

Understanding Cryptocurrency: A Descriptive Analytics Study of Bitcoin

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ABSTRACT

This exploratory applied study examines the nature and dimensions of cryptocurrency, namely bitcoin, a peer-to-peer network for facilitating digital barter. As the most widely used cryptocurrency, bitcoin has carved itself a niche market while also promoting the use of other cryptocurrencies. Through descriptive analysis and a visual analytic approach, the study highlights key characteristics and dimensions of bitcoin. The study helps understand the nature and extent of bitcoin use, assisting policymakers to shape and regulate the cryptocurrency marketplace in this contemporary volatile environment.

KEYWORDS

Bitcoin, Blockchain, Cryptocurrency, Descriptive Analytics, Visual Analytics, Visualization

INTRODUCTION

Bitcoin operates as a cryptocurrency platform (Cheun et al., 2017; Inci & Lagasse, 2019), leveraging a decentralized, peer-to-peer architecture to function as a virtual currency (Abramowicz, 2016; Bariviera, 2017; Hileman & Rauchs, 2017; Milutinovic, 2018; Tschorsch & Scheuermann, 2016; Urquhart, 2016). Promoted as an innovative kind of payment network and a novel kind of money, Bitcoin has gained significant attention in the fintech domain (Wile, 2014). To date, it has become the most successful virtual currency (John et al., 2022), capturing over 81% of the cryptocurrency market. Its prominence arises from two key features: it serves as an alternative currency independent of central banks and transactions are inherently distributed and decentralized in terms of control (Yermack, 2015). Unlike conventional currencies and financial instruments, it is neither issued nor regulated by any central bank (DeVries, 2016; Hileman & Rauchs, 2017; Kelly, 2014). Instead, individual participants can aggregate or “mine” bitcoins (BitcoinWiki, 2022). As such, it does not fit the conventional definition of a commodity currency (i.e., backed by tangible assets such as gold) or of a fiat currency (i.e., controlled by governments through central banks) (Shea, 2012).

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All transactions within the Bitcoin ecosystem are recorded on a transparent, publicly accessible distributed ledger called the “blockchain.” This decentralized database chronicles value transfers in a peer-to-peer network. The blockchain consists of blocks—batches of validated transactions—that are cryptographically interconnected. Bitcoin’s structure exemplifies a specific use of distributed ledger technology (Winklevoss, 2021). It employs a consensus method named “proof-of-work” to guarantee the ledger’s security and integrity. This mechanism compels network nodes to solve intricate mathematical challenges to craft new blocks and earn rewards. Its design permits the generation and transfer without requiring intermediaries or centralized entities.

The security of the blockchain platform is contingent on a specific algorithm used for mining bitcoin, which safeguards against double-spending and ensures transaction integrity. This algorithm, however, is energy-intensive (Vranken, 2017). Bitcoin represents a distributed system capable of addressing certain shortcomings of traditional currencies (Böhme et al., 2015; Vranken, 2017). Therefore, transaction costs can be expected to be lower as the issuance, settlement, and transaction confirmation are achieved through public consensus (Ali et al., 2014; Mikołajewicz-Woźniak & Scheibe, 2015). While the Bitcoin Foundation provides guidelines to comply with a standardized governance framework to ensure its security and promotion, it does not act as a centralized authority and does not issue currency (Beer & Weber, 2014).

In this study, we refer to it as “bitcoin,” but it is worth reiterating that it is a digital currency without any physical representation (Böhme et al., 2015; Vranken, 2017; Zohar, 2015). The blockchain—the underlying technology of the Bitcoin platform—facilitates transactions within a user network. These users transact with one another using the Bitcoin protocol over the Internet. The open-source nature enables users to store and trade the currency to purchase goods or exchange other currencies. Cryptocurrency, denoted by Bitcoin has distinct characteristics, including decentralized architecture, flexibility, transparency, fastness, and low transaction fees (Gerard, 2017).

“Miners” are individuals who create bitcoins and are rewarded with them in exchange. Their primary responsibility is to verify each transaction on the blockchain, ensuring the legitimacy of exchanges between users. Together, miners and the blockchain constitute the foundational infrastructure of the system. Developers and programmers also play vital roles in this construct (Böhme et al., 2015; Hileman & Rauchs, 2017). The open-source Bitcoin community, comprising both developers and miners, can adopt or reject proposed amendments to the protocol through a vote (Böhme et al., 2015). These community members also shoulder administrative duties, ensuring the maintenance of the protocol. A unique incentive framework sustains this structure; it intrinsically rewards miners, users, and programmers who adhere to the established rules. While the system has certain vulnerabilities, it remains robust and has exceeded performance expectations (Ciaian et al., 2016; Liu et al., 2022).

Statistical reports indicate growing interest in cryptocurrency, but there remains a degree of skepticism. Despite the promising prospects for the future of cryptocurrency, concerns such as fraud and theft are escalating (DeVries, 2016; Zohar, 2015). Recent literature on the topic has burgeoned, addressing various facets of this cryptocurrency. For instance, Almeida and Goncalves (2022) conducted a review on cryptocurrency volatility and risk (see, e.g., CoinMarketCap, 2022), while Al-Nefae and Aldhyani (2022) explored bitcoin forecasting and trading using analytics. Erfanian et al. (2022) delved into predicting prices through economic theories, Gadi and Sicilia (2022) analyzed the characteristics of heterogeneous cryptocurrencies, and Gupta and Chaudhary (2022) focused on volatility within the cryptocurrency market. Additional studies, such as those by Hsu (2022) on spillover effects in cryptocurrencies, Papadimitriou et al. (2022) on forecasting spikes, and Yan et al. (2022), who considers bitcoin as a safe-haven asset and a medium of exchange, further emphasize the breadth of this research area. Manimuthu et al. (2019) reviewed scholarly articles to understand how Bitcoin was addressed in the literature. Their paper reported on the attributes via a thorough

literature review. Their study is based on primary data from the existing literature and secondary data from relevant case studies in the public domain. Vranken (2017) discussed the developments in mining hardware and outlined alternative schemes that are less energy-demanding. John et al. (2022) surveyed the extant literature on the economics of blockchain. They formally clarified Bitcoin's economic significance. Holub and Johnson (2018) provided a state-of-the-art literature assessment by reviewing 1,206 papers. Wamba et al. (2020) attempted to clarify the definition of Bitcoin and related concepts. They analyzed 141 articles and evaluated the current knowledge level. Their findings showed that related technologies were evolving. Rahardja et al. (2021) also attempted to clarify the meaning of various cryptocurrency concepts. Many of these studies, however, have taken a broader approach, focusing on cryptocurrencies in general. Furthermore, to our knowledge, no other study offers a comprehensive empirical examination of Bitcoin in detail.

Here, we aim to fill this gap, offering detailed insight into the nature and dimensions of the network. Our primary objective is to comprehensively analyze the features of Bitcoin using descriptive and visual analytics, drawing from a historical perspective. Our research is anchored on four main themes: (1) the supply and demand dynamics of bitcoin, (2) the trends and volume associated with bitcoin transactions, (3) data related to bitcoin exchanges and mining, and (4) the nuances of bitcoin price dynamics. To steer our investigation, we pose the following research questions:

RQ1: How have the features of Bitcoin evolved over time, and what patterns emerge when subjected to descriptive and visual analytics?

RQ2: What overarching trends, behaviors, and market movements are most strongly associated with Bitcoin's evolution?

By meticulously examining these aspects, we provide a holistic understanding of Bitcoin's utility, value dynamics, and implications in the digital economy. Our findings aim to equip policymakers with nuanced insights, facilitating informed decision-making regarding cryptocurrency regulations in a continually evolving financial landscape. The remainder of this research is organized as follows. Methods employed in our research are introduced, followed by the results from our analysis. In the conclusion of the paper, we present key takeaways, managerial implications, and potential avenues for future research.

METHODS

In this research, we employed a data-driven approach (Raghupathi & Raghupathi, 2021). Our choice of a descriptive-analytical method stems from the nature of the available data (Berman & Israeli, 2022; Kaur & Phutela, 2018; Williams, 2011), which is primarily historical, thus limiting the potential for predictive modeling. For our descriptive analysis, we utilized the visual analytics approach (Börner et al., 2019; Cook & Thomas, 2005; Cui, 2019; Keim, 2001; Kohlhammer et al., 2011; Sun et al., 2013; Wong & Thomas, 2004). This involves designing and creating a series of charts to derive insights from the Bitcoin data. Both descriptive and visual analytics have been widely recognized as tools for exploratory data analysis, a notion backed by several prior studies (see, e.g., Raghupathi et al., 2021; Raghupathi & Raghupathi, 2018; Ren et al., 2020).

Our cryptocurrency data stems from Coin Metrics (<https://coinmetrics.io/data-downloads/>), a reputable platform that offers daily cryptocurrency metrics coupled with data aggregation and visualization tools. Key variables of our analysis include exchange volume, market cap, on-chain transaction volume, price, transaction count, and the value of newly minted coins, among others. We identified and examined the relationships between these variables, as presented in Table 1.

Table 1. Variables

Variables	Description
txVolume(\$)	A broad and largely unadjusted measure of the total value of outputs on the blockchain on a given day
adjustedTxVolume(\$)	Adjusted txVolume(USD)
txCount	Number of transactions on the public blockchain per day; Includes at least one operation of the types
marketcap(USD)	Unit price multiplied by the number of units in circulation
price(USD)	Price from CoinMarketCap
exchangeVolume(\$)	Dollar value of the volume at exchanges like GDAX and Bitfinex
generatedCoins	Number of new coins brought into existence on that day
Fees	Based on local currency rather than USD
activeAddresses	Number of unique sending and receiving addresses participating in transactions on a given day
averageDifficulty	A measure of how difficult it is to find a hash below a given target
paymentCount	For UTXO coins, defined as the sum of outputs' count minus one for each transaction; Payment count for smart contract assets, such as ETH or LSK, is calculated as the number of transfer transactions (i.e., contract creation, invocation, destruction transactions not included)
medianTxValue(\$)	For EOS, median transfer value (most transactions in EOS do not transfer EOS tokens)
medianFee	Median of fees
blockSize	Unit of work for file system
blockCount	Number of blocks
existCoins	The sum of generated coins per day
circulatedCoins	The number of coins that equal market cap divides the price

Note. Data stems from <https://coindatascience.com/data-downloads/>

^aYears/Scale: From January 9, 2009, to latest (i.e., February 2, 2019) with many missing values before April 30, 2013.

