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An analysis of the factors affecting Bitcoin's price

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Master Thesis

presented as partial requirement for obtaining the Master Degree in Statistics and Information Management

NOVA Information Management School

Instituto Superior de Estatística e Gestão de Informação

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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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Statement of Integrity

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, 07/04/2024]

Rodrigo Rolao Marques Campos Garcia

ABSTRACT

This master's thesis examines the factors influencing Bitcoin's price, including various market drivers. Key variables analyzed include the prices of Ethereum and gold, U.S. energy costs, inflation rates, the volume of daily Bitcoin transactions, and Google search trends for Bitcoin. The study employs statistical and econometric methods to assess the relationships between these factors and Bitcoin's price.

The findings reveal that Ethereum's price and the volume of daily Bitcoin transactions are positively correlated with Bitcoin's value. In contrast, gold prices show a moderate correlation, while energy costs and U.S. inflation rates have a less significant impact. Additionally, Google search trends highlight the influence of public interest and media attention on Bitcoin's price dynamics.

This research offers valuable insights for investors, market analysts, and policymakers, enhancing the understanding of the mechanisms that drive Bitcoin's pricing.

KEYWORDS

Bitcoin price; Ethereum; Gold; Price per Kilowatt/h; Energy; inflation rates in the U.S; number of daily Bitcoin transactions; Google searches; cost; cryptocurrency

Sustainable Development Goals (SDG):

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1. Introduction

Since Satoshi Nakamoto created Bitcoin in 2009, a groundbreaking innovation known as blockchain has been introduced to the world. This technology holds the potential to revolutionize various sectors beyond finance. As the foremost decentralized digital currency, Bitcoin is of significant interest to researchers studying price dynamics. Brokers, investors, and policymakers alike are eager to understand how financial systems are influenced by fluctuations in the Bitcoin price series. Bitcoin operates independently of central bank policies, and its value depends on factors such as supply-demand dynamics, scarcity, and technological advancements.

Bitcoin has emerged as one of the top-performing assets globally over the past decade. Satoshi Nakamoto first outlined the concept in a 2008 white paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System." This landmark document proposed a new electronic currency system that is entirely decentralized and operates without the need for trust. Bitcoin was conceived in response to the financial crisis of 2007-2008, aiming to provide individuals with a novel way to store wealth. Nakamoto's vision extended beyond merely replacing existing financial systems, and It aimed to establish a new paradigm for peer-to-peer transactions. When Bitcoin went live in 2009, Nakamoto mined its first block, known as the "genesis block." Embedded within this block was a message referencing a headline from The Times newspaper, "The Times 03/Jan/2009 Chancellor on the brink of second bailout for banks.". The significance of this message remains a topic of debate, with interpretations ranging from a critique of the current financial system to a persuasive statement about the value of this new digital currency.

From a technical standpoint, Bitcoin was revolutionary. It became the first digital asset with a capped supply of 21 million coins, like limited natural resources such as gold. This feature was intended to mitigate inflationary pressures. Bitcoin disrupted the status quo by introducing cryptocurrency, a digital or virtual currency secured by cryptography, making it nearly impossible to counterfeit or double-spend. This narrative challenged traditional banking and centralized control over currency, offering an alternative that could be transacted or stored independent of any authority or institution, accessible to anyone with internet access. As a pioneer in its field, Bitcoin opened the path for developing thousands of other digital assets, each serving distinct purposes. It catalyzed the emergence of a new market that operates under principles like traditional financial markets. The cryptocurrency market is rapidly becoming a significant sector within the financial industry, attracting retail investors and institutional entities. This crypto phenomenon has sparked discussions among governments and regulators on adapting to and regulating digital currencies.

Bitcoin's recognition as a legal tender in countries like El Salvador underscores its impact on the conceptualization of digital currencies within national economies, further solidifying its role in advancing the concept of digital assets. Blockchain, the underlying technology powering Bitcoin, has implications far beyond cryptocurrencies. Industries ranging from healthcare to finance are exploring various blockchain use cases and proofs of concept that promise enhanced transparency, accountability, and efficiency. Smart contracts, a byproduct of blockchain technology, are coded agreements designed to self-execute based on predefined conditions, eliminating the need for intermediaries.

Beyond being a financial asset, Bitcoin has become a cultural phenomenon, symbolizing a movement toward privacy and resistance to censorship. The story of Bitcoin has transcended into mainstream discussions about privacy rights, financial inclusion, and the democratization of money. Bitcoin's price likely results from converging factors across economic, technical, and social domains rather than a single causal variable.

This study will examine the price of gold and the inflation rate in the U.S. Gold has historically served as a safe haven and a reliable store of value. Similar characteristics have been attributed to Bitcoin during times of crisis or inflationary concerns. Investigating the relationship between gold and Bitcoin's price may provide evidence of whether investors perceive Bitcoin as a digital equivalent of gold. Additionally, we will include the inflation rate in the U.S. as an explanatory factor, hypothesizing that Bitcoin may serve as an alternative hedge against inflation, similar to the characteristics of gold.

The price of Ethereum, the second most significant cryptocurrency after Bitcoin, introduces a global dimension to the analysis and allows for an exploration of how broader cryptocurrency market dynamics could shape Bitcoin's price. Bitcoin and Ethereum operate on public blockchain systems with a shared technological foundation. Analyzing their prices can help identify the role of innovation, network effects, and market structure in influencing cryptocurrency values.

Electricity prices are crucial, given Bitcoin's energy consumption during mining. Mining, the primary method of creating new bitcoins and securing the network, requires substantial computational power, making electricity costs a critical determinant of mining profitability. By examining the relationship between electricity costs and Bitcoin's price, this study acknowledges the economic realities of cryptocurrency mining and its potential impact on market prices.

Google search data for Bitcoin is a proxy for investor interest and public sentiment, potentially offering real-time insights into market enthusiasm or caution towards these digital currencies. Google Trends data underscores the importance of public sentiment in valuing assets heavily influenced by speculative trading and investor sentiment.

The daily transaction volume on the Bitcoin network is another essential variable, providing insights into Bitcoin's utility, adoption, and liquidity as both a currency and an investment. A higher transaction volume may indicate robust and active participation, which could, in turn, influence Bitcoin's price by signaling increased usage and acceptance.

The primary objective of this study is to empirically assess the impact of these selected factors on Bitcoin's price, contributing to a deeper understanding of cryptocurrency market dynamics. This research aims to identify critical drivers of Bitcoin's price through rigorous regression analysis, offering valuable and practical insights for investors, policymakers, and scholars. The objective is to contribute to the academic discourse on cryptocurrencies and provide actionable insights to inform investment strategies and policymaking in the digital age. As the cryptocurrency landscape continues to evolve, this study is a timely and essential exploration of the complex factors driving Bitcoin's price, paving the way for future research and discussion in this rapidly evolving field.

This technology has the potential to revolutionize various business sectors beyond finance. As the primary decentralized advanced cash, Bitcoin is of extraordinary premium to scientists for concentrating on cost elements. Different broker vendors, financial backers, and policymakers are generally quick to know the eventual fate of the monetary framework driven by cost changes inside the Bitcoin value series. It has no connection to national bank strategies, and its worth relies upon the interest supply game, shortage, and innovation advancement.

2. Literature review

In the evolving landscape of modern currencies, Bitcoin is a significant force that has transformed perspectives on finance and economic innovation. Since its creation in 2009, Bitcoin has encountered significant changes, fostering discussion among money-related allies, business specialists, and policymakers. These trends highlight the complex factors influencing Bitcoin's price, a topic that has garnered significant academic attention. This research dives into the various drivers of Bitcoin's price, focusing on numerous independent variables reflecting technological, economic, and social impacts on the digital currency market.

Several studies have examined the factors influencing Bitcoin's price and the broader implications of cryptocurrencies in finance. Rejeb and Keogh (2021) conducted a comprehensive review to synthesize previous research on the role of digital currencies in modern finance. They identify benefits such as lower transaction costs, increased security, financial inclusion, and challenges, including regulatory uncertainty and high volatility. Their findings highlight the complexity of integrating advanced financial systems into the existing economic environment and call for changes in both academic and regulatory perspectives. Lori (2019) overviewed the monetary purposes of Bitcoin, supplementing its shortcomings regarding changes and the impact of the news and significant regional events.

A critical insight is that extended activity on social media platforms and Google searches for terms related to 'Bitcoin' have shown strong predictive power over short-term trends in Bitcoin's growth and returns (Polasik et al., 2015; Geoirgoula et al., 2015; Aalborg et al., 2019). However, identifying key factors rather than predicting returns or developing trading systems has been the primary focus in the literature on Bitcoin. In this context, Kristoufek (2015) studied the primary value drivers for Bitcoin, arguing that due to Bitcoin's unique and recurring periods of excessive price appreciation, its value is influenced by different factors at different times.

Bitcoin’s price drivers have been a topic of interest for researchers, investors, and regulators. Several studies have investigated different factors that could influence the price of Bitcoin, such as market liquidity, trading volume, investor sentiment, and macroeconomic indicators (Alexander et al., 2023). While there has not been a consistent approach to determining the relationship between these variables and the price of Bitcoin, recent evaluations provide valuable insights. For example, some studies have focused on the impact of macroeconomic factors on Bitcoin's price (Polasik et al., 2015). These studies have found that factors such as exchange rates, inflation, money supply, and industrial production can influence the price of Bitcoin. Research has also explored the relationship between Bitcoin’s price and other digital financial assets. These studies concluded that price changes in significant altcoins, such as Ethereum, Ripple (XRP), Litecoin, Bitcoin Cash, and EOS, can affect the price of Bitcoin (Sovbetov, 2018). Moreover, researchers have also investigated the effect of news and social media sentiment on Bitcoin price prediction (Li & Zhang, 2022; Goczek & Skliarov, 2019). They have used analytical methodologies to understand market sentiment and its impact on Bitcoin's price.

Among the central factors considered in this study is the price of Ethereum. Given Ethereum's position as a leading cryptocurrency and its critical role in developing decentralized applications, its market fluctuations are closely monitored for their potential wide-ranging effects on Bitcoin's price. This interconnection reflects both the cooperative and competitive dynamics within the digital currency ecosystem. Google searches for Bitcoin act as proxies for public interest and sentiment, providing insights into how online activity can precede or reflect market developments. The volume of searches is considered a persistent indicator of retail investor interest, which can drive price volatility in the short term.

The economics of Bitcoin mining, as influenced by the average price per kilowatt-hour in the U.S., also significantly affects Bitcoin's price. Mining, the relationship by which transactions are checked and new Bitcoins are made, is energy-elevated and delicate, driving prices. Similarly, risks associated with energy costs can impact mining effectiveness, supply parts, and, consequently, market costs. Inflation rates in the U.S. are considered to have a possible effect on Bitcoin's appeal as a tool for portfolio diversification.

