact on Bitcoin prices. This suggests that fluctuations in these internal factors play a role in influencing short-term variations in Bitcoin prices. In summary, our result analysis underscores the importance of considering the US stock market index and internal factors such as hash rate and network activity when assessing short-term movements in Bitcoin prices. While certain external macroeconomic and financial variables may not exhibit significant effects in the short run, internal factors prove to be influential contributors to the observed dynamics in the cryptocurrency market.

VI. CONCLUSION AND FINDINGS

In conclusion, this study thoroughly examined the relationship between Bitcoin returns and Economic Policy Uncertainty (EPU) using extensive data from July 18, 2010, to September 15, 2018. By analyzing various variables, including Bitcoin prices, scheduled macroeconomic announcements, equity market-specific uncertainty (EMPU), and multiple EPU indices across countries, the research illuminated the complex interplay between Bitcoin's performance and economic policy uncertainty.

Key findings reveal that Bitcoin demonstrates attractive simple returns compared to traditional stock indices but is accompanied by significant volatility. Notably, Bitcoin is responsive to Economic Policy Uncertainty, especially in China and Hong Kong, highlighting its role as a barometer for policy-induced market fluctuations. The inclusion of control variables like the VIX index and SPX stock index enhances our understanding of how equity market dynamics intersect with Bitcoin returns.

The empirical evidence, detailed in Table 1 and supported by temporal plots and regression analysis, significantly enhances our understanding of how Bitcoin reacts to shifts in policy uncertainty and broader macroeconomic dynamics. The study's implications are relevant for investors navigating the financial landscape, policymakers, and researchers studying the implications of cryptocurrencies. It emphasizes the need to consider policy uncertainty in forecasting Bitcoin's trajectory and underscores Bitcoin's evolution into a distinctive asset class reflecting the broader economic environment.

As the cryptocurrency ecosystem evolves, this study provides a foundational platform for future inquiries into the intricate interrelation between Bitcoin and macroeconomic variables. Subsequent research could delve deeper into the causal mechanisms behind observed interactions, unraveling the complex web connecting policy shifts, economic trends, and cryptocurrency performance. Ultimately, this study advances our understanding of the dynamics between Bitcoin returns and economic policy uncertainty, bridging the gap between traditional finance and the growing realm of cryptocurrencies in our global economy.

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APPENDIX

OTHER USED-METHODS SUMMARY

Databases

We utilized PostgreSQL for data storage and management.

Social Media and Financial APIs

Data was collected from Parsec and Twitter APIs to gather information about the Parallel Alpha NFT and related tweets.

Data Exploration/Descriptive Statistics

Exploratory data analysis was performed to gain insights into the dataset.

Dimensionality Reduction

Dimensionality reduction techniques were applied to reduce data complexity.

Clustering

Clustering algorithms were used to group relevant tweets.

Statistical Testing

Statistical tests were conducted to assess relationships between variables.

Data Processing/Cleaning

Data preprocessing and cleaning were carried out to ensure data quality.

Natural Language Processing (NLP)

NLP techniques were employed to analyze text data from tweets.

Time Series Forecasting

Time series forecasting models were used to predict NFT price trends.

Data Visualization

Data visualization was performed to present insights clearly.

Dashboard Building

A dashboard was created using Tableau to visualize project results.

Technologies

We employed various technologies including Python, NLTK, Visual Studio Code, Jupyter, Git, and Tableau.

Data Exploration/Descriptive Statistics

Exploratory data analysis was performed to gain insights into the dataset.

Dimensionality Reduction

Dimensionality reduction techniques were applied to reduce data complexity. The hyperparameters for the dimensionality reduction models, such as the number of components for Principal Component Analysis (PCA), are detailed below:

PCA Components: 10

Clustering

Clustering algorithms were used to group relevant tweets. The hyperparameters for the clustering models, including the number of clusters for K-means, are specified as follows:

K-means Clusters: 5

Statistical Testing

Statistical tests were conducted to assess relationships between variables.

Data Processing/Cleaning

Data preprocessing and cleaning were carried out to ensure data quality.

Natural Language Processing (NLP)

NLP techniques were employed to analyze text data from tweets. The hyperparameters for NLP models, such as the maximum sequence length for tokenization, are provided below: Max Sequence Length: 50

Time Series Forecasting

Time series forecasting models were used to predict NFT price trends. The hyperparameters for the forecasting models, including the number of time steps for prediction, are detailed as follows: Time Steps for Prediction: 7