^bPossible correlations/predictions: (1) predict price using previous variables like above; (2) volume vs. price. This kind of dataset is more suitable for time-series analytics or descriptive analytics.

^cSize: The dataset is separated into cryptocurrencies. Each currency (i.e., BTC) has a separate file. Regarding Bitcoin, the size is about 3460*14 (missing values before April 30, 2013).

Our methodological framework encompasses data collection, the selection of relevant variables, and data visualization. The breadth of our research is comprehensive, aiming to uncover a wide range of potential correlations and patterns between the variables. Our approach includes descriptive summaries, data visualizations, correlation matrices, and trend analysis.

Table 2 shows the summary statistics of key variables associated with bitcoin transactions. For each variable, the table provides the average (mean), standard deviation (Std), and minimum (Min) and maximum (Max) values observed on a daily level during the study period.

The correlation matrix is presented in Figure 1, where positive correlations are shown in green. A notable example is the strong positive correlation of 0.91 between *adjustedtxVolume* and *marketcap*. This implies that as *adjustedtxVolume* rises, there is a corresponding increase in *marketcap*. This correlation is intuitive since *marketcap* is a function of both price and volume. On the other hand, negative correlations are depicted in red. Figure 1 reveals several pairs with high negative correlations. Many of these pairs involve variables related to volume and price. The variable *blockSize* demonstrates noticeable correlations with *activeAddresses*, *txCount*, and *paymentCount*.

Table 2. Summary statistics

Variable	Mean	Std	Min	Max
txVolume(\$)	2,732,664,545	5,060,739,180	32,872,336	48,353,069,370
adjustedTxVolume(\$)	1,152,104,617	1,934,199,795	20,538,708	16,248,088,756
txCount	172,659	92,778	30,170	490,459
marketcap(\$)	38,791,598,710	57,689,037,520	779,254,976	326,141,280,256
price(USD)	2,336	3,386	68	19,475
exchangeVolume(\$)	1,597,749,766	57,689,037,520	0	23,840,899,072
generatedCoins	3,044	1,125	1,000	6,500
fees	81	131	8	1,496
activeAddresses	440,864	257,232	48,402	1,283,929
averageDifficulty	1,170,073,541,417	2,058,637,497,231	8,974,296	7,454,968,648,263
paymentCount	288,161	155,425	45,497	1,883,744
medianTxValue(\$)	173	336	0.024145	4,176
medianFee	0.000222	0.000259	0.00000678	0.00226
blockSize	92,945,708	47,550,962	14,163,674	204,023,669
blockCount	155	19	80	260

Note. N = 2,119

Figure 1. Correlation matrix

	date	Volume(USD)	txVolume	txCount	marketcap(USD)	price(USD)	exchangeVolume	generatedCo	fees	liveAddress	averageDiffi	paymentCount	medianTxValue	medianFee	blockSize	blockCount
date	1.00															
txVolume	0.49	1.00														
adjustedTx	0.58	0.94	1.00													
txCount	0.85	0.54	0.56	1.00												
marketcap	0.70	0.80	0.91	0.52	1.00											
price(USD)	0.69	0.81	0.91	0.51	1.00	1.00										
exchangeV	0.63	0.78	0.89	0.49	0.93	0.93	1.00									
generated	-0.88	-0.43	-0.52	-0.78	-0.59	-0.58	-0.52	1.00								
fees	0.34	0.68	0.68	0.57	0.49	0.49	0.51	-0.41	1.00							
activeAdd	0.88	0.69	0.73	0.94	0.71	0.71	0.65	-0.81	0.64	1.00						
averageDi	0.75	0.28	0.41	0.42	0.67	0.65	0.62	-0.58	-0.02	0.47	1.00					
paymentC	0.68	0.52	0.53	0.80	0.47	0.47	0.44	-0.60	0.53	0.79	0.27	1.00				
medianTx	0.32	0.77	0.82	0.37	0.73	0.74	0.79	-0.30	0.72	0.52	0.18	0.39	1.00			
medianFe	0.04	0.49	0.48	0.27	0.28	0.28	0.31	-0.17	0.87	0.33	-0.19	0.25	0.56	1.00		
blockSize	0.89	0.55	0.59	0.95	0.59	0.58	0.54	-0.80	0.52	0.96	0.47	0.81	0.37	0.22	1.00	
blockCour	-0.38	-0.01	-0.06	-0.27	-0.09	-0.09	-0.09	0.56	-0.03	-0.24	-0.22	-0.25	0.01	0.10	-0.26	1.00

RESULTS AND DISCUSSION

Bitcoin Supply and Demand

In this section, we focused on the generation, circulation, and valuation of bitcoin. Figure 2 illustrates the trajectory of its market capitalization from 2013 to 2018. Each bar represents the market capitalization in U.S. dollars (USD) for a given quarter. The grey trend line highlights the yearly variation in market capitalization. Before 2017, the market capitalization exhibited a consistent upward trajectory. However, post-2017, there was a pronounced surge. While the overall trend for market capitalization has been one of growth, notable volatility has been evident since 2017, reflecting the increasing adoption and acceptance of bitcoin by various institutions, businesses, and individuals (Higgins, 2017).

Figure 2. Quarterly variation of bitcoin market capitalization

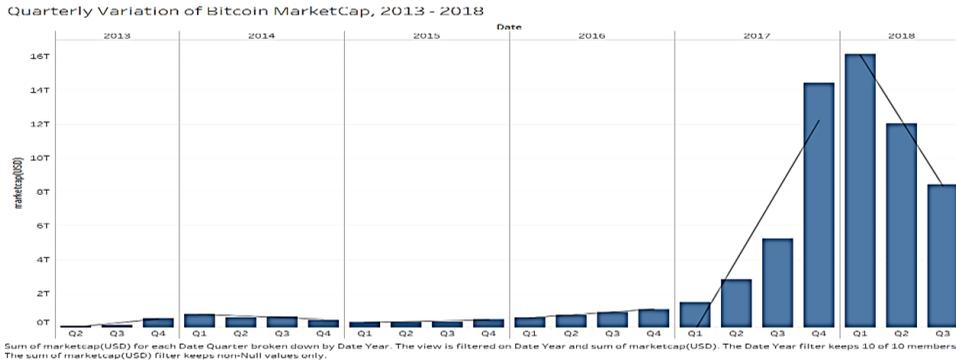


Figure 3 contrasts the number of newly mined bitcoins with those in circulation. Each bar indicates the quantity. The green bar represents newly mined bitcoins, while the blue bar signifies those in circulation. Excluding the initial four years (due to the absence of data), the quantity of newly mined and circulated bitcoins aligns closely with post-2013. The discrepancy observed in 2013 can be attributed to the unavailability of circulation data before April 28. Thus, it is a fair deduction that the number of newly minted coins mirrors the quantity in circulation. Once a bitcoin is mined, it enters the realm of circulated cryptocurrency.

Figure 4 illustrates the correlation between the price and the total number of bitcoins in circulation. The green line, representing the number in circulation, demonstrates a consistent upward trajectory.

Figure 3. Comparison of the number of generated and circulated bitcoins

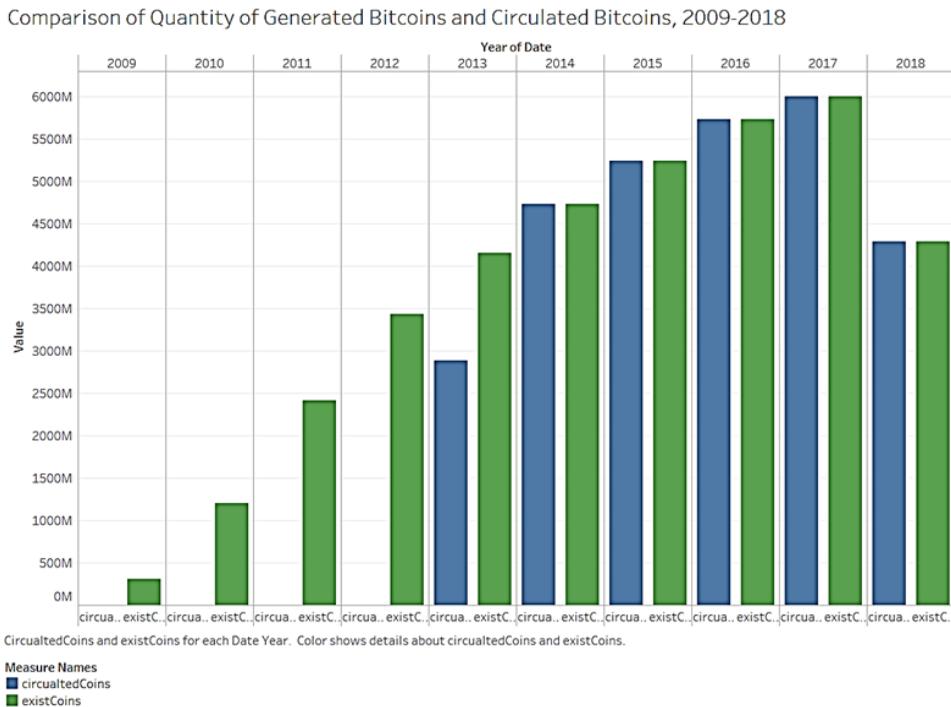
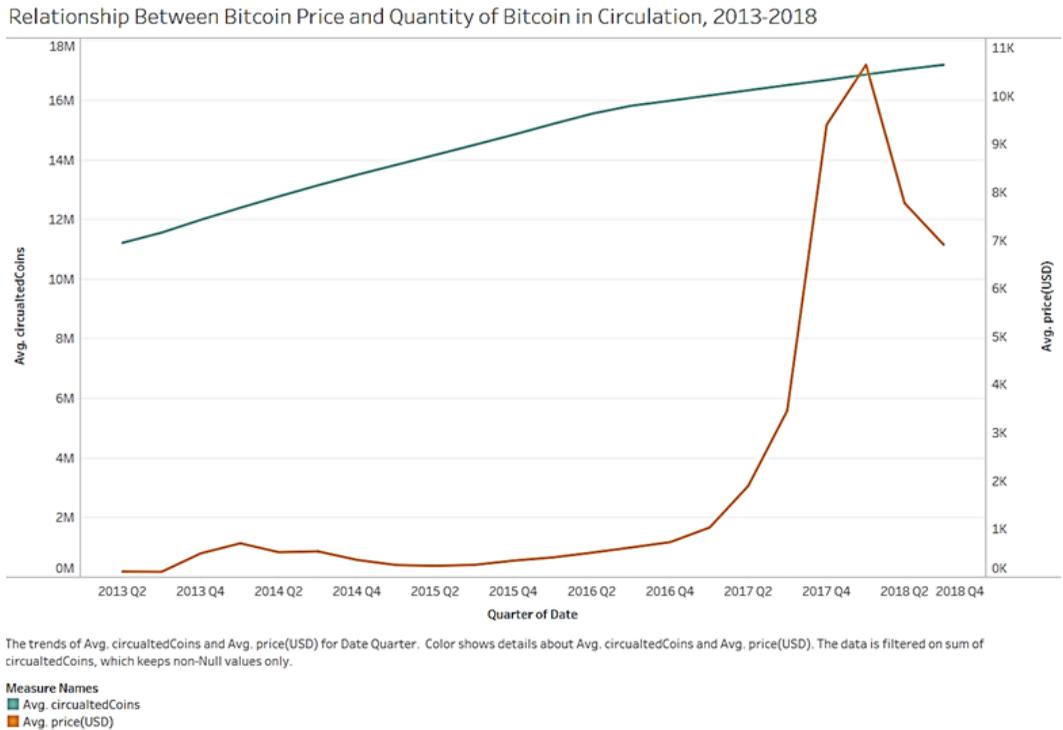


