A Predictive Modeling Study of Bitcoin and Its Complex Volatility

Livia Bedwell, Aaron Dittmer, Abhishek Majumdar, Neeley Rice, Jake Tolleson

TABLE OF CONTENTS

[Abstract 4](#_Toc89887408)

[Introduction 4](#_Toc89887409)

[Background 5](#_Toc89887410)

[History of Bitcoin 6](#_Toc89887411)

[External Factors Impacting Cryptocurrency Pricing 7](#_Toc89887412)

[Cryptocurrency Price Prediction Models 9](#_Toc89887413)

[Results & Discussion 10](#_Toc89887414)

[Scope 10](#_Toc89887415)

[Assumptions 13](#_Toc89887416)

[Stock-to-Flow Model 14](#_Toc89887417)

[Modeling and Prediction Comparison 19](#_Toc89887418)

[Data Collection & Preparation 23](#_Toc89887419)

[Conclusions 28](#_Toc89887420)

[Limitations & Future Research 30](#_Toc89887421)

[Works Cited 33](#_Toc89887422)

Table of Figures

[Figure 1 - Month price raised to the 0.08 power vs log of stock-to-flow 15](https://liveutk-my.sharepoint.com/personal/npolka_vols_utk_edu/Documents/BZAN%20542%20FINAL%20PROJECT%20BITCOIN.docx" \l "_Toc89887605)

[Figure 2 - Week price raised to the 0.12 power vs the log of Stock-to-Flow 17](#_Toc89887606)

[Figure 3 - Model performance for monthly predictions 20](#_Toc89887607)

[Figure 4 - Model performance for weekly predictions 21](#_Toc89887608)

[Figure 5 - Bitcoin week price: predicted vs actual. Line plotted on log scale. 24](#_Toc89887609)

[Figure 6 - Bitcoin month price: predicted vs actual. Lines plotted on log scale. 25](#_Toc89887610)

# Abstract

*As the potential value for cryptocurrency continues to rise, so does the value of predicting future price fluctuations. There is not a 100% accurate way to predict the future, even of a cryptocurrency’s price. However, data modeling can provide useful insight towards sound investment strategies. The following research investigates the cryptocurrency Bitcoin utilizing the concept of scarcity and stock-to-flow. Historical data is used to demonstrate a predictive pattern that can be used to identify a particular event impacting Bitcoin price jumps. The resulting models attempt to predict the future weekly and monthly prices of Bitcoin based off the following predictors: time until next halving, stock-to-flow, news sentiment index, QQQ, and NASDAQ. Multiple model types are investigated, and the stock-to-flow predictor proves most promising. Likely due to the complex behavior of Bitcoin, we found that the simple moving average has the best performance for predicting monthly and weekly Bitcoin prices.*

# Introduction

The main scope of this study was to conduct research on the volatility of tradable coins in the cryptocurrency market and identify trends that produced actionable insight for consumer investment strategies. The idea was to build a generic model that could be extended to multiple types of cryptocurrencies with minor customizations.

There are over 7,500 (Statista, 2021) different cryptocurrencies available for trade today. With the immense volatility resulting in significant gains and/or losses for investors, the cryptocurrency market is a growing sensation amongst a variety of investors around the world. However, as a potentially high-powered investing tool, the key interest in this market is not just how much the price of a coin fluctuates, but why it fluctuates. The value in our idea to begin research into this phenomenon came from being able to produce this actionable insight that could tell us about cryptocurrencies and why they rise and fall in such massive increments. The ability to understand historical trends and predict future change has practical implications for both existing and future investors hoping to maximize their return.

As a guidance to the reader, this research is not meant to promote any specific investment strategy for Bitcoin or other cryptocurrencies. Rather, our results built upon the concept of stock-to-flow as a potential predictor of future price fluctuations for Bitcoin specifically and observed how they compare across multiple models.

## Background

A thorough literature review was conducted on the history of Bitcoin, current events impacting the currency, and previous work on the topic of cryptocurrency prediction. The goal of the review was to gain inspiration on ways to approach the project as well as to identify potential predictors and models for use in the study.

### History of Bitcoin

In response to the worldwide economic recession in 2008, a vast majority of investors had widely growing concerns regarding centralized investments. Cryptocurrency investment became a tool for financiers to gain more control over their investments through a decentralized platform for trading. Bitcoin was the pioneer coin minted into circulation at less than $0.01 USD (Edwards, 2021) per coin and began trading at mass volumes between investors.