Bitcoin is often viewed as a digital alternative to traditional stores of value, such as gold. The volume of regular Bitcoin transactions is analyzed to measure its utility and adoption, with high liquidity often associated with lower price volatility. This suggests a more stable market that could attract additional institutional investors (Baur et al., 2018). An increase in the number of transactions can indicate growing acceptance and demand, positively influencing its price. Additionally, the price of gold is included to examine Bitcoin's relationship with traditional safe-haven assets. This analysis is crucial for understanding Bitcoin's role in investment portfolios, especially during periods of economic uncertainty.

This study aims to comprehensively evaluate these factors, drawing on recent empirical studies and theoretical research to offer insights into the elements that drive Bitcoin's price dynamics.

2.1. Analyzed metrics/drivers

2.1.1. Google Searches for Bitcoin

The complex relationship between public interest, as indicated by Google searches for Bitcoin, and the price of Bitcoin has been the subject of increasing scrutiny in financial technology research. This study aims to elucidate how changes in the volume of searches for Bitcoin on Google correlate with Bitcoin's market price movements. The premise is based on the hypothesis that search volumes can serve as a proxy for retail investor interest and sentiment, potentially influencing market dynamics due to the speculative nature of cryptocurrency markets. From a behavioral finance perspective, the relationship between Google searches and Bitcoin's price can be interpreted through investor sentiment and herd behavior.

Glaser (2014) explored this topic, suggesting that spikes in Google searches indicate heightened investor interest, which often precedes price rallies due to speculative trading. Kristoufek (2015) proposed a bidirectional causality between Google searches for Bitcoin and Bitcoin's price. Kristoufek's research revealed that spikes in search volumes for Bitcoin reflect increased public interest and precede price increases, suggesting that search data could predict market movements. This feedback loop demonstrates that as more individuals search for information on Bitcoin, potentially driven by news or word of mouth, the growing interest translates into trading activity that impacts its price.

Recent studies have sought to refine our understanding of this relationship by incorporating advanced analytics and machine learning techniques. For instance, Phillips and Gorse (2017) and Panagiotidis, Stengos, and Vravosinos (2019) used social media and search data to forecast cryptocurrency price movements, finding that peak search volume and social media discussions could effectively signal impending price volatility. Similarly, Jiang and Liang (2020) employed a combination of ARIMA (Autoregressive Integrated Moving Average) models and LSTM (Long Short-Term Memory) neural networks to predict Bitcoin's price based on Google Trends data. Their results highlighted the effectiveness of these advanced models in capturing the nuanced dynamics of this relationship, suggesting promising avenues for future research using cutting-edge analytical techniques.

This implies that aggregate search behavior can provide insights into market sentiment, a crucial price determinant in speculative and sentiment-driven markets as those for cryptocurrencies. Furthermore, the advent of sophisticated algorithmic trading and the increasing influence of social media amplify the impact of public interest on market prices. Algorithms that scrape web data, including search trends, to make trading decisions can magnify price movements, leading to self-reinforcing cycles. Rising prices lead to more searches, which drive higher prices (Liew & Budavári, 2021).

However, the relationship between Google searches and Bitcoin's price is not without its critics. Some argue that search volumes can provide a snapshot of interest. However, they cannot fully account for the multifaceted influences on Bitcoin's price, including regulatory announcements, technological advancements, and macroeconomic factors (Bouri et al., 2019). These factors, often external to the cryptocurrency ecosystem, can significantly impact Bitcoin's valuation, potentially overshadowing the effect of search trends (Pavlyshenko, 2019).

2.1.2. Inflation Rates in the US

The intricate relationship between macroeconomic factors and the valuation of cryptocurrencies, particularly Bitcoin, has garnered significant interest from both academic and practical perspectives. Among these macroeconomic variables, inflation rates play a crucial role in shaping market dynamics and investor sentiment toward cryptocurrencies. In traditional economic theory, assets like gold have been considered reliable hedges against inflation because they retain value over time as the purchasing power of fiat currencies declines. Bitcoin, often called 'digital gold,' has been positioned to serve a similar function.

The decentralized nature of Bitcoin, with its fixed supply cap of 21 million coins, offers a distinctive alternative in the context of inflationary pressures exerted by fiat currencies. A seminal paper by Smith (2020) examined the relationship between U.S. inflation rates and Bitcoin’s price, noting that during periods of high inflation, Bitcoin’s price has tended to increase. This observation suggests that investors may turn to Bitcoin as a store of value during uncertain economic times. The underlying hypothesis is that as the U.S. dollar loses value due to inflation, Bitcoin's attractiveness as an alternative investment grows, pushing its price upwards.

Further supporting this hypothesis, research by Bouri (2019) utilized quantile regression to analyze the relationship between Bitcoin's price and inflation rates across several countries, including the US. The findings indicated that Bitcoin behaves differently across various inflation scenarios, with its hedging capability more pronounced during severe inflationary conditions. This nuanced perspective suggests that Bitcoin can act as a hedge, but its effectiveness depends on the inflationary environment.

Recent developments in the U.S. economy have provided practical context to these theoretical studies. The unprecedented economic growth and monetary stimulus in response to the COVID-19 pandemic have raised concerns about rising inflation rates. Bitcoin's price experienced significant volatility during this period, with substantial increases observed alongside heightened inflation fears. Such market behavior underscores the perception that Bitcoin is increasingly seen as a hedge against inflationary pressures.

However, the relationship between U.S. inflation rates and Bitcoin’s price is complex. Blau, Griffith, and Whitby (2021) conducted a comprehensive time-series analysis to understand Bitcoin's behavior in response to inflation, suggesting that Bitcoin's price may increase with rising inflation. However, the strength of this relationship can vary depending on broader economic conditions and investor sentiment. For instance, a study by Gkillas and Katsiampa (2021) highlighted that Bitcoin's price response to inflation signals can be uneven, influenced by the overall economic climate and investor sentiment. The study points out that Bitcoin's reaction to inflation may be muted during economic stability, whereas during periods of financial uncertainty, the response can be more pronounced.

Additionally, the impact of macroeconomic indicators, including inflation rates, on Bitcoin is mediated by several factors, such as regulatory developments, technological advancements in the blockchain space, and global economic trends. As argued by Demir (2020), Wang and Chong (2021), and Liu and Zhang (2022), while inflation rates may influence Bitcoin's price, their effect is correlated with these broader factors, suggesting a complex interdependency rather than a direct causality.

Considering these discussions, it is evident that the impact of U.S. inflation rates on Bitcoin price represents a nuanced phenomenon. While empirical evidence supports the idea of Bitcoin serving as a hedge against inflation, the extent and consistency of this role are influenced by many factors. As the cryptocurrency market evolves and Bitcoin becomes further integrated into the global financial system, its relationship with inflation and other economic indicators will likely grow.

2.1.3. Price of Ethereum

The valuation of Ethereum, which ranks as the second most significant cryptocurrency by market capitalization after Bitcoin, plays a crucial role in the overall dynamics of the cryptocurrency market. This interrelationship underscores a fundamental aspect of the cryptocurrency ecosystem: the prices of major digital currencies are not isolated events. Rather, they are significantly interconnected. Research by Aalborg, Molnár, and de Vries (2019) further supports this connection, highlighting periods of strong correlation during high volatility, suggesting that Ethereum may act as a leading indicator or simultaneously respond to similar market developments as Bitcoin. Wang and Chong (2021) delve into these complex interdependencies, suggesting that significant changes in Ethereum's market price can have ripple effects on Bitcoin's valuation and, consequently, the broader digital currency market. This observation points to a symbiotic relationship where movements in the market value of one leading cryptocurrency can indicate broader market trends. The interconnectedness of cryptocurrency markets implies that changes in one primary cryptocurrency could influence others (Liu & Zhang, 2022). This network of influence reflects the economic environment that cryptocurrencies have engendered, where supply and demand, investor sentiment, and external financial factors are intricately linked (Wątorek, Kwapień, and Drożdż, 2023).

The connection between Ethereum's and Bitcoin's market behaviors reflects broader market dynamics, where shifts in one major cryptocurrency often spark reactions that ripple through the entire market. Ethereum's significance in this network is further enhanced by its technological advancements, such as smart contracts, which have expanded the utility of blockchain technology beyond simple currency transactions, thereby influencing investor perceptions and confidence across the cryptocurrency sphere (Corbet, Lucey, and Yarovaya, 2019).

Furthermore, the interaction between Ethereum and Bitcoin prices should reflect the maturing cryptocurrency market, where diversifying investment and speculation strategies across various digital currencies leads to more nuanced market movements. Research into the lead-lag relationship between Bitcoin and Ethereum suggests bidirectional causality, indicating that movements in Ethereum's price can predict changes in Bitcoin's price and vice versa (Sifat, Azhar Mohamad, and Mohammad Syazwan Bin Mohamed Shariff, 2019; Angela & Sun, 2020; Madichie , 2023). The insights provided by Wang and Chong (2021) into the interconnectedness of cryptocurrency prices underscore the importance of a comprehensive approach to understanding the cryptocurrency market. Understanding the interconnected nature of major cryptocurrencies' valuations is crucial for investors navigating the volatile market environment and for researchers aiming to decipher the intricate economic and technological ecosystem surrounding digital currencies.

2.1.4. Number of Daily Bitcoin Transactions

The number of daily Bitcoin transactions effectively measures its adoption and utility as a digital currency. An upward trend in these transactions signals growing endorsement and usage of Bitcoin, potentially exerting upward pressure on its market price. This relationship underscores the fundamental link between transactional activity and the perceived practical utility of Bitcoin as a genuine medium of exchange within the digital economy. The increased transaction volumes reflect heightened user engagement and suggest broader acceptance of Bitcoin across various sectors, enhancing its legitimacy and value as a digital currency. This perspective aligns with aspects of the Quantity Theory of Money, adapted for the cryptocurrency context.

Research conducted by Ciaian, Rajcaniova, and Kancs (2016) emphasizes the importance of transaction volume as a determinant of Bitcoin prices, illustrating how fluctuations in transaction activity can serve as a proxy for user interest and confidence in the cryptocurrency. This concept is further supported by Polasik (2015) and Kuzminska (2021), who argue that the number of daily Bitcoin transactions directly correlates with Bitcoin's utility and, consequently, its market valuation. As transaction volumes increase, the intrinsic value of Bitcoin as a tool for economic exchange becomes more pronounced, potentially influencing its attractiveness to both new and existing users. Analyzing transaction volumes can provide insights into the scalability and efficiency of the Bitcoin network. According to Böhme (2015), higher transaction volumes stress-test the Bitcoin network's capacity and challenge its ability to process payments efficiently and cost-effectively. Dyhrberg (2018) uses high-frequency data to examine the intraday effects of daily Bitcoin transactions on Bitcoin’s price volatility. Their study reveals that sudden spikes in transaction volume can lead to rapid but short-lived price fluctuations, highlighting the complex interplay between transaction activity and price volatility in the short term.

Furthermore, Yermack (2017) explores the implications of Bitcoin's daily transactions for its liquidity and stability as a currency. The study posits that rising transaction volumes can enhance liquidity but may also contribute to price volatility, given Bitcoin's limited supply and speculative interest. These dynamics underscore the dual role of transaction volumes in signaling both the growing adoption of Bitcoin and the challenges it faces in achieving price stability amidst speculative trading. Nasution, Sadalia, and Irawati (2023) have examined various factors, including trading volume and their impact on Bitcoin returns. They have found a positive, although modest, relationship between the number of daily Bitcoin transactions and Bitcoin’s price.