Figure 4. Relationship between price and the number of bitcoins in circulation



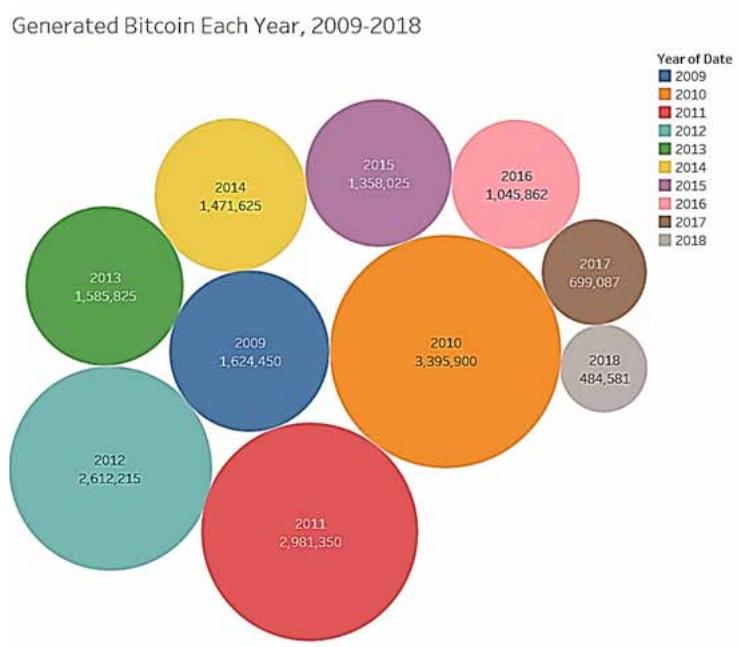
In contrast, the orange line, indicative of the price, experienced notable shifts during the first quarters of 2014 and 2018. The decline in price corresponds with an increase in circulated bitcoins from the first quarter of 2014 to the second quarter of 2015 and again from the fourth quarter of 2017 to the third quarter of 2018. Outside of these periods, both metrics tend to move in tandem. While there is a negative correlation between the price and the amount circulated during the aforementioned periods, they generally exhibit a positive correlation at other times.

Figure 5, depicted as a bubble chart, visualizes the number of bitcoins generated over the years presented. Each bubble's color signifies a different year, while its size indicates the number produced that year. The most substantial amount produced occurred in 2010, with the least in 2018. The declining trend in generation can likely be attributed to the increased difficulty of mining.

Figure 6 displays the trend of bitcoin's active addresses over time. The x-axis denotes the year, while the y-axis signifies the number of active addresses. The daily number of unique sending and receiving addresses experiences fluctuations. While there has been a notable decline in active addresses in 2019, this follows a steady increase over the previous five years. A pivotal moment was observed on December 14, 2017. Currently, the count stands at 933,538 active bitcoin addresses. Overall, the daily number of unique addresses shows an upward trend, highlighting the growing interest in mining and solidifying the currency's position as a top-tier cryptocurrency.

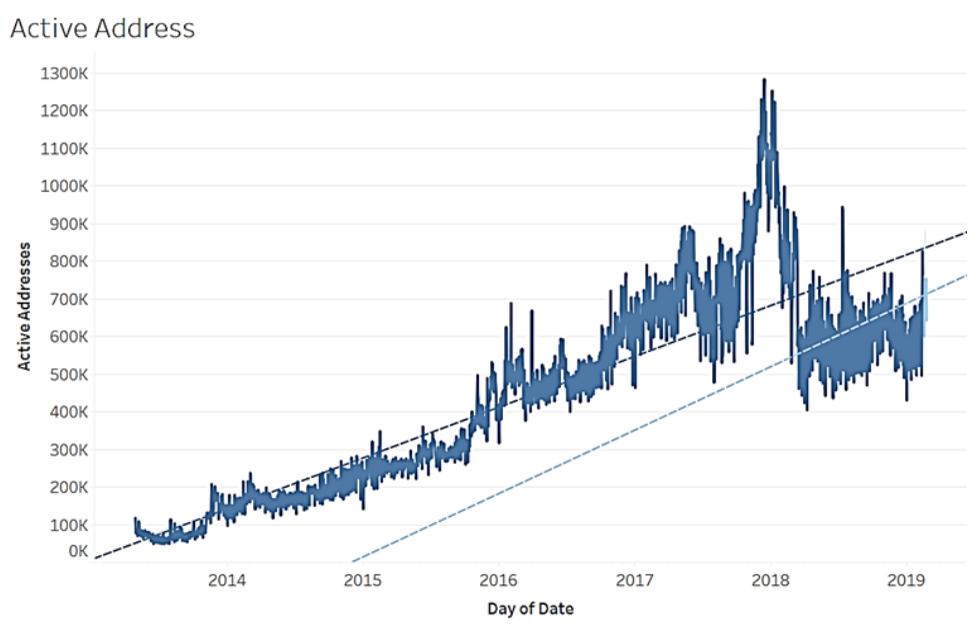
Figure 7 visually depicts the highest count of active bitcoin addresses each week, with the chart's height representing this peak value. It is evident that the activity was subdued before July 2011. Yet, a significant surge in active addresses began in the first week of that month. The peak of this trend was reached in the second week of December 2017, boasting 1,283,929 active addresses. Following this peak, a decline in active addresses was observed. Since its inception in 2009, the bitcoin blockchain has attracted an increasing user base, culminating in its pinnacle in December 2017 within the period of our study.

Figure 5. Generated bitcoins per year (2009-2018)



Date Year and sum of Generated Coins. Color shows details about Date Year. Size shows sum of Generated Coins. The marks are labeled by Date Year and sum of Generated Coins.

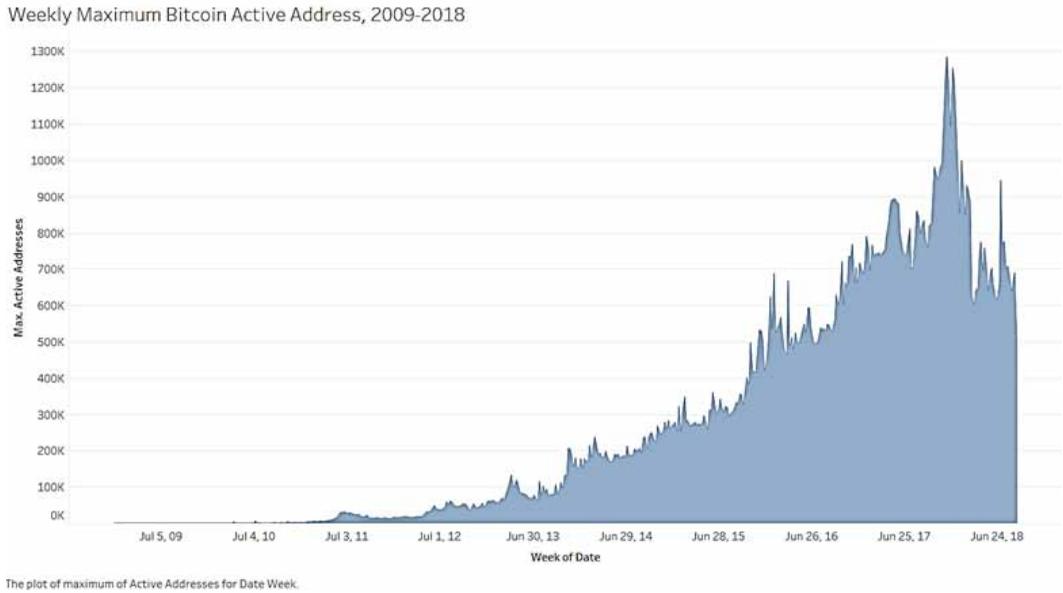
Figure 6. Bitcoin active addresses



The trend of sum of Active Addresses (actual & forecast) for Date Day. Color shows details about Forecast indicator.

Forecast indicator
 ■ Actual
 ■ Estimate

Figure 7. Weekly maximum of active bitcoin addresses



Bitcoin Transaction Trends and Volume

In this section, we present the transactional dynamics of bitcoin, encompassing transaction volume, transaction count, and the related fees. We start our analysis with the trend of the adjusted transaction volume, denominated in USD, as illustrated in Figure 8. On this graph, the x-axis delineates the years, while the y-axis corresponds to the adjusted transaction volume in USD. This volume saw a noteworthy uptick, culminating on December 8, 2017, with a peak value of 16,248,088,756.20 USD. Subsequently, a decline ensued. The most pronounced surges in transaction volume were witnessed between late October and early December of 2017. Following this period, from 2018 to November 15, 2019, there was a marked downtrend in the adjusted transaction volume, which then experienced a recovery, reaching 4,829,948,173 USD. Based on this trend, it appears that bitcoin’s adjusted transaction volume in USD may face further declines in the coming years.

The trends in bitcoin block count is illustrated in Figure 9, with the x-axis denoting the years and the y-axis representing the block count. This count remains stable, albeit with a slight decline over time. Notable fluctuations are evident in August and November of 2017. Based on this trend, we anticipate that the count may persist in its decline in the coming years.

