Differences among cryptocurrencies from three perspectives: volatility, electricity consumption, and inflation

1. Introduction

Bitcoin is a digital currency introduced[1] by Satoshi Nakamoto which became fully operational in January 2009. Bitcoin's value skyrocketed from $0.30 in 2010 to an all-time high of over $65,000 USD in 2021. This ushered a wave of blockchain-based financial innovations known as decentralized finance (DeFi). Today, a global cryptocurrency market has a market capitalization of 1.85 trillion USD with over 18 thousand different cryptocurrencies in existance[2].

Digital money existed long before Bitcoin's emergence. Thus, investor's enthusiasm[3] towards cryptocurrencies primarily refers to the promise of the underlying technology: blockchain. Conventional currencies and payment systems always require some central authority that must be trusted when two parties want to make a transaction. Cryptocurrencies circumvent this issue using blockchain technology.

Blockchain technology can potentially serve a much broader purpose than just settling cryptocurrencies transactions. Thus, under the umbrella term of decentralized finance emerged numerous blockchain utilizations: smart contracts (blockchain contracts that can be enforced without human interaction), non-fungible tokens (NFTs), video games based on blockchain, various applications in financial services including tokenization of stocks, and other. However, with the exception of cryptocurrencies, none of these applications has become mainstream so far.

With more than 18,000 cryptocurrencies in existence, there are substantial technical, functional, and conceptual differences between various cryptocurrencies. However, cryptocurrency research has been generally focused on Bitcoin and very little attention has been given to the understanding of cryptocurrency differences and the impact these characteristics might have on the markets.

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[1] Nakamoto (2008)
[2] https://coinmarketcap.com/
[3] Maybe a better term would be the one popularized by the title of Robert J. Shiller's famous book: *irrational exuberance.*

Let us emphasize two such differences. First, there are two main consensus mechanisms behind blockchain: proof-of-work and proof-of-stake. The proof-of-work is a common consensus mechanism used by most popular cryptocurrencies including Bitcoin. However, the proof-of-work mechanism consumes substantial amounts of electricity. Thus, proof-of-stake cryptocurrencies emerged as a potential solution to rising electricity consumption. Second, cryptocurrencies also differ in terms of their supply. There are cryptocurrencies with a limited supply of coins (including Bitcoin) but also those with unlimited supply (e.g. Ethereum).

There is now a growing research field regarding factors influencing cryptocurrencies. In this essay, we hypothesize that the blockchain mechanism upon which cryptocurrencies are based might influence volatility. Furthermore, we are interested in the relationship between market sentiment regarding electricity prices and global warming with both proof-of-work and proof-of-stake cryptocurrencies. Finally, we expect that the sentiment related to monetary policy news and inflation, in particular, might influence cryptocurrency prices based on their scarcity (limited vs unlimited supply).

2. Literature Review

Despite a large number of cryptocurrencies actively trading on the market, the existing literature focuses predominantly on Bitcoin. Considering Bitcoin's popularity and market capitalization, this is somewhat expected. However, cryptocurrencies differ significantly in terms of their characteristics. Thus, not only the majority of cryptocurrencies have been underrepresented in literature, there was very little effort to understand how these differences might impact the volatility and also drive various cryptocurrencies to respond differently to external shocks.

When it comes to volatility, researchers have usually attempted to model the volatility of specific cryptocurrencies. Understanding the volatility dynamics received particular interest in academic literature provided that cryptocurrencies have been characterized with extreme price movements. Briere et al. (2013) show that Bitcoin has substantially higher volatility compared with other assets classes but also higher average return. Yermack (2013) compared the volatility of Bitcoin to several major fiat currencies including the Japanese Yen, Swiss Franc, and Euro. This study contributed to the early understanding that Bitcoin's high volatility (compared to traditional currencies) prevents it from serving as a means of payment. Similarly, Sapuric & Kokkinaki (2014) compared the volatility of the Bitcoin exchange rate against several major currencies (Euro, Swiss Franc, Russian Ruble, and Japanese Yen) finding that the volatility of Bitcoin is substantially higher.