These findings have significant practical implications for both market participants and regulators. Understanding the relationship between the number of daily Bitcoin transactions and market dynamics offers investors and financial analysts a critical tool for assessing Bitcoin's market behavior and potential risk factors. For policymakers and regulatory bodies, these insights can guide the development of frameworks that accommodate the growth of cryptocurrencies while managing their integration into the broader financial system.

2.1.5. Average price per KW/h in the US

Bitcoin mining, an essential process for securing transactions and maintaining the blockchain network, is inherently energy intensive. This operation demands significant computational power, resulting in substantial electricity consumption by miners globally. As Krause and Tolaymat (2018) noted, the efficiency of Bitcoin mining operations is heavily contingent upon the cost of electricity, as energy expenditures constitute a significant portion of operational costs. The average price of electricity, measured in kilowatt-hours (kWh) in the US, is a critical determinant of mining profitability. Lower electricity costs can significantly enhance mining profitability, making certain regions more attractive for mining activities.

Zhu, Dickinson, and Li (2017) examined various economic factors, including electricity costs. Their findings suggest a complex interplay between these factors and Bitcoin's market dynamics, underscoring the importance of energy costs in Bitcoin's value. Vranken (2017) and Hayes (2019) highlight the relationship between electricity costs and Bitcoin mining, noting that the economic viability of mining operations depends on the balance between costs incurred for electricity and the rewards received for mining activities. Miners contribute to the security and functionality of the Bitcoin network through the proof-of-work mechanism, and their distribution and concentration levels are critical to the network's overall health and the supply dynamics of Bitcoin. Therefore, regions offering lower electricity rates often become focal points for mining operations, given the lower operational costs and higher potential for profitability.

This geographical clustering of mining activities due to variable electricity costs can have broader implications for the Bitcoin network. Hayes (2015) explores how the influx of miners affects the issuance of new bitcoins entering the market as the mining rate and difficulty level adjust over time. These supply dynamics, in turn, influence Bitcoin's market price by impacting the equilibrium between supply and demand. Krause and Tolaymat (2018) provide a comprehensive review of the energy consumption of digital currencies, including Bitcoin, arguing that the economic viability of mining operations is fundamentally tied to local electricity costs, with disparities in these costs across different geographical regions affecting where mining activities are concentrated. Moreover, Bitcoin's energy use has sparked stakeholder discussions regarding sustainable energy sources and more energy-efficient mining technologies. Mora (2018) stated that the impact of electricity costs on Bitcoin’s price is moderated by additional factors, such as technological advancements in mining hardware and regulatory changes affecting mining activities. Their study suggests that while electricity costs are a fundamental factor, their direct impact on Bitcoin’s price may be nuanced by these additional factors. Furthermore, the significant growth of mining practices seeking lower electricity costs reshapes the nature of the Bitcoin network. As noted by Goodkind, Jones, and Berrens (2020), the proliferation of miners can lead to changes in the network's geographic distribution, potentially affecting network latency, security, and the decentralized philosophy of Bitcoin.

2.1.6. Gold’s Price

Bitcoin's comparison to 'digital gold' underscores its perceived role as a store of value and a hedge against economic instability, like traditional gold. This comparison between Bitcoin and gold market prices offers a unique lens through which we can examine investor behavior and market sentiment. Bitcoin and gold prices have exhibited some correlation, particularly during economic turmoil, suggesting that Bitcoin is sometimes viewed as a safe haven asset similar to gold. However, several macroeconomic factors can evolve and influence this relationship (Jareño, 2020). During periods of financial volatility, investors often gravitate towards assets considered safe havens—assets believed to retain value while the broader market is declining. Bitcoin and gold have been identified as such assets, though their price relationship and the extent to which they are influenced by market trends and investor sentiment can vary significantly (Kumar, 2023).

Kristoufek (2015) investigates the mechanisms driving Bitcoin’s price, including the impact of investor sentiment, and draws comparisons with gold. The study reveals that similar market sentiments influence both assets, although the effect is more pronounced and volatile in the case of Bitcoin. However, Su (2020) found that increases in Bitcoin’s price can lead to decreases in gold’s price, indicating that Bitcoin's success could undermine gold's hedging capability. Baur and Lucey (2020), and Zhang and Wang (2021) researched the relationship between Bitcoin’s and gold’s prices, identifying periods of economic uncertainty during which both assets have experienced price increases. This correlation suggests that investors may view Bitcoin as a viable alternative to gold, diversifying their portfolios against market volatility and economic downturns. The price of Gold has an inverse relationship with Bitcoin's price during specific periods (Meiryani, 2022). Research conducted by Dyhrberg (2016) investigates this relationship, highlighting Bitcoin's similar responses to financial market vulnerabilities as gold, thereby establishing the narrative of Bitcoin as a digital version of the precious metal. This study suggests that, like gold, Bitcoin can act as an effective hedge against stock market movements and benefit portfolio diversification. However, the volatile nature of Bitcoin's price, driven by speculative trading and regulatory news, often results in deviations from this relationship, demonstrating a complex relationship influenced by many factors beyond investor sentiment and economic conditions.

Further research by Baur, Hong, and Lee (2018) explores the safe haven properties of Bitcoin compared to gold, examining their performances during periods of market decline. Their findings reveal that while both assets are sought after during periods of economic distress, the extent to which they act as a safe haven can vary over time and across different financial conditions. This variability highlights the nuanced and dynamic nature of market perceptions towards these assets, shaped by ongoing developments in the cryptocurrency space, changes in regulatory landscapes, and shifts in global economic indicators. Moreover, the growing institutional interest in Bitcoin, evidenced by the entry of hedge funds and traditional financial institutions into the cryptocurrency market, has complicated its comparison with gold. As Bitcoin gains broader acceptance and recognition as an asset class, its market behavior and role as a safe haven continue to evolve, reflecting the changing attitudes of investors towards digital currencies and their place within the larger financial ecosystem.

3. Data and Methodology

3.1. Data Collection

This study will collect time-series data on Bitcoin prices and potential influencing factors, including Google search data for Bitcoin, Gold prices, U.S. inflation rates, average electricity prices in the U.S. (in kW/h), and Ethereum prices from 4/27/2018 until 31/12/2023. Data for Bitcoin and Ethereum prices were sourced from Coinmarketcap, Google searches for Bitcoin were retrieved from Google Trends, and the number of daily Bitcoin transactions, the price of Gold, and inflation rates in the US were retrieved from Yahoo Finance. The time frame for the data collection was determined based on data availability and the relevance to the study objectives. Gold's price, Bitcoin's price, Ethereum's price, and the average price per Kilowatt/Hour in the U.S. are expressed in dollars. Google trends for bitcoin are represented on a scale between 0 and 100.

3.1.1. Dependent Variable

The dependent variable in the study is the price of Bitcoin, which represents the cost of 1 Bitcoin in Dollars (USD). This research focuses only on Bitcoin’s price. The three reasons for this decision are as follows:

- In scientific literature, most studies on cryptocurrency focus on bitcoin.

- Bitcoin’s share in the crypto market has almost always been above 45% till December 2023.

- Since bitcoin's market cap amounts to Hundreds of billions of dollars ($ 800 billion in December 2023), this cryptocurrency is less susceptible to manipulation by large investors than others with less market cap (Coinmarketcap, 2023). To give the reader an impression of the difference between Bitcoin’s market cap and other currencies' market cap, the market cap of the second largest coin, Ethereum, is given. It amounts to 275 billion in December 2023. The base of bitcoin is, therefore, more stable than that of altcoins. This choice must ensure that reliable research can be carried out.

3.1.2. Independent variables

- Google Search data for Bitcoin (Google trends BTC): This variable reflects the search interest over time for Bitcoin as a proxy for public interest or sentiment.
- Gold Price: The market value of gold, considered a safe-haven asset, may influence or correlate with Bitcoin price movements.
- Inflation Rates in the US: The annual percentage change in consumer prices might impact Bitcoin as a potential hedge against inflation.
- Average Electricity Price (AVG price kw/h in the US): As electricity prices influence Bitcoin mining costs, this variable may affect the overall market price of Bitcoin.
- Ethereum Price: Ethereum's market price may be related to Bitcoin prices due to market dynamics within the cryptocurrency sector.
- Number of Daily Bitcoin Transactions: This variable measures the total volume of transactions processed daily on the Bitcoin network. It serves as an indicator of the cryptocurrency's usage and network activity.

3.2. Methodology

Inspired by (Li & Zhang, 2022), data analysis will be performed using formulas and a data analysis tool pack from Microsoft Excel, including the computation of descriptive statistics. ADF unit root test method will be performed to observe whether the time series is stationary, then perform co-integration according to the situation, the testing of assumptions for multiple regression (homoscedasticity), and the execution of multiple regression analysis to estimate the coefficients of the independent variables.

The model's robustness will be evaluated using various diagnostics, including residual analysis and multicollinearity assessment using the Variance Inflation Factor (VIF).

3.2.1-Model Specification

The relationship between the Bitcoin price and the selected variables will be examined through linear regression for all six independent variables and multiple regression analysis for the ones selected after some analysis (8 to 11). The model for all variables (7) is specified as follows:

$$\hat{Y}\text{ BTC } t = \beta 0 + \beta 1 \text{ ETH/\$ } t + \beta 2 \text{ Gold Price } t + \beta 3 \text{ Googletrendsbtc } t + \beta 4 \text{ inflation rates t} + \beta 5 \text{ nr dailyBtctrans } t + \beta 6 \text{ KW/H } t + \epsilon$$

Where:

- $\beta 0$ is the intercept,
- $\beta 1$ to $\beta 6$ are the coefficients of the independent variables,
- ϵ is the error term.

3.2.2-Hypothesis Testing

The null hypotheses for this study assert that there is no relationship between each independent variable and the price of Bitcoin. These will be tested against alternative theories that posit that a statistically significant relationship exists. A p-value of less than 0.05 will be considered to reject the null hypothesis.

Assuming that the independent variable(s) does not affect the dependent variable in all null hypotheses is consistent with standard practices in statistical hypothesis testing. It ensures objectivity, simplifies interpretation, and aligns this research with established statistical methods.

Table 0.1-Null hypothesis being tested.