Figure 10 shows the variation in quarterly bitcoin transaction count from 2009 to 2018. Each circle on the graph denotes the transaction count in a certain quarter, with its size indicative of the volume and its position on the vertical axis representing the precise transaction count. There are two periods of rapid growth: between the first quarter of 2012 and the first quarter of 2013 and from the third quarter of 2014 to the second quarter of 2017. Significant fluctuations can be observed between the second quarter of 2017 and the first quarter of 2018. Transaction activities intensified once circulation began, peaking in activity during 2017. From 2018 onward, however, there has been a downtrend in transaction activity.

Figure 11 shows the trend of transaction fees. The x-axis represents the year; the y-axis represents transaction fees. Bitcoin transaction fees plummeted in 2018. They reached their peak in December 2017, which indicates the fees are low. New investors should investigate if it is because of declining demand or other factors.

Figure 8. Bitcoin adjusted transaction volume (USD) (Note. Data ranges from January 2014 to February 2019)

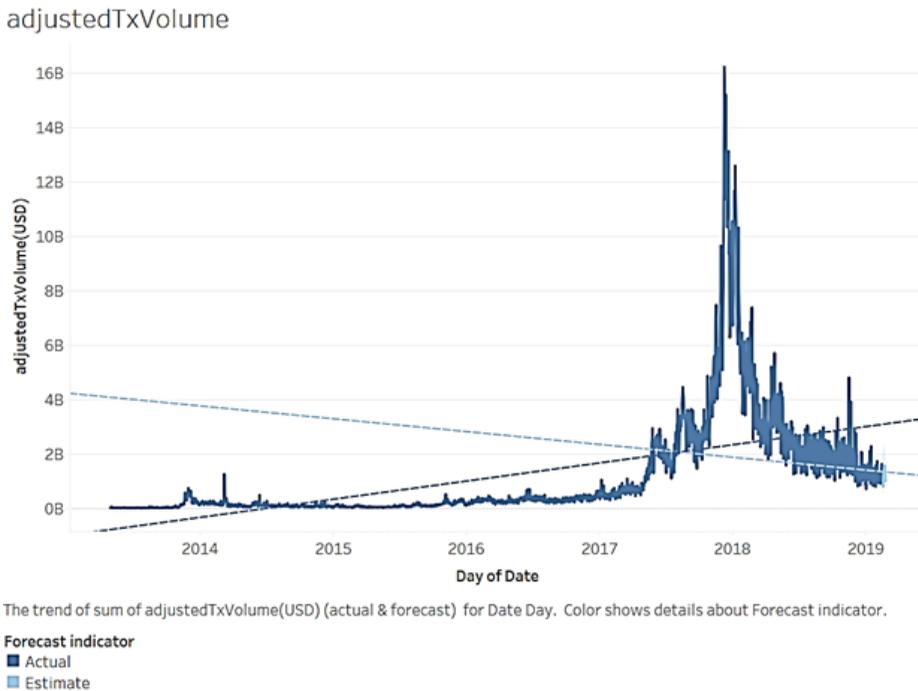
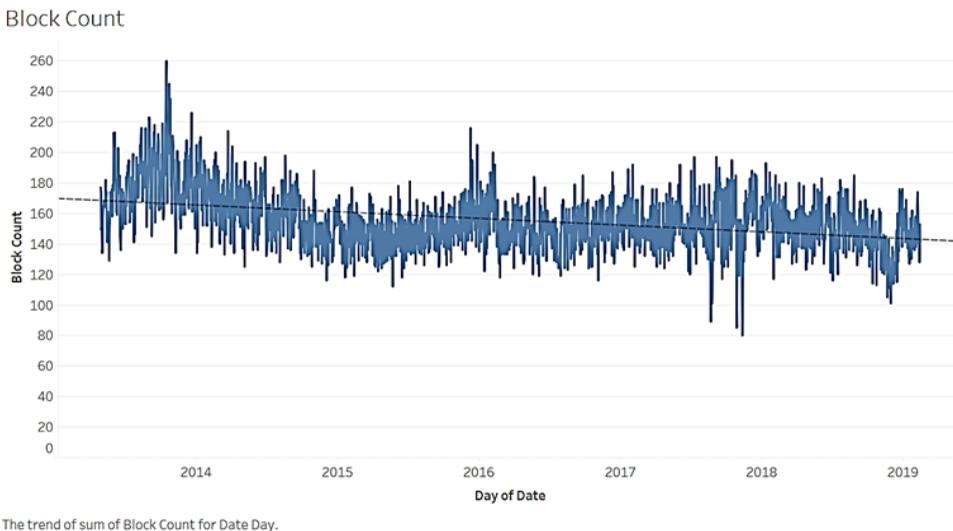


Figure 9. Daily bitcoin block count (Note. Data ranges from January 2014 to February 2019)



The heat map in Figure 12 shows the average bitcoin transaction fees for each year. The square color stands for the year. The square size represents the average transaction fee. Fees were low in 2009 and 2010. They started to increase, reaching their peak in 2017. An average of 275 USD of fees was applied per transaction each day, which is extremely high.

Figure 10. Quarterly bitcoin transaction count (Note. Data ranges from 2013 to 2018)

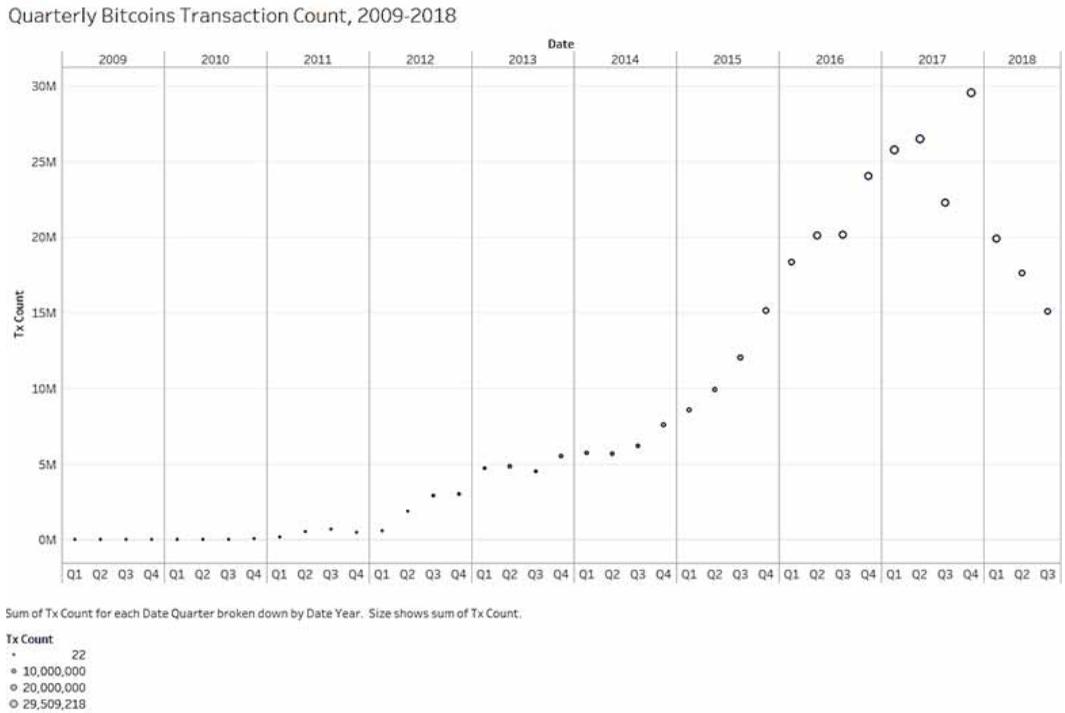
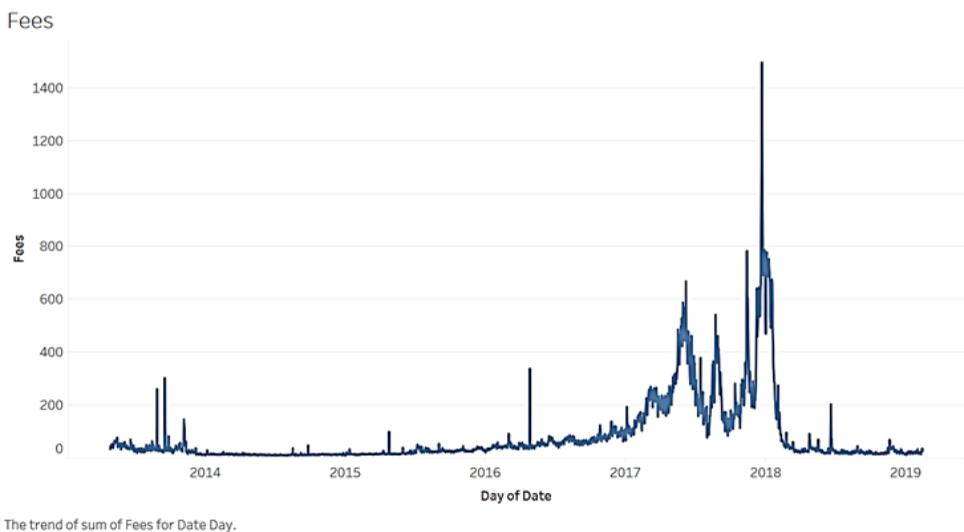


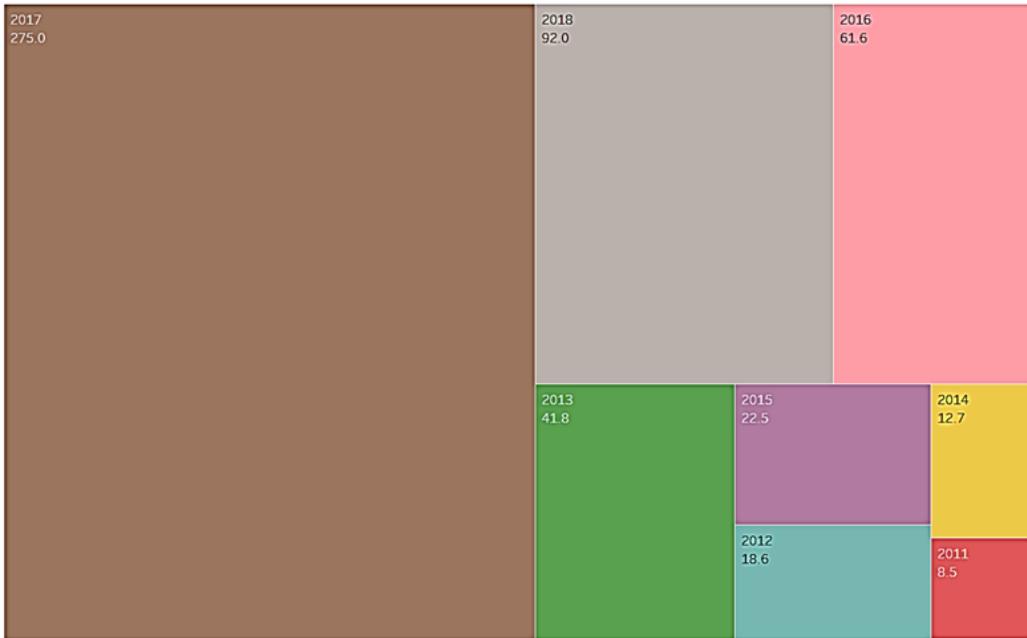
Figure 11. Bitcoin transaction fees (Note. Data ranges from 2013 to February 2019)



The trend in the bitcoin median fee is shown in Figure 13. The x-axis represents the year; the y-axis represents the median transaction fees. As the figure indicates, the patterns of median transaction fees are like the patterns of fees. Bitcoin median fees have fluctuated in recent years. They began to decrease dramatically in December 2017, making the investment more affordable.