Glaser et al. (2014) were among the first to employ the GARCH model for such a purpose. Since GARCH family models have been used extensively in modeling cryptocurrencies volatility. Gronwald (2014) used an autoregressive jump-intensity GARCH model to model the extreme price swings of Bitcoin.

Bouoiyour and Selmi (2015) were interested in GARCH models goodness-of-fit based on Bitcoin time series ranging from 2010 until 2015. Their findings indicate that the threshold-GARCH estimates reveal the long duration of persistence while the EGARCH displays less volatility persistence. Furthermore, they found evidence for the existence of leverage effects since the volatility of Bitcoin was more influenced by negative shocks than positive ones. Using information criteria, Katsiampa (2017) evaluated the performance of six different

GARCH models on Bitcoin time series data eventually concluding that the Asymmetric Component GARCH provides the best performance.

Stavroyiannis (2018) utilized a GJR-GARCH model to determine whether Bitcoin violates the VaR more than other speculative assets including gold. His conclusion underlines the high volatility of Bitcoin and the stronger tendency to violate VaR as compared to gold. Ardia et al. (2019a) used MSGARCH to successfully detect regime changes in the volatility of Bitcoin. Furthermore, Bayesian estimations for GARCH family models have been proposed by some authors including Bauwens et al. (2010) who utilized the Bayesian MCMC algorithm to estimate MSGARCH.

As opposed to solely focusing on Bitcoing, Chu et al. (2017) provided a GARCH modeling on the seven most popular cryptocurrencies by fitting 12 different types of GARCH models and using information criteria to evaluate the models. Their conclusion indicates that IGARCH and GJR-GARCH models provide the best fit in-sample for most of the cryptocurrencies. Interestingly enough, Letra (2016) fitted a GARCH(1,1) model on daily data and web content from Google Trends, Wikipedia, and Twitter tweets. Findings suggest that Bitcoin returns are driven by popularity while web content has some degree of predictive power. Burnie (2018) focused on correlations between various cryptocurrencies finding strong tendencies.

Some attempts to employ high-frequency data in modeling Bitcoin volatility were also made. Most notably, Baur and Dimpfl (2018) modeled a Bitcoin realized volatility showing that the volatility of Bitcoin is excessive when compared to fiat currencies.

Since external shocks are within the area of our interest, it is worth mentioning several papers investigating the impact of external shocks on cryptocurrencies volatility. Aysan et al. (2019) analyze the effects of geopolitical risks on bitcoin returns and volatility. Their findings suggest that Bitcoin volatility is increasing with increased geopolitical risks. Wang et al. (2020) find that Bitcoin volatility increases with the increase in economic policy uncertainty while Lyócsa and Molnár (2020) point to increased volatility on days of cryptocurrency-related hacking attacks.

Finally, there are several influential studies explaining the relationship between public sentiment and financial markets. Brown & Cliff (2005) argue that mispricing of stock valuation can be explained by sentiment. Engelberg (2008) investigates earning announcements news for approximately 5000 companies over a period between 1999 and 2005. He finds that earning announcements published in news articles contain predictive power over future returns.

Liao et al. (2019) discuss whether news affects mergers and acquisitions. Their findings indicate that the more optimistic sentiment embedded in the news leads to a higher chance of reaching successful acquisitions. However, they also speculate that if the acquirer receives high media coverage, it will on average experience negative post-acquisition returns.

Zhang et al. (2011) were pioneers of investigating a potential correlation between Twitter sentiment and financial markets (specifically: Dow Jones, NASDAQ, and S&P 500). However, they did not detect the correlation between either positive or negative emotions embedded within tweets with stock markets. Using the supervised machine learning approach, Liu (2017) reaches the same conclusion.