Variable	**Null Hypothesis (H0)**	**Reference**
Price of Ethereum	H1-Ethereum price doesn't affect bitcoin price.	Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019)

Variable	Null Hypothesis (H0)	Reference
Price of Gold	H2-Gold price doesn’t affect bitcoin price.	Dyhrberg, A. H. (2016)
Inflation Rates in the US	H3-Inflation rates don’t affect Bitcoin price	Blau, B. M., Griffith, T. G., & Whitby, R. J. (2021)
Google Searches for Bitcoin	H4-Google searches for bitcoin don’t affect bitcoin price.	Kristoufek (2013), Pavlyshenko (2019)
Average Price per Kilowatt Hour in the US	H5-Electricity prices don’t affect Bitcoin price	Zhu, Dickinson, and Li (2017)
Number of Daily Bitcoin Transactions	H6-The number of daily Bitcoin transactions doesn’t affect the Bitcoin price	Nasution,Sadalia ,and Irawati (2023)

4-Empirical Study

4.1. Statistics and Correlation

This section provides an overview of the statistical aspects of the data used in this study. First, we’ll examine the descriptive statistics to get a sense of the basic properties and trends in the dataset. Next, we’ll perform a stationarity test to ensure the data is suitable for further analysis. Finally, we’ll look at correlations between the variables to see how they relate to each other, helping us understand potential influences on Bitcoin’s price. These steps form the foundation for the deeper analysis that follows.

4.1.1-Descriptive Statistics

Table 0.2-Descriptive statistics for all variables

	Bitcoin Price	*Ethereum Price*	*Gold price*	*Google trends btc*	*inflation rates*	*nr bitcoin transactions*	*AVG Electricity price kw/ h in the US*
Mean	22404.30945	1298.034342	1565.397301	23.10409639	3.505204819	23062168.67	0.14652241
Standard Error	355.2900878	25.20123584	6.355220794	0.291379284	0.038212016	108989.8763	0.000293433
Median	19170.7	1223	1549.1	18	2.4	23000000	0.139
Mode	7530.8	1629	1274.2	13	2.2	22000000	0.136
Standard Devia	16184.23373	1147.970926	289.4940846	13.27295804	1.740640184	4964725.146	0.0133665
Sample Varian	261929421.4	1317837.248	83806.82503	176.1714152	3.029828249	2.46485E+13	0.000178663
Kurtosis	-0.524014213	-0.120335989	-1.600661388	2.237703311	-1.39929933	1.352059075	-1.132654283
Skewness	0.74137037	0.824595578	0.079880194	1.594187286	0.377357776	0.653731265	0.763894312
Range	64299.2	4721.72	1029.5	58	5.4	34000000	0.038
Minimum	3228.7	84.28	1060.2	9	1.2	10000000	0.133
Maximum	67527.9	4806	2089.7	67	6.6	44000000	0.171
Sum	46488942.1	2693421.26	3248199.4	47941	7273.3	47854000000	304.034
Count	2075	2075	2075	2075	2075	2075	2075

The descriptive statistics above show the count, sum, standard error, median, mode, sample variance, kurtosis, Skewness, range, minimum value, maximum value, mean, and standard deviation of the (in)dependent variables from April 2018 – December 2023. The variables Bitcoin's price, Gold's price, Ethereum's price, number of daily Bitcoin transactions, the average cost per KW/H in the US, Inflation rates in the US, and Google trends for Bitcoin are in absolute values. The prices are in dollars (except Google trends; this is measured on a scale from 0 to 100).

4.1.2. Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test was performed for all variables before the regression analysis, indicating that all your variables are stationary. Stationarity means that the statistical properties of these variables (such as mean, variance, and autocorrelation) do not change over time. This is an essential prerequisite for many time series analysis techniques, including linear regression, because many statistical models assume that the underlying data are stationary.

Table 0.3 -Results from ADF test vs Dickey-Fuller critical values

ADF Test	t-stat	Dickey-Fuller critical values (1%)	Dickey-Fuller critical values (5%)	no trend	trend
ETH	-25.5459	-3.43	-2.86	-3.43	-3.96
Google trends bitcoin	-26.2687	-3.43	-2.86	-3.43	-3.96
Inflation	-26.2692	-3.43	-2.86	-3.43	-3.96
Gold	-25.7378	-3.43	-2.86	-3.43	-3.96
AVG KW/H price	-26.397	-3.43	-2.86	-3.43	-3.96
nr daily bitcoin transaction	-39.1897	-3.43	-2.86	-3.43	-3.96
Bitcoin Price	-25.9398	-3.43	-2.86	-3.43	-3.96

As we can see from the ADF test t-stat values, all variables' values exceed critical values for 1% and 5%, giving us confidence that there is no unit root, and all variables are stationary. The results show that all seven series passed the test; that is, there is no unit root, and they are stationary series. They all passed the unit root test at the 1% and 5% significance levels, which shows no need for co-integration tests.

4.1.3. Correlation

When looking at the correlation matrix, Ethereum's price, Gold's price, and Google trends for Bitcoin are highly correlated with the dependent variable (Bitcoin's price), which is>0.6 (Pearson).

Table 0.4-Correlation Matrix

	Bitcoin Price	*Ethereum Price*	*Gold price*	*Google trends btc*	*inflation rates*	*nr bitcoin transactions*	*AVG Electricity price kw/ h in the US*
Bitcoin Price	1						
Ethereum Price	0.930847354	1					
Gold price	0.727781693	0.789972006	1				
Google trends b	0.763646481	0.626147103	0.40365276	1			
inflation rates	0.49544848	0.645544005	0.815083	0.231650178	1		
nr bitcoin trans	0.132656988	0.0247455	0.22737079	-0.015858901	-0.036225411	1	
AVG Electricity p	0.314367579	0.404300043	0.8057855	0.031909267	0.775640873	0.307751043	1

To understand if there is any multicollinearity, we look into the Variance Inflation Factor (VIF) for each variable with a high correlation with the dependent variable (the price of Bitcoin).

Table 0.5- VIF Values

VIF	
Ethereum Price	3.800122
Gold Price	2.759938
Google searches for Bitcoin	1.706719

As we can see, the VIF value for all three variables (Ethereum Price, Gold Price, and Google Trends for Bitcoin) is between 1 and 5, which suggests a moderate correlation—often not enough to be overly concerned about. We can proceed with using this variable for our regression models.

4.2. Models

In this part of the study, we focus on the models used to understand the factors affecting Bitcoin's price. Choosing the right models is key to capturing the relationships between the different variables in a way that makes sense. We'll start by discussing how the models were selected, and then move on to the results they produced. This will help us get a clearer picture of what drives Bitcoin's price and how various factors work together in the market.

4.2.1. Choosing the models

We will have another four models besides the seven models presented previously (1-6 for each variable and 7 for all variables):

1. Model 8: Price of Ethereum, Google Trends for Bitcoin, and Gold Price

Price of Ethereum: There is a very high correlation of 0.931 with Bitcoin price, including Ethereum price, which helps capture overall movements in the cryptocurrency market, as these two cryptocurrencies often move in the same direction.

Google Trends (BTC): This is included again due to the strong correlation (0.763) to capture public attention.

Gold Price: This is also included due to the significant relationship (0.728) to see how investor behavior regarding gold reflects on Bitcoin price.

2. Model 9: Number of Daily Bitcoin Transactions and Inflation Rates in the US

Number of Daily Bitcoin Transactions: Included to explore its independent influence.

Inflation Rates in the US: The correlation of 0.495 suggests a moderate relationship with Bitcoin price. Inflation can affect the perceived value of Bitcoin as an alternative asset to fiat currency, especially in times of high inflation.

3. Model 10: Number of Daily Bitcoin Transactions and Average Price per Kilowatt/Hour in the US

Number of Daily Bitcoin Transactions: Even with a weak correlation (0.133), exploring its impact on the model is essential.

Average Price per Kilowatt/Hour in the US: The correlation of 0.314 indicates a moderate relationship. Since Bitcoin mining consumes a lot of electricity, the cost of electricity can impact Bitcoin price, reflecting miners' operational costs.

4. Model 11: Google Trends, Number of Daily Bitcoin Transactions, and Gold Price

Google Trends (BTC): The correlation between Bitcoin price and Google searches for Bitcoin is 0.763, indicating a strong positive relationship. This suggests that an increase in search interest may be associated with an increase in Bitcoin price, possibly due to greater attention and potential buying by investors.

Number of Daily Bitcoin Transactions: The correlation is relatively low (0.133), indicating a weak relationship. However, it is relevant to include this variable to see if, despite the low correlation, it has a significant effect on Bitcoin price when controlled for other variables.

Gold Price: The correlation of 0.728 with Bitcoin's price suggests a significant relationship. Gold is often seen as a "safe haven," and this relationship can indicate whether investors are treating Bitcoin similarly.

4.2.2-Models Results

All results below are presented in Appendix A.

1. Model 1(Electricity Cost)

$$\hat{Y}\ \text{BTC}\ t = -\ 33367.7 + 380638.1\ \text{AVG KW/H}\ t$$

In this regression model, the intercept $\beta 0=-3367.7$ and the coefficient $B1=380638$ indicate that for every 1 cent increase in the price of electricity per Kilowatt-Hour (kWh) in the US, the price of Bitcoin is expected to increase by $3806.38. It can be inferred that if electricity were free (price=0), the price of Bitcoin would theoretically have a negative value, underscoring the significant impact of electricity costs as a major component of Bitcoin production expenses.

The F-statistic is significant at the 5% level, and the p-values are lower than 0.05, indicating a statistically significant relationship between the average cost of each kWh in the US and the price of Bitcoin. However, the R^2 value of 9.8% suggests that this model explains only a tiny proportion of the variation in Bitcoin prices.

2. Model 2(Ethereum's price)

$$\hat{Y}\ \text{BTC}\ t = 5369.946 + 13.1232\ \text{Eth/\$}\ t$$

When performing the Ordinary Least Squares (OLS) regression analysis, we observe a correlation coefficient R of 0.930847 and an R^2 value of 0.866477. This indicates that approximately 86.65% of the variation in the dependent variable is explained by Ethereum price fluctuations. The adjusted R^2, slightly lower at 0.866412, confirms the model's robust explanatory power even after accounting for the number of predictors, which in this case is one.

The intercept coefficient $\beta 0$ is 5369.946, suggesting the predicted value of the dependent variable when Ethereum's price is zero. However, such an interpretation should be approached cautiously since Ethereum's price is unlikely to be zero, making this extrapolation beyond the scope of the data. The coefficient for Ethereum's price $\beta 1$ is 13.1232, indicating that a one-unit increase in Ethereum's price is associated with an average rise of 13.1232 units in Bitcoin's price.

The t-statistic for the Ethereum coefficient is very high at 115.9844, with a p-value approaching zero, providing strong evidence of a statistically significant positive relationship between Ethereum's price and Bitcoin's price. Additionally, the F-statistic of 13452.39, with a nearly zero p-value, strongly supports the model's validity over a null hypothesis that Ethereum's prices have no effect. The model suggests a substantial impact of Ethereum prices on the dependent variable, with a high confidence level in this association.

However, it is essential to note that despite the strong fit indicated by the R^2 value, the model only captures the influence of Ethereum's price, excluding other potential factors that may affect Bitcoin's price.

3. Model 3 (Gold price)

$$\hat{Y}\ \text{BTC}\ t = -41286.7 + 40.6868\ \text{Gold Price}\ t$$

This regression model examines the influence of gold prices on Bitcoin's price, revealing a moderately strong relationship indicated by an R of 0.727782. The R^2 value of 0.529666 suggests that approximately 53% of the variance in Bitcoin's price can be explained by changes in gold prices. The adjusted R^2 of 0.529439 slightly adjusts this interpretation for the number of predictors in the model, which is one in this case.