Figure 12. Average bitcoin transaction fees by year (2009-2018)

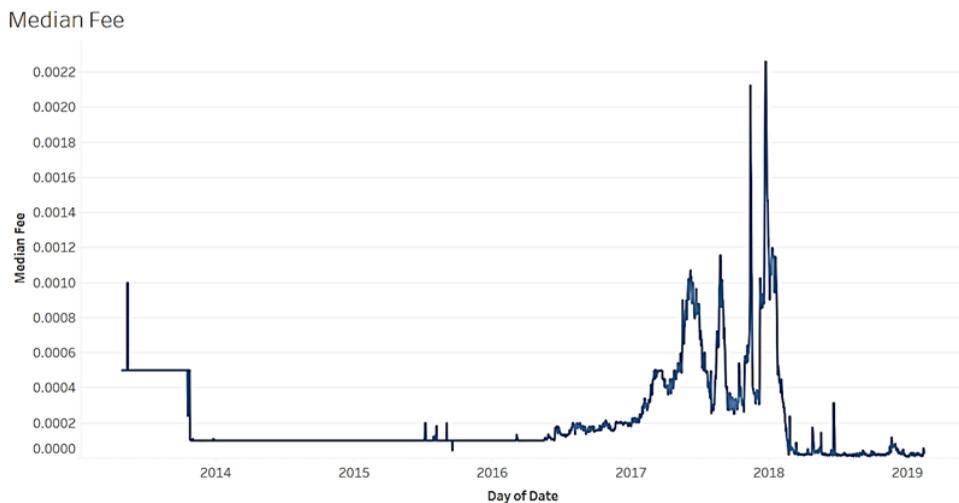
Average Bitcoin Transaction Fees Every Year, 2009-2018



Date Year and average of Fees. Color shows details about Date Year. Size shows average of Fees. The marks are labeled by Date Year and average of Fees.

- Year of Date
- 2009
 - 2010
 - 2011
 - 2012
 - 2013
 - 2014
 - 2015
 - 2016
 - 2017
 - 2018

Figure 13. Bitcoin median fees (Note. Data ranges from 2013 to February 2019)



The trend of sum of Median Fee for Date Day.

The relationship between the average fee and average median transaction value (2013-2018) is shown in Figure 14. The purple line stands for the average fee; the orange line stands for the average median transaction value. Based on the figure, there is a likelihood for fee and median transaction value to be similar. If the purple line is moved to the right, the two lines almost experience the same likelihood and variation. We can deduce that the average fee is a premonition of the median transaction value. This can be used to predict median transaction value in the future.

We next analyzed the median transaction value (2013-2018) in Figure 15. The bar length represents the median transaction value; colors represent years. The median transaction value experienced a

Figure 14. Relationship between average fee and average median transaction value (Note. Data ranges from 2013 to 2018)

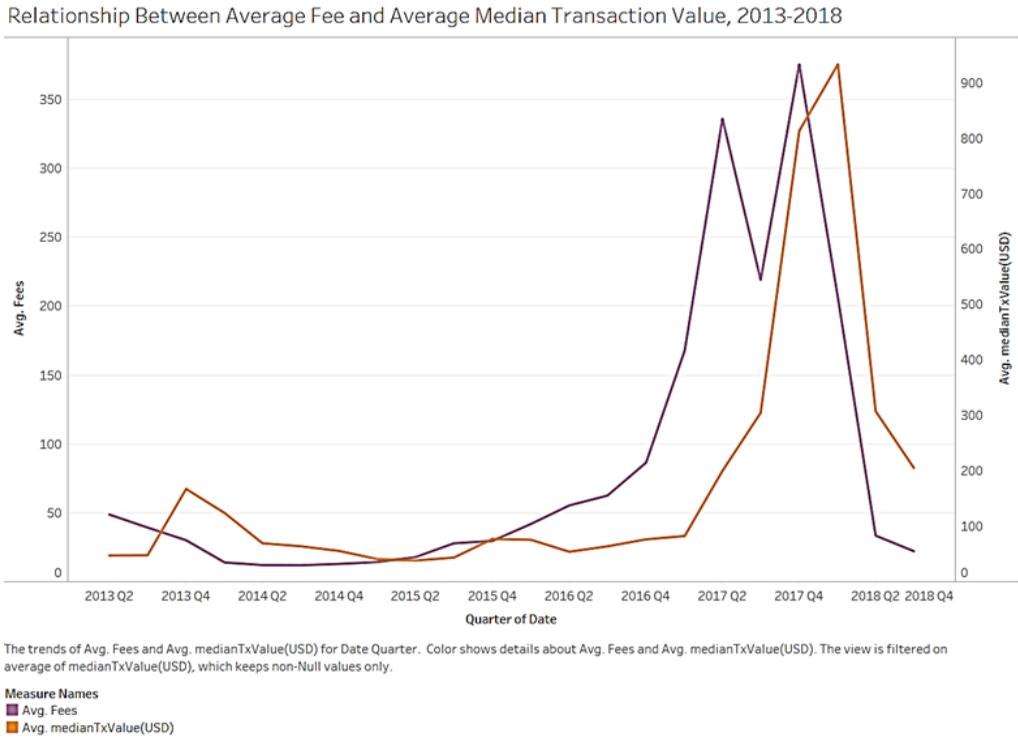
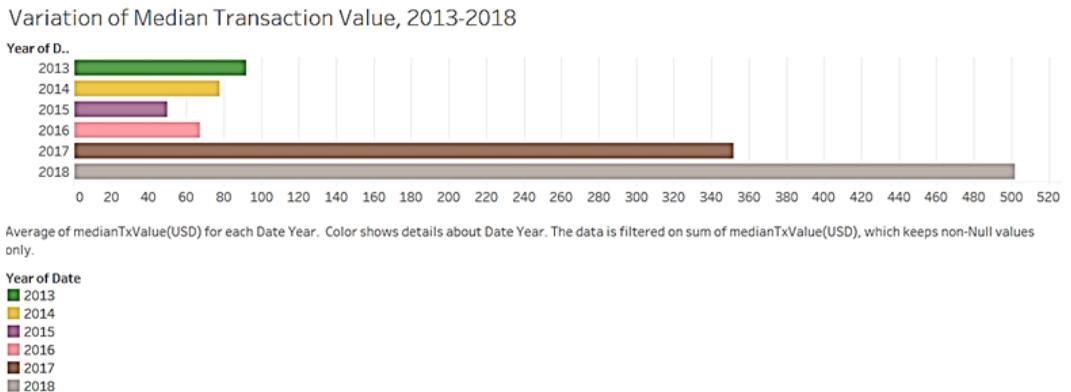


Figure 15. Variation of median transaction value (2013-2018)



decline from 2013 to 2015 but bounced back after 2015. And there was a leap in the median transaction value after 2017. The median transaction value is not adversely influenced by extreme numbers. Therefore, it offers a realistic reflection of the transaction value. There is a trend in the increase of the transaction value after 2015. The value experienced rapid growth in 2017 and 2018.

The relationship between the median transaction value and transaction count (2013-2018) is developed in Figure 16. The blue line shows an increase after the second quarter of 2014. The red line has rapid growth after the second quarter of 2017. The whole trend of the blue line and red line is similar. However, the red line experienced a more volatile change during the five years. It is reasonable to assume that there is a positive relationship between median transaction value and transaction count. After the second quarter of 2018, however, the relationship transits to the negative. The relationship cannot be established without more data.

Figure 17 presents how median fee and median transaction value influence transactions. Payment count is used as a measurement to reflect people’s willingness to make a transaction. The orange triangles represent payment count at a certain median fee. The grey triangles represent payment count at a certain median transaction value. The variation trends are similar between payment count and median fee and between payment count and median transaction value. There is a rapid increase in the payment count when the median fee is between 0.0003 and 0.001, and the median transaction value is between 500 and 3,500. When the median fee is between 0.0003 and 0.001, there is a positive relationship between payment count and median fee. When the median transaction value is between 500 and 3,500, there is a positive relationship between payment count and median transaction value. If the median fee or transaction value can be predicted, bitcoin transactions may be controlled.