Bollen et al. (2011) measured six dimensions of mood (i.e. calm, alert, sure, vital, kind, and happy) and binary sentiment polarity (positive or negative) in tweets finding the correlation of sentiment with stock markets. Similarly, Mittal & Goel (2012) found a correlation between happiness and calmness with Dow Jones.

3. Subject of the Research

Broadly speaking, there are two main consensus mechanisms behind blockchain: proof-of-work and proof-of-stake. Blockchain is a decentralized peer-to-peer system with no central authority. Thus, without central authority serving as an intermediator, a consensus mechanism is needed to settle transactions between different parties.

The proof-of-work is a common consensus mechanism used by most popular cryptocurrencies including Bitcoin, Ethereum, Litecoin, Monero, and others. According to Cryptoslate exchange[4], the 10 largest proof-of-work cryptocurrencies measured by market capitalization account alone for more than 63% of the cryptocurrency market. However, the proof-of-work mechanism consumes substantial amounts of electricity. In fact, the estimated power demand of the Bitcoin network alone is currently approximately 129 TWh[5] annually. As such, the Bitcoin network alone consumes approximately five times more electricity than the whole of Slovakia, two times more than Czechia, and about the same as Norway..[6]

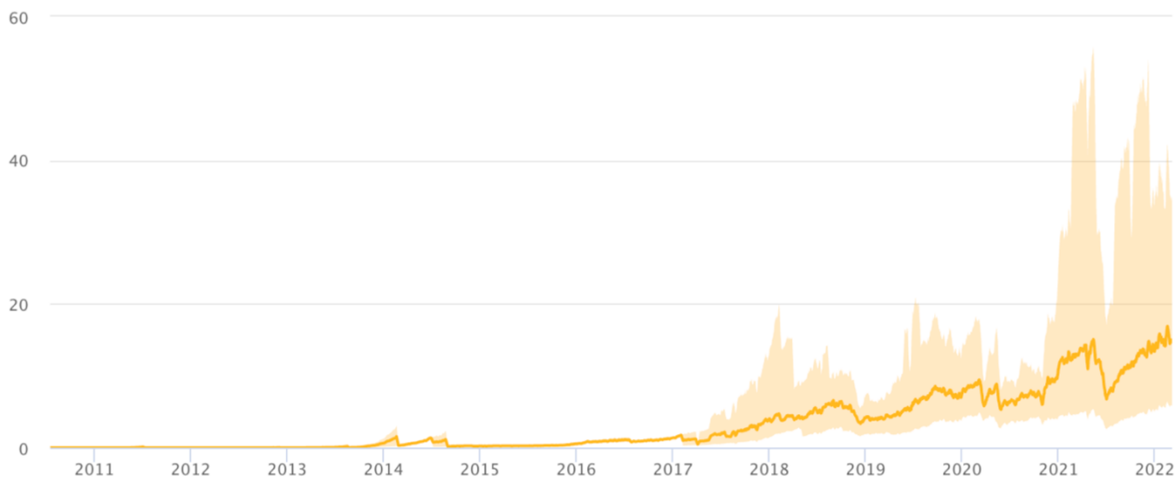

Figure 1: Daily Bitcoing network power demand 2011 – 2022
(Source: https://ccaf.io/cbeci/index)

Obviously, the near-exponential jump in electricity consumption by Bitcoin and other proof-of-work cryptocurrencies has been severely criticized by Gallersdörfer et al. (2020), Li et al. (2019), de Vries (2021), Mora et al. (2018), Dittmar et al. (2018), and others.

[4] https://cryptoslate.com/cryptos/proof-of-work/
[5] https://cbeci.org/
[6] https://www.iea.org/countries/norway

Proof-of-stake cryptocurrencies emerged as a potential solution to rising electricity consumption. Platt et al. (2021) found that the electricity consumption of proof-of-work-based Bitcoin is three times higher than that of the highest consuming proof-of-stake cryptocurrency.