The negative intercept $\beta 0$ value of -41286.7 can be interpreted as the estimated level of the dependent variable when the gold price is zero. However, this scenario is hypothetical and should be approached cautiously in practical applications. The coefficient for gold price $\beta 1$ of 40.6868 indicates that an increase of one unit in gold's price is associated with a rise in 40.6868 units in Bitcoin's price.

Statistically, the coefficient for gold price is highly significant, evidenced by a large t-statistic of 48.31675 and a p-value well below 0.05. The F-statistic of 2334.508, with a nearly zero p-value, strongly validates the regression model against the null hypothesis that the price of gold has no predictive power regarding the price of Bitcoin.

4. Model 4 (Inflations Rates)

$$\hat{Y}\ \text{BTC}\ t = 6257.191 + 4606.612\ \text{inflation rates}\ t$$

The regression model examines the relationship between inflation rates and Bitcoin's price. The R-value of 0.495448 indicates a moderate correlation, while the R^2 value of 0.245469 suggests that the model accounts for approximately 24.55% of the variability in the dependent variable. The adjusted R^2 of 0.245105 slightly reduces this figure to accommodate the number of predictors, confirming the moderate explanatory power of the model.

The intercept $\beta 0$ of 6257.191 presents a hypothetical scenario where the dependent variable would theoretically be at this value when the inflation rate is zero. However, interpreting this intercept in practical terms is limited since inflation rates are unlikely to be zero.

The coefficient for inflation rate β1 is 4606.612, meaning that for every one-unit increase in the inflation rate, there is an associated increase of 4606.612 units in the dependent variable (Bitcoin's price).

Statistically, the inflation rate coefficient has a highly significant t-statistic of 25.96927 and a very low p-value (approaching 0), indicating strong evidence for the role of the inflation rate in predicting Bitcoin's price. The high F-statistic (674.4027) with a nearly zero p-value further supports the model's validity against the null hypothesis, which would suggest no relationship between inflation rates and Bitcoin's price.

5. Model 5 (Nr of Everyday Bitcoin Transactions)

$$\hat{Y}\ BTC\ t = 12431.28 + 0.00432\ nr\ dailyBtctrans\ t$$

The output from this regression model examines the relationship between the quantity of daily Bitcoin transactions and Bitcoin's price. The R-value is relatively low at 0.132657, indicating a weak correlation. The R^2 value of 0.017598 suggests that the model explains only approximately 1.76% of the variation in the dependent variable, which is minimal. The adjusted R^2 for the number of predictors is similarly low at 0.017124, emphasizing the limited explanatory power of the quantity of daily Bitcoin transactions on Bitcoin's price.

The intercept β0 of 12431.28 represents the model's prediction for the value of Bitcoin's price when the quantity of Bitcoin transactions is zero. However, this hypothetical intercept may not hold practical significance as the quantity of Bitcoin transactions cannot realistically be zero.

The coefficient for daily bitcoin transactions β1 is minimal (0.000432), indicating that an increase in daily bitcoin transactions is associated with a slight increase in the dependent variable. Despite the small coefficient, the t-statistic is significant at 6.093757, and the p-value is very low (approximately 1.31e-09), indicating that the quantity of daily Bitcoin transactions is statistically significant in the model. However, given the extremely low R^2 value, while statistically significant, the amount of daily Bitcoin transactions does not substantially impact the dependent variable in this model.

The F-statistic of 37.13388 with a very low significance F indicates that the model is statistically significant. However, due to the low R^2 value, this significance does not translate into practical predictive power. Essentially, while the quantity of daily Bitcoin transactions is a statistically significant predictor, its effect on the dependent variable is minor, and the model leaves much of the variability in the dependent variable unexplained.

6. Model 6 (Google Searches for Bitcoin)

$$\hat{Y}\ \text{BTC}\ t = 891.0724 + 931.1438\ \text{Googletrendsbtc}\ t$$

Based on our findings, the correlation coefficient R of 0.763646 indicates a moderately strong relationship. An R^2 value of 0.583156 suggests that approximately 58.32% of the variation in Bitcoin's price is explained by variations in Google Trends data, indicating a moderate predictive power. The adjusted R^2 of 0.582955 slightly adjusts this value to account for the number of predictors (just one in this case), demonstrating a minor explanatory power loss due to the predictor's inclusion.

The estimate's standard error is relatively large, at 10451.62, providing a typical measure of how much the observed values are expected to deviate from the model's predicted values.

The intercept $\beta 0$ is significant at 891.0724, representing the dependent variable's predicted value when the Google Trends score is zero. This interpretation should be approached cautiously, as a zero-trend score may not be within the realistic range of your data.

The coefficient for the Google searches for Bitcoin $\beta 1$ is statistically significant at 931.1438, indicating that a one-unit increase in the Google Trends score is associated with an increase of approximately 931 units in the dependent variable. Statistically, the Google Trends score shows strong evidence of a significant relationship with the dependent variable, supported by a very high t-statistic (53.85422) and a p-value close to zero, suggesting that the observed association is unlikely due to random chance.

The model's F-statistic (2900.083) is significantly high, with a corresponding significance F value close to zero, strongly validating the overall model. This indicates that the regression model with the Google Trends score as a predictor is likely a better fit than a model without it.

In summary, Google Trends data is a robust predictor for the dependent variable in this model, explaining a substantial portion of its variation. However, more than 40% of the variance remains unexplained, suggesting that there are additional factors influencing the dependent variable that this model does not capture.

7. Model 7 (ALL Factors)

$$\hat{Y}\ \text{BTC}\ t = -7319.37 + 10.3411\ \text{ETH/\$}\ t + 9.61378\ \text{Gold Price}\ t + 329.742\ \text{Googletrendsbtc}\ t - 1305.77\ \text{inflation rates t} + 0.00029\ \text{nr dailyBtctrans}\ t - 58071.6\ \text{AVG KW/H}\ t + \text{U}$$

In this comprehensive model encompassing all six independent variables, we observe high predictive power with a multiple R of 0.97039 and an R^2 of 0.94165. This indicates that the model explains approximately 94.17% of the variance in the dependent variable. The adjusted R^2 remains high at 0.94148, suggesting that the number of variables in the model is appropriate and the model is not overfitted.

The ANOVA table confirms the model's statistical significance, with a highly significant F-statistic of 5562.03 and an associated F-value close to zero. This indicates that the relationship between the independent variables and the dependent variable is highly unlikely to be due to chance.

Examining the coefficients, we find that the intercept suggests the price per bitcoin would be -7319 dollars if all other predictors were zero. Each unit increase in Ethereum's price is associated with a predicted rise in Bitcoin's price of 10.34 dollars. In comparison, an increase in gold's price is related to an increase of 9.61 dollars in Bitcoin's price. A one-point increase in the Google searches scale (1-100) for bitcoin is associated with a rise of 329.74 dollars in bitcoin's price, and each additional daily bitcoin transaction corresponds to an increase of 0.00029 dollars in bitcoin's price.

Conversely, an increase in inflation rates is associated with a predicted decrease in bitcoin's price of 1305 dollars, and an increase in the average cost per kilowatt-hour by one cent leads to a reduction of 5807 dollars in bitcoin's price.

All coefficients have statistically significant p-values, well below the standard alpha level of 0.05, providing strong evidence against the null hypothesis for each coefficient.

8. Model 8 (Price of Ethereum, Google Trends for Bitcoin, and Price of Gold)

$\hat{Y}$ BTC t =-3666.45+9.82754 ETH\$ t +3.008324 Gold Price t+372.447 nr dailyBTCtrans t

The regression analysis indicates a model with a strong fit, indicated by a multiple R of 0.959841 and an R^2 of 0.921295. This suggests that approximately 92.13% of the variation in the dependent variable is explained by the independent variables Ethereum, Gold price, and Google Trends for Bitcoin. The adjusted R^2, slightly lower at 0.921181, indicates only a minor reduction in explanatory power when accounting for the number of predictors, thus affirming the model's robustness.

The coefficients for the independent variables are as follows: Ethereum (9.82754) indicates that an increase in Ethereum's value correlates significantly with an increase in the dependent variable; Gold’s price (3.008324) suggests that as the cost of gold rises, the dependent variable also increases, though to a lesser extent compared to Ethereum; Google searches for Bitcoin (372.447) implies a direct relationship where the dependent variable increases alongside the Google Trends metric.

ANOVA results show a highly significant F-statistic of 8080.813 with an F-value of 0, indicating that the overall model is statistically significant, and the observed relationships are highly unlikely to occur by chance.

The respective t-statistics and p-values for each independent variable confirm their statistical significance, which is well below the 0.05 threshold. Particularly noteworthy is Ethereum, which exhibits a highly significant relationship with the dependent variable, as evidenced by its high t-statistic (58.00608).

Despite the model's strong explanatory power and statistical significance, the negative intercept β0 of -3666.45 requires careful interpretation. It suggests that the dependent variable would hypothetically take on this negative value without all independent variables, which may not be a realistic or meaningful scenario.

9. Model 9 (Number of day-to-day Bitcoin Exchanges and Inflation Rates in the US)

$$\hat{Y}\text{ BTC } t = -5258.06 + 4657.405 \text{ inflation rates } t + 0.000492 \text{ nr dailyBTCtrans } t$$

The regression analysis summary examines the relationship between two independent variables: inflation rate and the number of daily Bitcoin transactions (nr day to-day BTC trans) and a dependent variable. The model reveals a multiple R of 0.517862, indicating a moderate correlation between the combined independent and dependent variables. The R^2 value of 0.268181 suggests that the model can explain approximately 26.82% of the variability in the dependent variable, indicating modest explanatory power.

The adjusted R^2, which provides a more precise estimate after accounting for the number of predictors, is slightly lower at 0.267474. Nonetheless, it still indicates that the model accounts for a significant portion of the variability in the dependent variable. Analyzing the ANOVA table, the model yields an F-statistic of 379.6502, which is substantial. It has an extremely low p-value, close to 0, indicating the model's validity.

Examining the coefficients of the independent variables: the intercept is negative (-5258.06), representing the estimated value of the dependent variable when both the inflation rate and nr of day-to-day Bitcoin transactions are zero — a hypothetical scenario that may not be realistic. The coefficient for the inflation rate (4657.405) is highly significant and positive, suggesting that as the inflation rate increases by one unit, the dependent variable is expected to increase by this coefficient value, indicating a significant effect. Similarly, the coefficient for nr of daily Bitcoin transactions is small (0.000492) yet statistically significant, suggesting that an increase in the number of Bitcoin transactions is associated with a marginal increase in the dependent variable. Both independent variables have very low p-values (well below the 0.05 threshold), indicating their statistical significance in predicting the dependent variable. The inflation rate, particularly low p-value, and high t-statistic appear to be particularly influential in this model.