Figure 16. Relationship between median transaction value and transaction count (Note. Data ranges from 2013 to 2018)

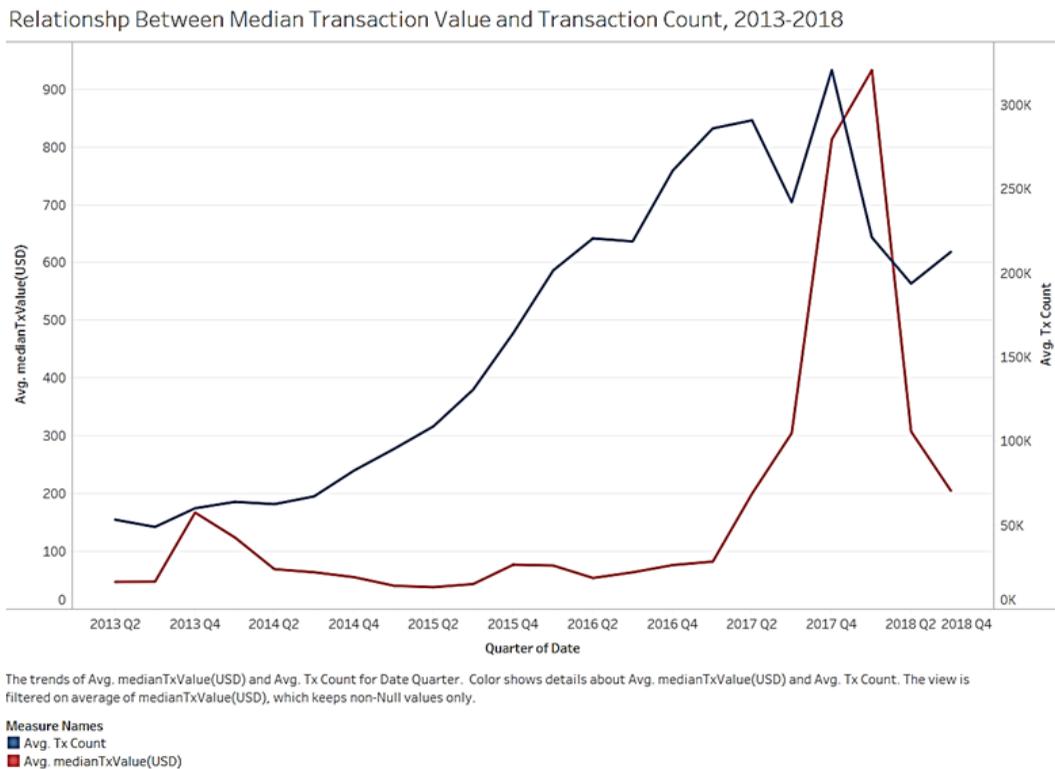
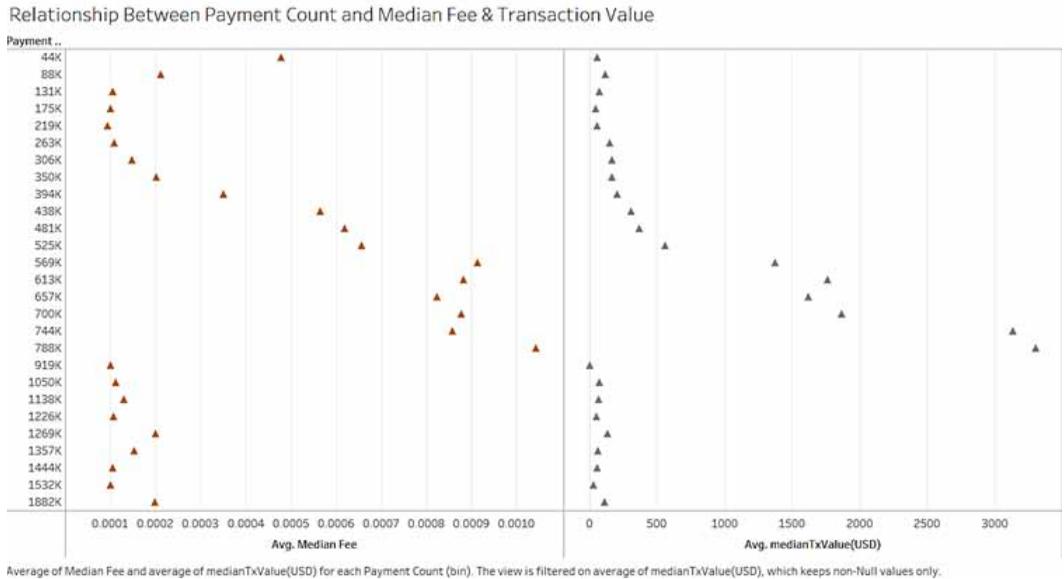


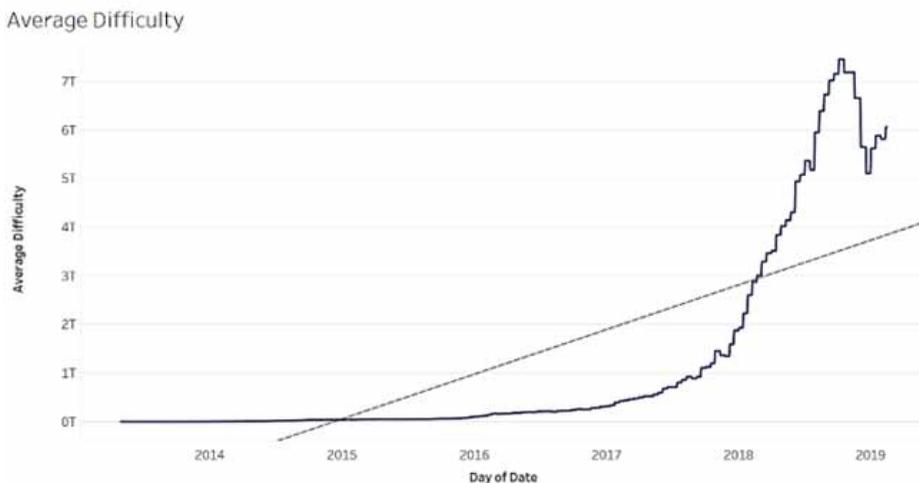
Figure 17. Relationship between payment count, median fee, and transaction value



Bitcoin Exchange and Mining Data

In this section, we focused on bitcoin’s interaction with exchanges and its mining difficulty, as displayed in Figure 18. The x-axis represents the time, while the y-axis represents the degree of difficulty. The graph depicts an exponential surge in mining difficulty, culminating with it doubling every four months as of late 2017 and persisting until October 2018. Subsequently, there was a decline in the rate of difficulty. The peak average difficulty level was registered on October 5, 2018, at 7,454,968,648,263. With the continual influx of investors and miners into the Bitcoin ecosystem, such marked escalations in difficulty are anticipated. Yet, this rising difficulty might deter potential investors and miners. As

Figure 18. Bitcoin’s average mining difficulty (Note. Data ranges from January 2014 to February 2019)



The trend of sum of Average Difficulty for Date Day.

the graph underscores, post its zenith, there was a pronounced drop in difficulty toward the close of 2018. However, there was a revival in early 2019, signaling a word of advice for newcomers: tread carefully when contemplating investments in cloud mining.

The relationship between the quantity of generated bitcoins and the mining difficulty from 2009 to 2018 offers valuable insights. In Figure 19, the top chart displays the average difficulty, while the bottom chart displays the average number of generated bitcoins. The bar heights indicate the respective values for mining difficulty and the volume generated. Since 2009, the average mining difficulty has been on a steady uptrend, witnessing a pronounced spike in 2018. Conversely, the average number produced has been on a downturn from 2010 to 2018, with the peak production occurring in 2010. The trend line suggests an inverse correlation between the average mining difficulty and the average number produced.

Figure 20 analyzes the average annual bitcoin exchange volume from 2013 to 2018. Each year is denoted by a distinct color: green for 2013, yellow for 2014, purple for 2015, pink for 2016, brown for 2017, and grey for 2018. The size of each segment corresponds to the average exchange volume for that particular year. Notably, 2017 and 2018 dominate the chart, accounting for exchange volumes of 2,382,866,906 and 6,657,660,744, respectively. The years preceding 2017 saw a lower transaction volume. On the whole, the surge in the number of mined bitcoins appears to have driven the dramatic uptick in exchange volume.

Next, we delved into the connection between quarterly transaction volume and exchange volume from 2013 to 2018. As depicted in Figure 21, the green area illustrates the transaction volume, while the blue area signifies the exchange volume. The top line traces the fluctuations in average quarterly transaction volume, and the bottom line mirrors changes in average exchange volume. The transaction volume remained consistent until 2017, only to experience a sharp surge that year, followed by a swift decline in 2018. The exchange volume echoed these patterns over the same time frame. A

Figure 19. Relationship between average difficulty and average generated coins (Note. Data ranges from 2009 to 2018)

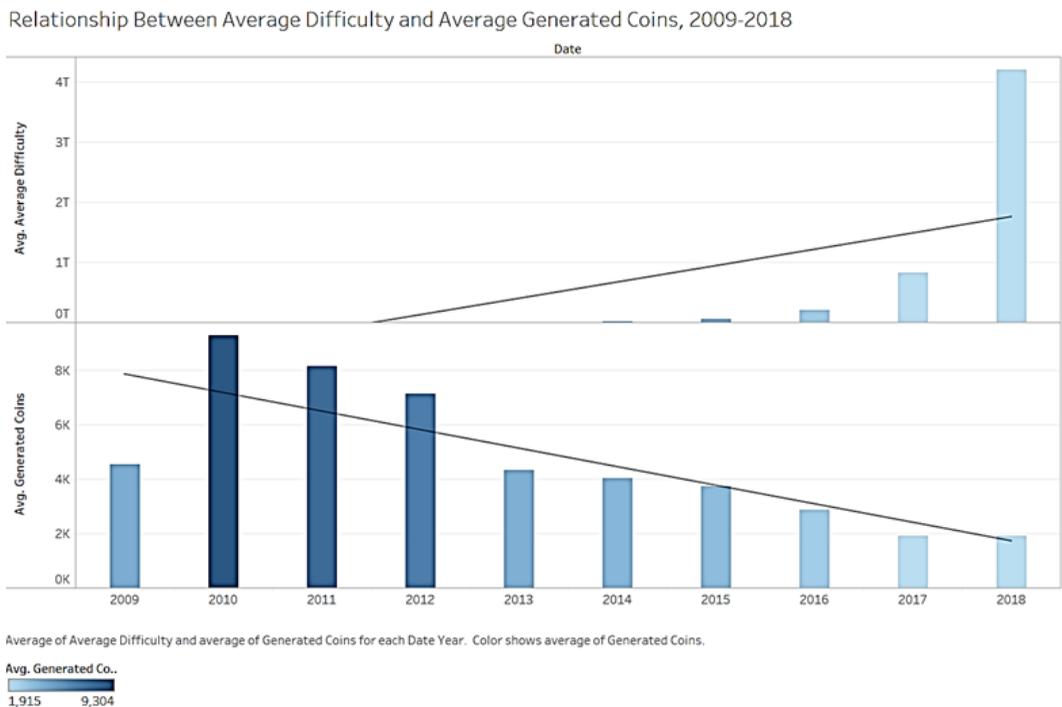


Figure 20. Average bitcoin exchange volume per year (2013-2018)