However, in terms of market capitalization proof-of-stake cryptocurrencies are still marginal compared to proof-of-work cryptocurrencies. According to Coinmarketcap exchange[7] top 10 proof-of-stake cryptocurrencies in terms of market capitalization amount to approximately 8.6% of Bitcoin's market capitalization alone.

In the previous section, we have discussed that high volatility has been well-established for Bitcoin and other major cryptocurrencies. However, literature has not devoted enough attention to the distinction between proof-of-work and proof-of-stake cryptocurrencies. Thus, high volatility might be a specific feature of proof-of-work cryptocurrencies due to their reliance on energy. Prices of basic energy (natural gas, electricity, heating oil) are generally more volatile than prices of other commodities. Thus, this relationship between proof-of-work cryptocurrencies and electricity consumption might contribute to volatility.

We propose modeling and comparing volatilities between proof-of-work and proof-of-stake cryptocurrency classes to detect and understand these potential differences. Why is this important? Although proof-of-stake is still marginal in terms of market capitalization, this might change. The second-largest cryptocurrency by market capitalization Ethereum is fully transitioning to a proof-of-stake mechanism[8]. This is also true for Dogecoin[9] (currently the 13th largest cryptocurrency by market capitalization) and other cryptocurrencies might follow. In other words, proof-of-stake will take a much larger share of the overall cryptocurrency market in the following years.

If proof-of-stake cryptocurrencies are less volatile, transitioning to a new consensus mechanism will contribute to a more stable cryptocurrency market overall. Cryptocurrencies were meant to serve primarily as money. However, there is a rather strong consensus in the literature that so far, cryptocurrencies are in reality serving mainly a role of speculative assets.[10]

[7] https://coinmarketcap.com/
[8] https://ethereum.org/en/developers/docs/consensus-mechanisms/pos/#:~:text=Proof%2Dof%2Dstake%20is%20the,blocks%20they%20don't%20create.
[9] https://www.binance.com/en/news/top/6912062
[10] Yermack (2015), Ciaian et al. (2016), Baur et al. (2018), Shahzad et al. (2019) and many others

Transitioning to less volatile consensus mechanisms might lead to increased adoption of cryptocurrencies as money.

Furthermore, this might yield several important policy outcomes too. Less volatile cryptocurrency markets might nudge governments into issuing their own CBDC (central bank digital coins). At the moment, China has confirmed the development of a government-back digital coin[11] so-called eCNY. According to the Atlantic Council[12] 9 nations have already issued CBDCs, 15 are enrolled into a pilot program, 16 are developing digital coins, while 40 are officially researching and considering (including USA and EU).

For most developed nations high electricity consumption of traditional cryptocurrencies is a major stumbling block when it comes to larger adoption of this asset as well as potential issuance of CBDCs. This is because proof-of-work cryptocurrencies are simply not aligned with global warming initiatives as such. Government-backed digital coins that would significantly increase the nation's ecological footprint would be disregarded. However, a proof-of-stake mechanism would allow governments to issue CBDC without compromising global warming policies.

Furthermore, we are also interested in the relationship between market sentiment related to electricity prices and global warming with cryptocurrency prices. In other words, we would like to compare how proof-of-work and proof-of-stake cryptocurrencies differ in their response to new information related to electricity and concerns about climate change.

Whenever investors are worried about the high electricity consumption of proof-of-work cryptocurrencies, these assets should perform worse than proof-of-stake cryptocurrencies. These worries could be present particularly when the electricity price is high (prices of energy commodities are high) when temperatures are unpleasantly high, and, of course, when people express these concerns. Direct information about sentiment related to climate change and cryptocurrencies can be extracted from Twitter.