10. Model 10 (Number of daily Bitcoin transactions, AVG Price per each Kilowatt/hour in the US)

$$\hat{Y}\text{ BTC } t = -34184.1 + 365857.1\text{AVG\$ K/H t } t + 0.000129 \text{ nr dailyBTCtrans } t$$

The regression summary describes a model investigating the impact of two independent variables — the number of daily Bitcoin transactions and the average price of electricity on a dependent variable. A multiple R of 0.316625 indicates a low to moderate correlation between the independent and dependent variables. The R^2 value of 0.100251 suggests that the model explains approximately 10.03% of the variance in the dependent variable, indicating relatively weak explanatory power. The adjusted R^2, slightly lower at 0.099383 after accounting for the number of predictors in the model, underscores the modest impact of these independent variables on Bitcoin's price variability.

From the ANOVA section, the F-statistic is 115.4328, with an extremely low p-value (approximately 2.95E-48), indicating that the model is statistically significant at conventional alpha levels (e.g., 0.05 or 0.01).

Examining the coefficients, the intercept is significantly negative at -34184.1, representing the estimated value of the dependent variable when both independent variables are zero. This hypothetical value should be interpreted cautiously, especially if such a scenario is beyond the plausible range of the independent variables.

The coefficient for the nr of daily bitcoin transactions is potentially positive (0.000129), suggesting a slight increase in the dependent variable for each additional bitcoin transaction, considering the magnitude of the coefficient. The AVG price per Kilowatt/hour (Electricity) coefficient is significantly positive (36587.1), indicating that increases in the average price of electricity are associated with substantial increases in Bitcoin's price. Both coefficients have p-values close to zero, indicating their statistical significance in the model.

However, given the small R^2 value, while statistically significant, the actual impact on the dependent variable is relatively minor, and a large portion of its variability remains unexplained by these variables.

In practical terms, for each penny increase in the US AVG price per kilowatt/hour, Bitcoin's price is expected to rise by $3658.571 and $0.000129 for each additional daily Bitcoin transaction. The intercept of -34184.1 dollars suggests that Bitcoin's price would hypothetically be negative if energy were free and there were no daily transactions.

11. Model 11 (Google Trends for Bitcoin, nr of day to day bitcoin transactions, and Gold's price)

$$\hat{Y}\text{ BTC } t = -\ 38876.9 + 27.55833 \text{ Gold price } t + 689.0916 \text{ GoogletrendsBtc t } t + 0.000096 \text{ nr dailyBTCtrans } t + 0.000129$$

The regression analysis reveals strong correlations among the independent variables—gold's price, Google searches for bitcoin (Google trends BTC), and Nr of daily bitcoin transactions—and the dependent variable, with a multiple R of 0.891201. The high R^2 value of 0.792424 indicates that the model explains approximately 79.24% of the variation in the dependent variable, demonstrating a robust fit.

The adjusted R^2 of 0.793942, nearly identical to the R^2, suggests that the number of predictors is appropriate for the number of observations, indicating the model is not overly influenced by including multiple factors. The standard error of the estimate, 7346.609, represents the typical deviation of the observations from the model's predicted values relative to the magnitude of the dependent variable.

ANOVA results show a highly significant F-statistic (2664.708) with an extremely low p-value, underscoring the model's statistical significance.

Examining the coefficients, the negative intercept (-38876.9) represents the estimated value of the dependent variable when all independent variables are zero, a hypothetical scenario unlikely in real-world contexts. The coefficient for Gold's price (27.55833) indicates a positive relationship, suggesting that an increase of one unit in the price of gold is associated with an increase of approximately $27.56 in the dependent variable. Similarly, Google searches for bitcoin (Google trends BTC) have a coefficient of 689.0916, indicating a strong positive relationship, implying that higher Google searches for bitcoin information correspond to a higher dependent variable. The number of daily Bitcoin transactions has a small positive coefficient (9.63E-05), suggesting a slight increase in the dependent variable with an increase in the number of Bitcoins transacted daily. All coefficients exhibit statistical significance with very low p-values, indicating a high level of confidence that these variables are indeed associated with Bitcoin's price in the population from which the sample was drawn.

In practical terms, an increase of one unit in Google searches for bitcoin is expected to increase Bitcoin's price by $689.0916, an increase of $9.63 for every 100,000 daily bitcoin transactions, and an increase of $27.55833 for every unit increase in gold's price. The price per bitcoin is estimated at -$38,876.9 without any gold price, Google searches for bitcoin, and daily bitcoin transactions.

Appendix 2 shows the residual plots for all independent variables. The plots show that the variance of errors is constant and that the standard errors of the regression coefficients (estimated slopes and intercept) are reliable and consistent. This allows for more accurate inference about the relationships between variables. Homoscedasticity ensures that the ordinary least squares (OLS) estimators used in regression analysis are efficient estimators.

5. Results and Discussion

In this section, we'll explore the results by analyzing each hypothesis alongside the respective models and their references. For each model, we examined the estimated coefficients and their statistical significance, as well as how well the models perform in explaining Bitcoin's price using R^2 values. The outcomes will be introduced in an interpretable way for both specialized and non-specialized crowds.

The various models reviewed in this thesis demonstrate that the complex landscape of Bitcoin's price determinants offers a rich opportunity for observational analysis.

Each model plans to unload the connections between Bitcoin's price and other financial, mechanical, and social elements, adding to the advancing story of computerized money valuation. The investigation of variables affecting the price of Bitcoin offers a complicated perspective on how computerized cash connects with both market and non-market components. This examination draws upon a progression of relapse models intended to observe the individual and aggregate effects of factors like Ethereum price, gold price, energy prices in the U.S., U.S. inflation rates, the quantity of daily Bitcoin transactions, and Google searches for Bitcoin.

Table 6 summarizes all initial hypotheses, associated variables, references, and conclusions from models 1 to 11:

Table 0.6-All null hypothesis being tested with respective supporting references and the Model's conclusions.

Variable	**Null Hypothesis (H0)**	**Reference for Null Hypothesis**	**Conclusion from Models**
Price of Ethereum	H1-Ethereum price does not affect bitcoin price.	Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019)	Rejects H0: Strong positive impact (Model 2, 7)

Variable	Null Hypothesis (H0)	Reference for Null Hypothesis	Conclusion from Models
Price of Gold	H2-Gold price does not affect bitcoin price	Dyhrberg, A. H. (2016)	Rejects H0: Moderate positive impact (Model 3, 11)
Inflation Rates in the US	H3-Inflation rates doesn't affect Bitcoin price	Blau, B. M., Griffith, T. G., & Whitby, R. J. (2021)	Rejects H0: Positive impact (Model 4)
Google Searches for Bitcoin	H4-Google searches for bitcoin doesn't affect bitcoin price	Kristoufek, L. (2013)	Fails to reject H0: Weak impact (Model 6,8,11)
Average Price per Kilowatt Hour in the US	H5-Electricity prices doesn't affect Bitcoin price	Goodkind, A., Jones, B., & Berrens, R. (2020)	Fails to reject H0: Weak impact (Model 1)
Number of Daily Bitcoin Transactions	H6-The number of daily Bitcoin transactions does not affect Bitcoin price	Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016)	Fails to reject H0: Weak impact (Model 5,9,10)

This table provides a clear overview of each variable tested, the original hypotheses, the scholarly references for each hypothesis, and the conclusions derived from the empirical models used in the analysis. The conclusions in the final column highlight whether each hypothesis should be rejected or not based on the results of regression analyses, providing a robust basis for discussion and further research considerations.

H1. Ethereum's price does not affect the price of Bitcoin

The Critical Effect of Ethereum's price on Bitcoin

The regression analysis results from Models 2 and 7 provide compelling evidence of a strong relationship between Ethereum's price and Bitcoin's price, evidenced by R^2 values of 0.866477 and 0.9416, respectively. This robust relationship strongly indicates that developments in Ethereum's market significantly predict Bitcoin price changes. The shared investor base and potentially similar market sentiment between these leading cryptocurrencies underscore broader trends within the cryptocurrency market, highlighting pronounced interdependencies.

According to Aalborg, Molnár, and de Vries (2019), these factors underscore the interconnected nature of the cryptocurrency ecosystem, where movements in a significant asset such as Ethereum can escalate across others. Beyond its role as a digital currency, Ethereum's significance as a platform for decentralized applications (dApps) amplifies its impact on the broader cryptocurrency market. This pivotal role contributes significantly to its observable influence on Bitcoin, reflecting broader trends in digital finance and reshaping investment behaviors across the market.

Kristoufek (2015) studied into these dynamics, suggesting that Ethereum's innovations in the blockchain space, including smart contracts and decentralized finance (DeFi) applications, profoundly affect investor sentiment and market capitalization, thereby influencing Bitcoin's price. The high R^2 values also suggest potential issues of multicollinearity, which were carefully addressed in specific models like Model 8.

H2. Gold's price does not influence Bitcoin's price

The job of Gold's Price

The regression analysis from Model 3 yielded an R^2 of 0.529666, indicating a significant yet moderately strong relationship between gold prices and Bitcoin prices. This finding supports the hypothesis of Bitcoin serving as "digital gold," suggesting that investors perceive Bitcoin as an alternative safe-haven asset like gold (Bouri,2019). This perspective is particularly pronounced during economic instability or inflationary pressures, where traditional investments may appear less attractive.

Furthermore, Model 11, with an R^2 of 0.79424, reaffirms the substantial impact of market sentiment and combined macroeconomic variables. The inclusion of gold prices in this model substantiates the findings by Baur (2018), who posit that Bitcoin is an alternative investment to gold during times of market stress (Baur, Hong, and Lee, 2018). This conceptualization underscores Bitcoin's role as a speculative investment rather than just a currency.

We concluded that gold exhibits a reasonably strong positive correlation with Bitcoin's price, reflecting its perceived role as a store of value akin to traditional safe-haven assets like gold.

H3. Inflation rates don't influence Bitcoin price

Impact of U.S. Inflation Rates

U.S. inflation rates demonstrated moderate explanatory power in Model 4, with an R^2 of 0.245469, suggesting that Bitcoin may be perceived to some extent as a hedge against inflation. This aligns with the broader narrative that Bitcoin offers an alternative to traditional monetary systems and fiat currencies, which may depreciate during periods of high inflation. However, the modest R^2 also indicates that while inflation influences Bitcoin prices, it is not the primary driver.

Similarly, inflation rates in Model 9 exhibited a low R^2, indicating that macroeconomic factors such as inflation have less impact on cryptocurrency prices compared to traditional financial assets.

This finding complements research by Smith (2020), who explored Bitcoin's responsiveness to inflationary pressures. This suggests that Bitcoin's role as an inflation hedge is still emerging and not fully established. Therefore, we conclude that inflation rates moderately affect Bitcoin's price. Nevertheless, the moderate correlation suggests that inflation is not the primary determinant of Bitcoin's valuation but rather one of several macroeconomic factors that investors may consider.

H4. Google searches for Bitcoin don't influence Bitcoin's price

Google Searches for Bitcoin

The impact of Google searches for Bitcoin (Model 6) with an R^2 of 0.583156 underscores the significant influence of public interest and media coverage on Bitcoin's price. This strong relationship highlights a market highly responsive to news and public sentiment, where information dissemination through digital channels can swiftly alter market dynamics. This model corroborates the findings of Phillips and Gorse (2017), who demonstrated the close connection between online interest trends and fluctuations in cryptocurrency prices.