Average Bitcoin Exchange Volume Per Year, 2013-2018

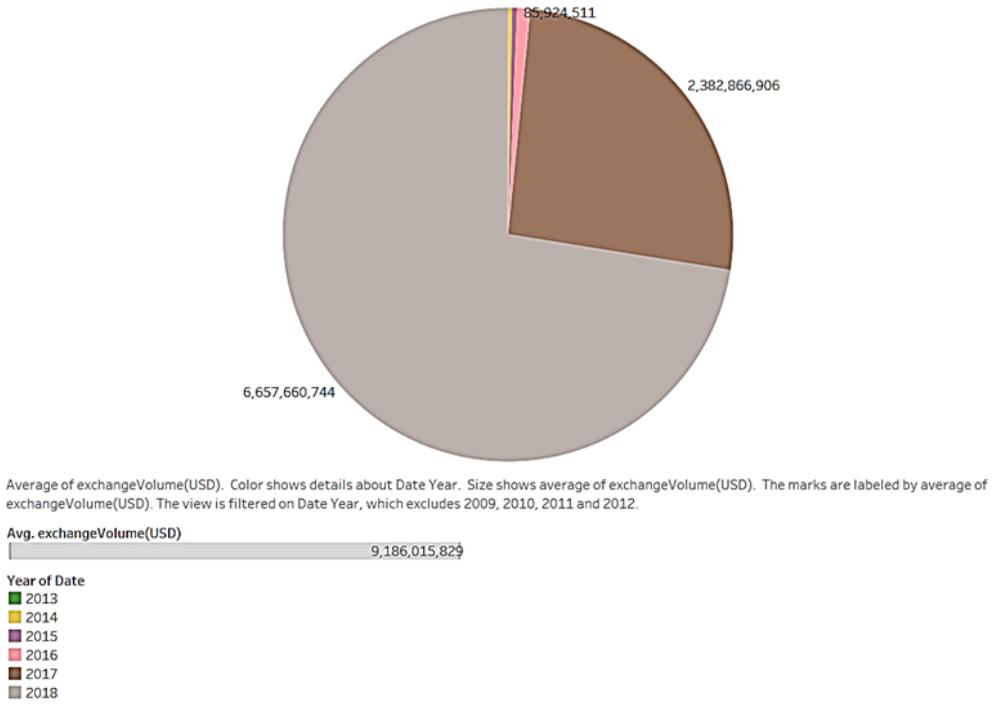
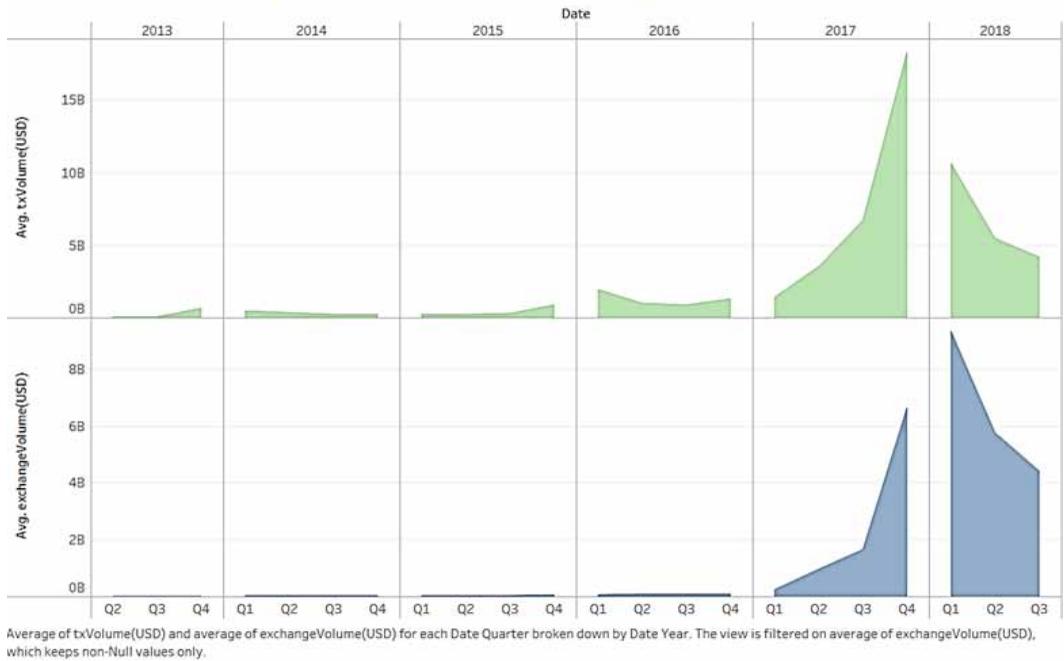


Figure 21. Relationship between quarterly average transaction volume and exchange

Relationship Between Quarterly Average Transaction Volume and Exchange Volume, 2013-2018



synchronized shift between the average transaction volume and exchange volume becomes evident, with this alignment becoming more pronounced post-2017.

Figure 22 depicts the progression of exchange volume in terms of USD. The x-axis marks the years, while the y-axis denotes the exchange volume. There was a notable surge in exchange volume between 2016 and 2018. The volume soared from \$31 billion to an impressive \$870 billion during this period. In 2018, the volume almost tripled, surpassing the \$2 trillion threshold. Bitcoin stands out as the world’s most prominent and frequently traded cryptocurrency. Investors should still approach investments with caution.

Figure 23 displays the trend of the average block size from 2009 to 2018. Each square’s position corresponds to the average block size for a given year, and the collective arrangement of the squares

Figure 22. Exchange volume in USD (Note. Data ranges from 2013 to February 2019)

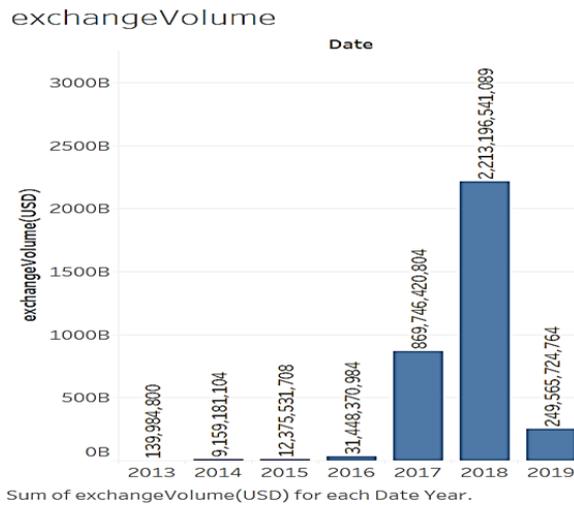
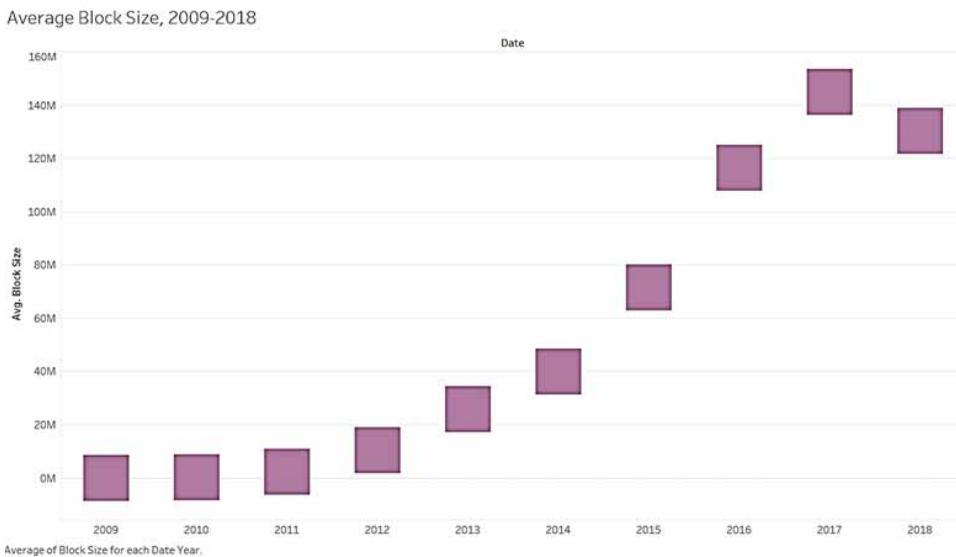


Figure 23 Average annual block size (Note. Data ranges from 2009 to 2018)



outlines the overall trend. The data reveals a clear upward trajectory from 2011 to 2017, followed by a subsequent decline. As bitcoin began to gain traction and circulate more widely, the block size of its blockchain witnessed substantial growth, indicating enhanced efficiency in handling transactions.

Bitcoin Price Dynamics

Here, we focused on currency's price movements and its associations with other metrics. Figure 24 shows the trend of prices in USD. The x-axis represents the time; the y-axis represents the price in USD. Patterns of bitcoin transaction fees, median fees, and price are similar. They all increased through December 2017 and decreased afterward.