[11] https://www.reuters.com/world/china/china-will-advance-cbank-digital-currency-improve-its-design-governor-says-2021-11-09/
[12] https://www.atlanticcouncil.org/cbdctracker/

Finally, cryptocurrencies also differ in terms of their supply. For example, there is a limited total supply of Bitcoin (21 million coins). New Bitcoins are regularly created in the process called mining, but the Bitcoin algorithm regularly decreases mining rewards by halving and will stop once 21 million coins are generated. There are many other cryptocurrencies with limited total supply including Litecoin, Cardano, and Stellar.

However, there are also cryptocurrencies with an unlimited supply. For example, Ethereum is not limited in terms of an overall number of coins but there is a cap on the speed of new coins creation (i.e. 2% annually). Other cryptocurrencies featuring unlimited supply are Dogecoin, Monero, and EOS.

It is not clear which of these two types of cryptocurrencies should be preferred. Limited total supply would make cryptocurrency more scarce and therefore possibly more valuable. Therefore, speculators might prefer cryptocurrencies with a limited supply. However, limited supply contrasted to a growing economy could make these cryptocurrencies deflationary. As such, these cryptocurrencies would not be an ideal candidate for conventional money. On the other hand, an unlimited total supply (i.e. 2% annual increase in the total supply of cryptocurrency) would make cryptocurrency behave more like conventional money.

Thus, we would like to understand how cryptocurrencies respond to news about monetary policy and inflation based on their scarcity. If market sentiment related to inflation is strongly negative, investors might perceive deflationary cryptocurrencies with a limited total supply as a hedge against inflation. Thus, increased demand would lead to an increase in prices for cryptocurrencies with a limited supply.

4. Data and Methodology

Both proof-of-work and proof-of-stake cryptocurrency prices are publicly available. Data for most cryptocurrencies will be collected via Bitstamp exchange (https://www.bitstamp.net/). Bitstamp is one of the oldest cryptocurrency exchanges operating since 2011 as well as the first fully EU-licensed and regulated bitcoin exchange in Europe.

However, Bitstamp features a total of 53 cryptocurrencies. Depending on the chosen basket of proof-of-work and proof-of-stake cryptocurrencies for which modeling would be performed, additional data might be needed. In such cases, Binance (https://www.binance.com/en) exchange would be used. Binance is among the world's largest cryptocurrency exchanges operating since 2017 and allowing extraction of historical data via API calls.

For the purpose of sentiment analysis, Twitter would be used. Twitter is a well-known online social network where users post short 140-character messages called ”tweets”. Most tweets (with the exception of intentionally protected ones) are publicly available even for non-registered Twitter users. According to Somula (2020), approximately 500 million tweets are posted in a day, which is around 6000 tweets per second.

Data will be collected using the Twitter streaming API framework for tweet collection. Twitter Streaming API returns a real-time random sample of all public tweets allowing users to pre-select the language and location of tweets. For the sentiment classification Li et al (2014b) lexicon-based method would be followed. This method uses a pre-defined dictionary, in which individual words are labeled either as positive/negative, or they are denoted by certain emotional labels (e.g., “happy”, “sad”, „optimistic“, etc.)

GARCH models variance as the weighted average of long-run variance (α_0), new information that is represented by current period’s variance (α_i) and the variance predicted for this period (β_j).

GARCH (m, s) can be written in a following form:

$$a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ ... + \alpha_m a_{t-m}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \ \beta_s \sigma_{t-s}^2$$

$$\sigma_t^2 = \ \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \, \sigma_{t-j}^2$$

where $\{\epsilon_t\}$ represent independent and indentically distributed random variables (iid) with zero mean and variance of 1. Stationarity condition dictates that $\sum_{i=1}^{\max(m,s)} (\alpha_i + \ \beta_i) < 1$. We refer to α_i as ARCH paramter while β_i is GARCH paramter. Thus, if s = 0 GARCH equation will reduce to ARCH equation.

In order to examine the relationship between Twitter sentiment and cryptocurrency prices we follow Bollen et al. (2011).

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