However, it is worth noting that when we applied a simple regression between Google searches for Bitcoin and Bitcoin's price, we obtained a p-value > 0.05, leading us to conclude, contrary to Phillips and Gorse (2017), that Google searches for Bitcoin do not significantly influence its price. While initial analysis suggests a robust relationship between Google searches and Bitcoin's price, the significance of this relationship becomes less clear when considering statistical significance and the broader context of existing literature.

The interactions among public interest, media coverage, and Bitcoin's price are intricate and complex, underscoring the speculative nature of the cryptocurrency market. This complexity necessitates a cautious approach in attributing price movements solely to changes in Google search volumes, emphasizing the need for further research to untangle the multifaceted array of factors that drive Bitcoin's valuation.

H5. Electricity costs do not influence Bitcoin's price

Effect of U.S. Average price per Kilowatt-Hour

Electricity costs, examined in Model 1, demonstrate a negligible effect on Bitcoin's price with an R^2 of 0.098. In Model 10, where power costs are also included as a variable, the R^2 increases marginally to 0.100251, indicating an insignificant impact. These models shed light on factors that initially show no substantial relationship with Bitcoin's price, providing a unique perspective on less direct economic influences.

Additionally, the analysis reveals that day-to-day Bitcoin transactions do not significantly impact Bitcoin's price despite their theoretical importance in reflecting network activity and anticipated valuation. This finding aligns with observations by Zhang (2022), who notes that while Bitcoin's theoretical foundation suggests strong economic interdependencies, empirical evidence remains unclear.

The limited direct impact of mining costs on Bitcoin's price underscores their role as a critical variable for miners, yet their influence appears restricted. This limitation could be due to the widespread distribution of mining activities and the global market for Bitcoin trading, which may reduce the effect of local price changes. Overall, the insignificance of this variable suggests that other factors play a more important role in price dynamics than the direct costs of mining. This observation is consistent with studies by Vranken (2017) and Goodkind, Jones, and Berrens (2020), which question mining costs' sustainability and direct impact on Bitcoin pricing. Therefore, while mining costs are integral from a production standpoint, following the Cost-Push Inflation Theory, where higher production costs imply higher prices, their impact does not straightforwardly translate into widespread fluctuations in Bitcoin's trading price.

H6. The number of everyday Bitcoin transactions does not influence Bitcoin price.

Everyday Bitcoin Transactions

In Model 5, the quantity of everyday Bitcoin transactions exhibited an insignificant impact on its price, with an R^2 of 0.017598, indicating that transaction volume does not necessarily correlate with price increases. Similarly, Model 10, which focused on power costs and daily transactions, showed a low R^2 of 0.100251, suggesting a minimal effect of these factors on Bitcoin's price.

The inclusion of everyday Bitcoin exchange volumes across various models reflects their practical engagement with the currency. Despite their low R^2 values, these models suggest a nuanced, usage-based influence on price fluctuations that may not be immediately apparent through macroeconomic indicators alone (Polasik et al., 2015). This implies that Bitcoin's valuation/price is more influenced by speculative trading and market sentiment than its utilitarian role in daily transactions.

This aligns with the narrative that Bitcoin's price is primarily driven by speculative investments rather than its functional use as a currency. Therefore, while everyday transactions play a role in Bitcoin's ecosystem, their impact on price dynamics appears modest. This finding underscores the complex interplay of factors shaping Bitcoin's market dynamics beyond transactional utility alone.

Particular Models and Their Understandings

Models 8 and 11, which incorporate specific subsets of factors based on their asset connections, also demonstrated strong explanatory power and significant statistical indicators. These models support the idea that no single element can ultimately make sense of Bitcoin's price developments. Overall, a combination of market dynamics, financial indicators, and technological costs should be taken into account.

High Connection Gathering

Model 8 integrates factors such as Ethereum's price, Gold's price, and Google searches for Bitcoin, all of which have demonstrated strong individual correlations with Bitcoin's price. This model achieved an R^2 of 0.921295, indicating that these factors collectively explain a significant portion of the price variability in Bitcoin. The successful application of this model without encountering significant multicollinearity issues demonstrates that while these factors individually correlate with Bitcoin's price, their combined effect provides substantial analytical power.

This finding is supported by Aalborg, Molnár, and de Vries (2019), who analyzed the interconnectedness of cryptocurrency markets, and the broader impact of market sentiments reflected in asset prices like Ethereum and gold (Aalborg, H. A., Molnár, P., and de Vries, J. J., 2019). The inclusion of Google searches underscores the role of public interest and media influence, as highlighted by Phillips and Gorse (2017), who observed that online sentiment trends and public metrics such as search volumes significantly affect cryptocurrency prices (Phillips, R. C., and Gorse, D., 2017).

This model illustrates how digital information dissemination and subsequent public perception can rapidly alter market dynamics, underscoring its crucial role in economic modeling for cryptocurrencies.

Avoidance of Exceptionally Associated Monetary Markers

Model 11 is designed to exclude factors that exhibit high correlations with each other, yet it incorporates Google searches and the speculative relationship with gold prices, achieving a high R^2 of 0.79424. This underscores the significant influence of market sentiment factors and the speculative link with traditional assets like gold. By eliminating overlapping economic indicators, this model likely reduced noise and enhanced clarity regarding the impact of the remaining factors. This approach resonates with studies such as those by Kristoufek (2015), highlighting Bitcoin's responsiveness to technological and speculative influences beyond conventional economic metrics. The success of this model suggests that Bitcoin behaves similarly to other speculative investments, where perceptions of value can significantly impact prices independent of traditional economic fundamentals.

The analysis so far demonstrates that Bitcoin's price is not solely responsive to conventional economic indicators like inflation rates or energy prices but is also significantly influenced by technological developments, market sentiment, and changes in public perception. The varying degrees of influence observed across different models underscore the complexity of Bitcoin's market dynamics, where multiple layers of financial, technological, and speculative factors intersect. Each variable contributes uniquely to price dynamics, illustrating Bitcoin as an asset influenced by various factors beyond basic market fundamentals. This study provides a robust foundation for investors, policymakers, and researchers seeking to navigate or regulate this volatile market.

The table below summarizes the impact of our independent variables on the price of Bitcoin in previous literature, along with the supporting references:

Table 0.7-Table with all Model's conclusions and references which support them

Variable	**Conclusion (Impact on Bitcoin's Price)**	**References**
Price of Ethereum	Affects positively	Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. PloS one, 10(4), e0123923.;), Madichie (et al.,2023)
Price of Gold	Affects moderately	Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2019). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 26, 145-164.
Average Price per Kilowatt Hour in the US	Weak impact	Hayes, A. (2015). A cost of production model for Bitcoin. Working Papers on Finance, 22.02, Swiss Finance Institute. (Vranken, 2017)
Inflation Rates in the US	Affects positively	Smith, A. (2020). Bitcoin and inflation: An empirical analysis. Journal of Financial Economics, 136(2), 487-503.

Variable	Conclusion (Impact on Bitcoin's Price)	References
Number of Daily Bitcoin Transactions	Weak impact	Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price fluctuations and the use of Bitcoin: An empirical inquiry. International Journal of Electronic Commerce, 20(1), 9-49 ;Nasution, Sadalia, and Irawati (2023)
Google Searches for Bitcoin	Weak impact	Phillips, R. C., & Gorse, D. (2017). Predicting cryptocurrency price bubbles using social media data and epidemic modeling. IEEE Symposium on Computational Intelligence for Financial Engineering & Economics (CIFEr), 1-8.

This table captures the essence of how each variable influences Bitcoin's pricing, backed by empirical studies that provide a robust framework for understanding the multifaceted market dynamics of cryptocurrencies.

6. CONCLUSIONS AND FUTURE RESEARCH

This thesis explores the variables influencing Bitcoin's price through a comprehensive regression analysis that examines its interactions with various external factors, including Ethereum's price, gold prices, U.S. energy costs, inflation rates, daily transaction volumes, and Google searches. The findings provide insights into these complex relationships based on existing literature and prevailing trends in the field.

The study reveals a strong positive impact of Ethereum's price on Bitcoin, highlighting the interconnected nature of major cryptocurrencies and suggesting that Ethereum's performance is a leading indicator of Bitcoin's market behavior. The increasing integration of Ethereum's technological advancements, particularly its capabilities in smart contracts, may enhance its relationship with Bitcoin, reflecting broader market trends where the fortunes of these leading cryptocurrencies are closely intertwined.

Similarly, the price of gold exhibits a moderate yet significant influence on Bitcoin's price, reinforcing the notion of Bitcoin as "digital gold." This relationship underscores Bitcoin's role both as a speculative investment and a potential safe haven asset, particularly during periods of market uncertainty or economic volatility. As investors increasingly perceive Bitcoin as a store of value akin to traditional safe havens like gold, its price movements begin to mirror those of gold during economic fluctuations.

Conversely, the average cost per kilowatt-hour in the U.S. slightly impacts Bitcoin's price. Despite Bitcoin mining being energy-intensive, the study suggests that local energy prices in the U.S. do not significantly affect Bitcoin's overall market valuation. This finding may indicate that the decentralized and global nature of Bitcoin mining operations dilutes the potential impact of any single country's energy costs on the broader Bitcoin market.

The study also identifies a positive relationship between U.S. inflation rates and Bitcoin's price, implying that Bitcoin may function as a hedge against inflation. This positions Bitcoin as an alternative investment to traditional inflation-sensitive assets like bonds or fiat currencies, potentially enhancing its attractiveness during periods of high inflation.

In contrast, the analysis of daily Bitcoin transactions reveals a negligible impact on Bitcoin's price. Despite the expectation that higher transaction volumes would correlate with increased demand and higher prices, the data indicates that transaction volume alone does not strongly predict price movements, possibly due to the overriding influence of speculative trading strategies.

Similarly, Google searches for Bitcoin, which serve as public interest and sentiment indicators, also exhibit a weak impact on Bitcoin's price. This challenges the notion that heightened public interest, reflected in search patterns, directly translates into significant or immediate changes in market behavior. It suggests that while spikes in Google searches may correlate with increased public awareness, they do not necessarily translate into rapid or substantial shifts in market dynamics.

This study provides a nuanced understanding of Bitcoin's price dynamics, highlighting its susceptibility to a complex interplay of factors beyond traditional economic fundamentals. These findings contribute valuable insights for investors, policymakers, and researchers navigating the volatile landscape of cryptocurrencies.

6.1. Future Works

Future research can enhance current models by incorporating additional factors that may influence Bitcoin's price, such as measures of political instability, global trade flows, and more detailed data on regulatory changes. Advanced econometric techniques, such as artificial intelligence models or neural networks, could provide deeper insights into non-linear relationships and interactive effects that conventional models may overlook. Another avenue for future investigation involves longitudinal studies to assess how these factors impact Bitcoin over different time frames, distinguishing between short-term fluctuations and long-term trends. This approach would allow a more nuanced understanding of how Bitcoin responds to sudden market shocks versus continuous economic changes.