Figure 25 illustrates the relationship between bitcoin price and its median transaction value. Within the figure, individual points indicate the price for specific median transaction values. The

Figure 24. Bitcoin price in USD (Note. Data ranges from January 2014 to February 2019)

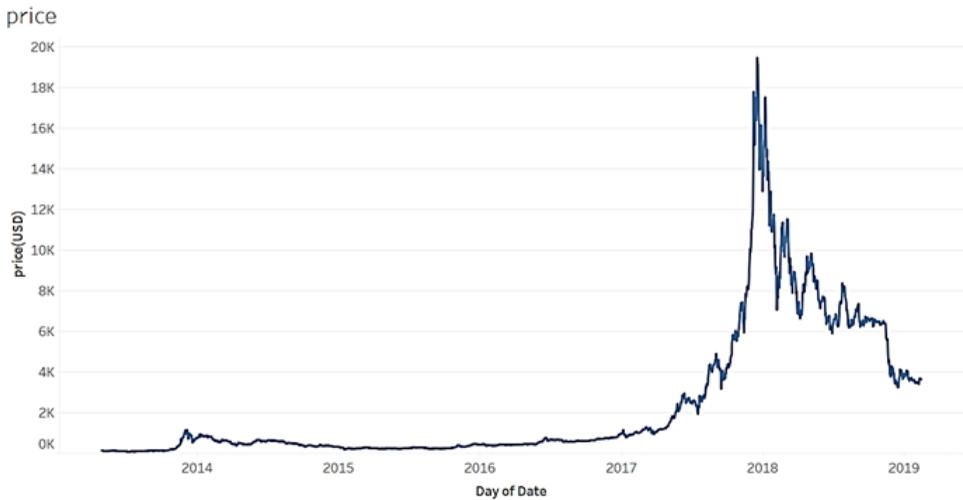
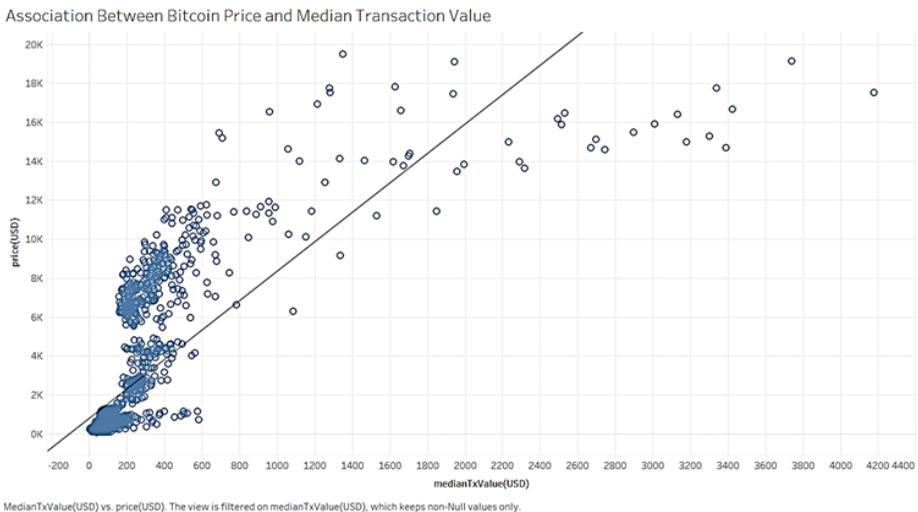


Figure 25. Association between bitcoin price and median transaction value



grey trend line provides a visual representation of the correlation between the price and the median transaction value.

Table 3 presents detailed findings from the trend line analysis. The coefficient for the median transaction value is 7.551, which indicates a strong positive association with the price. With a p-value of less than 0.0001, this relationship is statistically significant. Based on the provided R² value of 0.59, we can infer that the median transaction value explains approximately 60% of the variance in the price.

Figure 26 illustrates the relationship between the number of active addresses and the bitcoin price. Each data point represents the price for a specific number of active addresses on a given day. These active addresses encompass both unique sending and receiving addresses involved in daily transactions. The grey trend line provides a visual representation of the correlation between the price and the active address count, with further details available in Table 4.

Table 4 displays the findings from the trend analysis. The coefficient for active addresses is 0.009, suggesting a positive association with price. With a p-value of less than 0.0001, this relationship is statistically significant. The provided R² of 0.49 indicates that the number of active addresses explains around 50% of the variation in the bitcoin price.

CONCLUSION, IMPLICATIONS, AND FUTURE RESEARCH

In this study, we aimed to comprehensively analyze the features of Bitcoin, a prominent cryptocurrency that facilitates peer-to-peer transactions without the need for intermediaries. Our objective was to

Table 3. Estimation of the trend line for median transaction value

Variable	Coefficient	SE	t	p-value
medianTxValue	7.551	0.141	53.72	<0.0001
intercept	782.117	55.025	14.214	<0.0001
N	1,961			
R ²	0.59			

Figure 26. Relationship between price and the number of active addresses

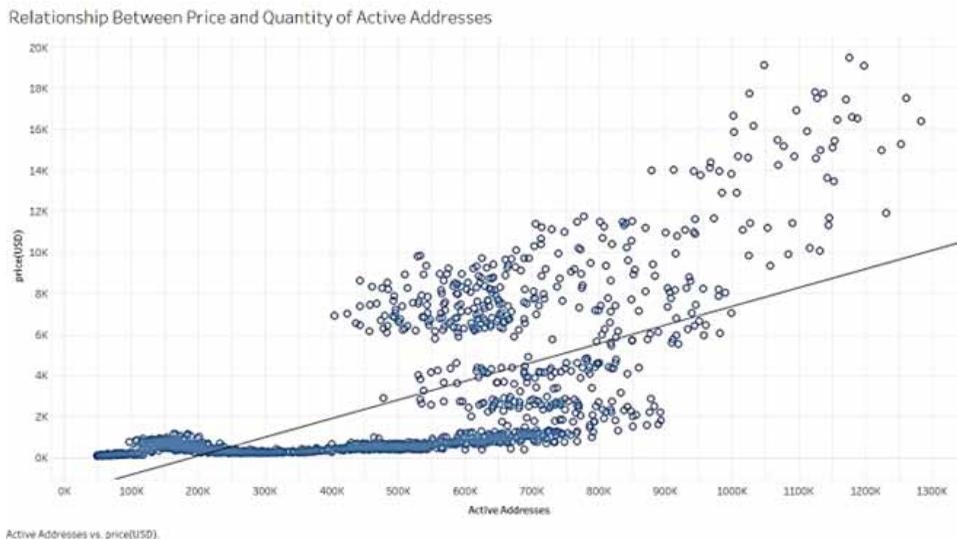


Table 4. Estimation of the trend line for active addresses

Variable	Coefficient	SE	t	p-Value
Active Addresses	0.009	0.0002	43.12	<0.0001
Intercept	-1,760.5	105.62	-16.67	<0.0001
N	1,961			
R ²	0.49			

answer two primary research questions: (1) How have the features of Bitcoin evolved over time, and what patterns emerge when subjected to descriptive and visual analytics? (2) What overarching trends, behaviors, and market movements are most strongly associated with Bitcoin's evolution? Our analysis shows a multifaceted portrait of Bitcoin's behavior over the studied period, allowing for the illustration of complex and sometimes, paradoxical dynamics. Specifically, we focused on four main themes in our descriptive analysis: (1) bitcoin's supply and demand dynamics, (2) transaction trends and volume of bitcoin, (3) insights on bitcoin exchanges and mining, and (4) the nuances of bitcoin price dynamics. The results are as follows.

First, for supply and demand, we found that market capitalization has exhibited a general growth trend with significant volatility evident post-2017, indicating heightened adoption by various entities. The number of newly minted bitcoins closely mirrors the quantity in circulation after 2013. While the price and the total number of circulated bitcoins mostly show a positive correlation, there are periods where they inversely correlate. Furthermore, bitcoin's active address count has been on the rise, with a peak in December 2017, highlighting its growing prominence and user base in the cryptocurrency world.

Second, regarding trend and volume of transactions, our findings suggest that adjusted transaction volume in USD peaked in December 2017 and has then been on a decline, with block count also showing a slightly decreasing trend over the years. Transaction activities intensified and reached their zenith in 2017 but have seen a decline post-2018. Both average transaction fees and median transaction fees spiked in 2017 and dramatically decreased afterward, making investments potentially more affordable. There is a correlation between median transaction value and transaction count, and both these metrics influence the overall payment count, suggesting that predicting either can potentially control transaction trends.

Third, for exchanges and mining, our analyses indicate that mining difficulty experienced an exponential increase, especially in late 2017, peaking in October 2018 before witnessing a decline. There is an inverse relationship between mining difficulty and the quantity produced, with mining becoming harder as fewer were generated over the years. The average annual exchange volume saw a massive surge in 2017 and 2018, correlating with the increase in mined bitcoins. Additionally, blockchain efficiency improved over the years, as evidenced by the growth in average block size from 2011 to 2017.

Fourth, regarding the price dynamics, we found that price movements show correlations with various metrics. The median transaction value has a strong, statistically significant positive relationship with price, explaining approximately 60% of its variance. Similarly, the number of active addresses also positively correlates with price, accounting for around 50% of the price variation.

Implications

While bitcoin is the most prominent cryptocurrency by trading volume, its volatility, and recent price declines signal that investors should exercise caution when considering investments. Transaction fees, though relatively low, spiked for periods of high trading activity. Investors should monitor fees as an

indicator of market demand. The relationship between fees and median transaction value provides a lever for estimating capacity needs.

Rapid growth in blockchain size implies the technology is scaling to support increasing Bitcoin adoption. However, variability in the link between active addresses and prices points to a multitude of factors driving prices beyond simple usage metrics. Instances, where active addresses and prices do not align may be attributed to speculative investments rather than the underlying value or utility.

Overall, the analysis underscores Bitcoin's inherent complexity as it continues maturing. While technical dimensions such as processing volumes and blockchain efficiency are progressing, the interplay between investor speculation, user adoption, and real economic valuation remains uncertain.

Limitations

This research has limitations in its scope. First, due to data availability constraints regarding the time covered, this study focused on descriptive analytics and visualizations. As more extensive quantitative and qualitative cryptocurrency data emerges, more advanced modeling techniques could reveal additional insights. Second, the scope was limited to Bitcoin as one example of a cryptocurrency. Expanding the investigation to multiple cryptocurrencies could offer a more comprehensive understanding of the domain. Nevertheless, this study offers a solid starting point for characterizing the nature of the cryptocurrency.

Future Research

Our descriptive approach enables an initial data-driven perspective on foundational Bitcoin behaviors, setting the stage for future research on this and other cryptocurrencies. Specifically, there are two relationships that exhibit core complexities in valuation and growth dynamics that future research could further disentangle. First is the inverse correlation between mining difficulty and coin production. Second is the fluctuating linkage between user activity and pricing. As more historical data becomes available, predictive modeling using statistical and machine learning methods could uncover insights into price volatility, trading volumes, and other trends. Time series analysis may also elucidate patterns and trends behind Bitcoin's fluctuating adoption. With cryptocurrencies still in an early and unstable phase, further empirical research into the effects of regulation, improved security, and governance protocols could inform efforts to stabilize the market. Investigating mechanisms to detect fraud, prevent theft, and address environmental sustainability concerns could help address key challenges surrounding decentralization. As the landscape matures, longitudinal studies on user profiles, geographic usage patterns, and comparisons with altcoins may reveal nuances to Bitcoin's evolution and real-world utility. Research illuminating the factors that engender trust and adoption of cryptocurrencies as an everyday currency could support mainstream acceptance.

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