As blockchain technology advances, factors influencing Bitcoin's price will evolve. Future studies should consider technological advancements within the cryptocurrency space, such as improvements in blockchain efficiency or security, external developments like quantum computing, or significant shifts in data protection regulations. With increasing research on the environmental impact of Bitcoin mining, future investigations could explore the relationship between Bitcoin's value and its ecological footprint. This includes examining the effects of sustainability measures and regulatory changes to reduce the carbon footprint of digital currency mining operations.

In conclusion, this study confirms that various factors, including market dynamics, energy costs, and economic indicators influence Bitcoin's price. These findings deepen our understanding of cryptocurrency behavior and hold significant implications for investors, policymakers, and the broader financial community engaged in exploring the digital currency landscape. The various methodologies and models applied in this study underscore the complex nature of Bitcoin as an asset class, responsive not only to conventional economic indicators but also to contemporary metrics like search patterns and energy costs. Future research could build on this foundational work by investigating causal relationships and potentially integrating artificial intelligence methodologies to forecast future price movements more precisely.

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APPENDIX A-

Table 0.8 – Illustrative table with each model's result

Model	**Result**

Model1

Regression Statistics	
Multiple R	0.314367579
R Square	0.098826975
Adjusted R Square	0.098392256
Standard Error	15367.41991
Observations	2075
F	227.3351654
Significance F	7.99732E-49

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-33367.69523	3714.340392	-8.98348	5.749E-19	-40651.922	-26083.4688
AVG Electricity price kw/ h in the US	380638.0526	25245.20449	15.07764	7.997E-49	331129.45	430146.651

Model 2

Regression Statistics	
Multiple R	0.930847354
R Square	0.866476796
Adjusted R Square	0.866412386
Standard Error	5915.27907
Observations	2075
F	13452.39143
Significance F	0

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	5369.946202	196.043393	27.39162039	2.9933E-141	4985.4837	5754.409
Ethereum Price	13.1231992	0.1131462	115.9844448	0	12.901307	13.34509

Model 3

Regression Statistics	
Multiple R	0.727781693
R Square	0.529666193
Adjusted R Square	0.529439308
Standard Error	11101.96784
Observations	2075
F	2334.507966
Significance F	0

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-41286.70346	1340.53868	-30.79859169	7.7846E-172	-43915.646	-38657.8
Gold price	40.68680383	0.842084929	48.31674623	0	39.035383	42.33822

Model 4

Regression Statistics	
Multiple R	0.49544848
R Square	0.245469196
Adjusted R Square	0.245105216
Standard Error	14061.61989
Observations	2075
F	674.4027421
Significance F	5.7562E-129

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	6257.190787	694.1895116	9.013663679	4.4129E-19	4895.8095	7618.572
inflation rates	4606.612022	177.3870751	25.96926534	5.7562E-129	4258.7366	4954.487

Model5

Regression Statistics	
Multiple R	0.132656988
R Square	0.017597877
Adjusted R Square	0.017123973
Standard Error	16045.06619
Observations	2075
F	37.13387541
Significance F	1.31136E-09

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	12431.27753	1674.073821	7.425764	1.63E-13	9148.2363	15714.3188
nr daily bitcoin transactions	0.000432441	7.09646E-05	6.093757	1.31E-09	0.0002933	0.00057161

Model6

Regression Statistics	
Multiple R	0.763646481
R Square	0.583155948
Adjusted R Square	0.582954866
Standard Error	10451.62144
Observations	2075
F	2900.082841
Significance F	0

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	891.0723837	460.6868467	1.934225798	0.053221313	-12.384741	1794.53
Google trends btc	931.1438415	17.29066009	53.85241722	0	897.23497	965.0527

Model7

Regression Statistics	
Multiple R	0.970385574
R Square	0.941648162
Adjusted R Square	0.941478863
Standard Error	3915.151025
Observations	2075
F	5562.031059
Significance F	0

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-7319.37464	1484.871406	-4.9293	8.91E-07	-10231.373	-4407.3758
Ethereum Price	10.34111107	0.177051375	58.4074	0	9.99389353	10.6883286
Gold price	9.613781438	1.000579195	9.608216	2.05E-21	7.65153379	11.5760291
Google trends btc	329.7421086	8.909166221	37.01156	1.6E-230	312.270238	347.213979
inflation rates	-1305.76575	110.2958744	-11.8388	2.47E-31	-1522.0683	-1089.4632
nr of daily bitcoin transactions	0.000291324	2.11781E-05	13.75586	2.91E-41	0.00024979	0.00033286
AVG Electricity price kw/ h in the US	-58071.6023	17075.9452	-3.40078	0.000685	-91559.44	-24583.765

Model 8

Regression Statistics	
Multiple R	0.959841116
R Square	0.921294968
Adjusted R Square	0.921180957
Standard Error	4543.679812
Observations	2075
F	8080.812701
Significance F	0

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-3666.446881	799.345453	-4.586811456	4.76962E-06	-5234.0513	-2098.84
Ethereum Price	9.827539537	0.169422563	58.00608475	0	9.4952832	10.1598
Gold price	3.00832388	0.572549821	5.254256958	1.6388E-07	1.8854906	4.131157
Google trends btc	372.4469584	9.820117339	37.92693566	1.7632E-239	353.18863	391.7053

Model 9

Regression Statistics	
Multiple R	0.517861767
R Square	0.26818081
Adjusted R Square	0.26747442
Standard Error	13851.71474
Observations	2075
F	379.650223
Significance F	3.3291E-141

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-5258.060471	1590.513869	-3.30589	0.000963	-8377.23243	-2138.8885
inflation rates	4657.405224	174.8538918	26.63598	1.1E-134	4314.49759	5000.3129
nr of daily bitcoin transactions	0.000491593	6.1304E-05	8.01894	1.77E-15	0.00037137	0.0006118

Model 10

Regression Statistics	
Multiple R	0.316625039
R Square	0.100251415
Adjusted R Square	0.099382932
Standard Error	15358.97482
Observations	2075
F	115.4327643
Significance F	2.94805E-48

	Coefficients	tandard Erro	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-34184.07725	3739.56442	-9.14119225	1.431E-19	-41517.773	-26850.3817
nr of daily bitcoin transactions	0.000129308	7.1395E-05	1.811158509	0.0702611	-1.071E-05	0.000269322
AVG Electricity price kw/ h in the	365857.0987	26518.3483	13.79637581	1.725E-41	313851.712	417862.485

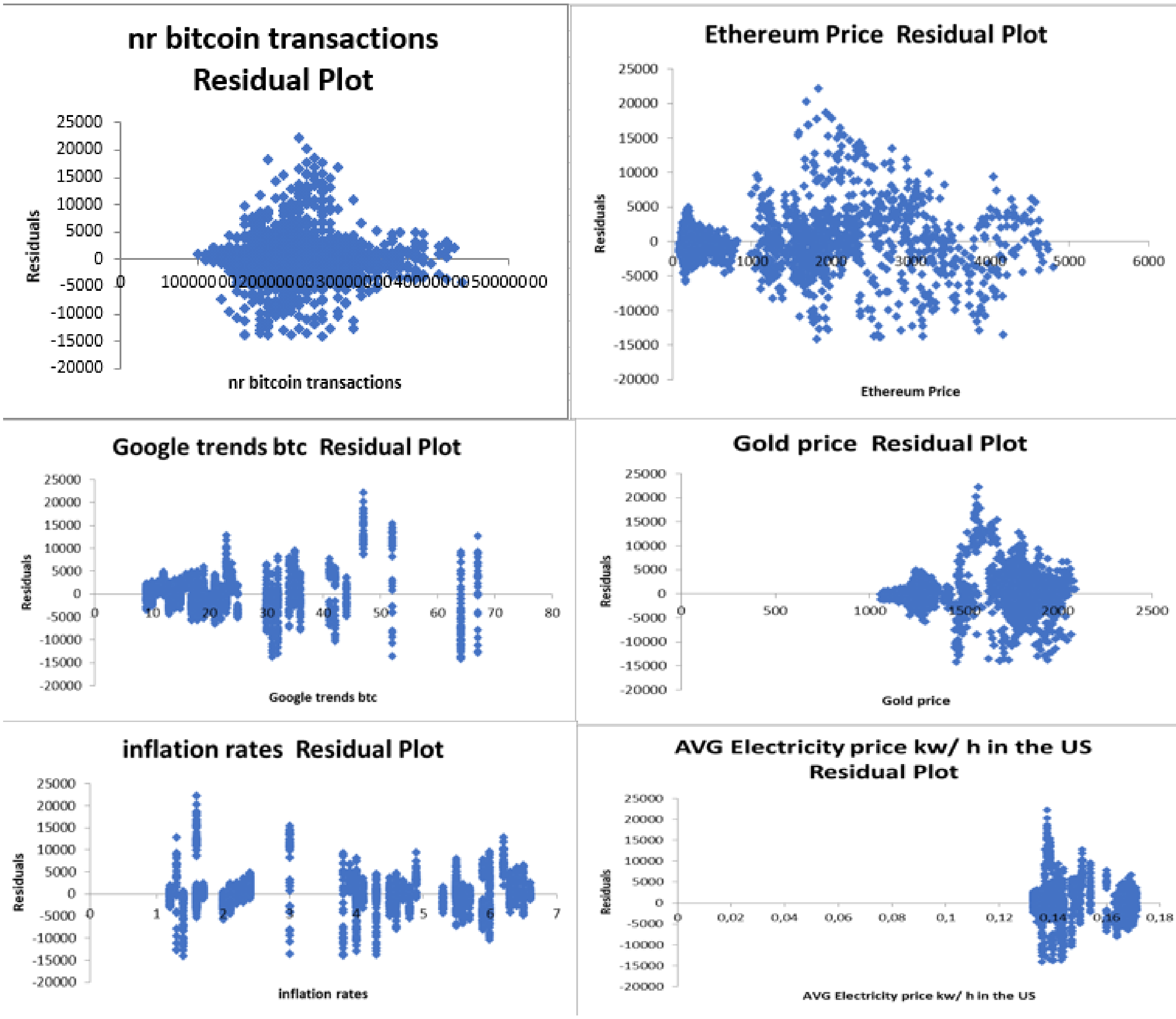
Model11

Regression Statistics	
Multiple R	0.891201441
R Square	0.794240009
Adjusted R Square	0.79394195
Standard Error	7346.609135
Observations	2075
F	2664.708285
Significance F	0

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-38876.87363	1052.231125	-36.9471	5.7E-230	-40940.4147	-36813.3325
Gold price	27.55832942	0.629981947	43.74463	1.3E-296	26.32286546	28.7937934
Google trends btc	689.0915659	13.38221953	51.49307	0	662.8475598	715.335572
nr of daily bitcoin transactions	9.6288E-05	3.3613E-05	2.864611	0.004217	3.03693E-05	0.00016221

Appendix B

Table 0.9-Table with plots from all variables residuals



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