Bitcoin mining is a complex process by which individuals mint blocks of Bitcoin into circulation and make them available for trade amongst investors. This process is performed by solving complex algorithms through advanced software that make the Bitcoin blocks available to execute into circulation. A person who performs this activity is called a miner. Miners are rewarded blocks of Bitcoin at a rate specific to the number of coins minted into circulation. The rate of reward for miners is reduced by 50% for every increment of 210,000 blocks issued in circulation (Hong, 2021). Unlike many other currencies, there is a finite number of Bitcoin that can be mined and thus added into circulation. The current estimate for mining of the final Bitcoin is sometime in February 2140. (Hong, 2021)

### External Factors Impacting Cryptocurrency Pricing

Just as in other currencies, the price of a given cryptocurrency may be impacted by various external events, news reporting, and market conditions. Exact ties between crypto price and such situations are rather speculative, but an understanding of their relationship is important for identifying potential predictors of price.

One of the biggest external factors impacting the current market conditions for crypto is the role of government. A unique aspect of decentralized currencies is that they are not tied to governing bodies or regulatory entities of any individual nation in the way that traditional currencies are. Thus, the topic of how different national governments treat and interact with cryptocurrencies such as Bitcoin is not only tricky, but constantly evolving. For instance, in the United States, there are multiple agencies that define cryptocurrencies differently. The Securities and Exchange Commission defines cryptocurrency as a security (Securities and Exchange Commission, 2017) the Commodities and Free Trade Commission defines cryptocurrency as a commodity (US Commodity Futures Trading Commission, 2019) and the United States Treasury Department defines cryptocurrency as a currency (US Department of the Treasury, 2021). There are also several different globally recognized definitions for cryptocurrencies. For example, in the United Kingdom these decentralized coins are seen as a property, which can incur capital gains tax (HM Revenue & Customs, 2018). Furthermore, regulators across the world’s nations are grappling with how to manage the necessity to prevent harm without stifling innovation (Editorial Board, 2021). Some governments, such as China, have even outlawed transactions of cryptocurrency entirely (NPR, 2021). These different regulations and governmental definitions for the cryptocurrency market can potentially impact the global investment behavior amongst investors in nations with different governing bodies.

### Cryptocurrency Price Prediction Models

As cryptocurrencies such as Bitcoin continue to return record high price points in the modern era, so does speculation around the future pricing and valuation of those currencies. Multiple sources have conducted both accurate and inaccurate predictions as to what the future price of Bitcoin is going to be based on its past behavior. While these predictions acted as great starting points for investigating ideas about what makes Bitcoin tick, the studies resulted in a lot of investor speculation for how this asset truly fluctuates. For example, as previously mentioned, the rate at which miners mint blocks of Bitcoin into circulation as well as their reward rate have served as premier predictors in the evaluation of the future price of Bitcoin and can potentially be reconducted at a coin-by-coin basis for different cryptocurrencies.

In order to motivate our research, it is important to understand why the market price of Bitcoin fluctuates. Literature is limited regarding what drives cryptocurrency demand. Huang et al 2018 attempts to predict daily returns using technical indicators (Huang, Huang, & Ni, 2018). McNally 2016 tries to classify Bitcoin’s price direction 30 days out, but results were not very promising (McNally, 2016). The most promising research into why Bitcoin’s market price fluctuates comes from the pseudo-anonymous financial analyst who writes under the moniker PlanB. The analyst suggests treating Bitcoin as a commodity and that the price of Bitcoin is related to its scarcity (PlanB, 2019). To measure scarcity, PlanB uses a calculation that is popular to use for commodities, known as stock-to-flow. This, essentially, indicates that predicting Bitcoin’s future price has been most accurately evaluated when modeling its behavior similarly to other commodities, such as gold and silver.

# Results & Discussion

## Scope

For the purposes of the study, the scope was limited to Bitcoin transactions.

Out of over 7,500 (Statista, 2021) different types of crypto, Bitcoin was chosen as the cryptocurrency to use in our models because it is the most dominated and highly traded cryptocurrency. The volume of datasets for other crypto currencies like Ethereum, Litecoin, and Binance are not large enough to provide any significant observations or inference from our study and hence those coins are outside of the scope within this body of work.

## Assumptions

In the initial process of modeling our findings, it became necessary to perform under certain assumptions. A key assumption was that not all Bitcoin have been mined. This was important for the models to continue to perform until the mining process of the coin is complete. Bitcoin was also evaluated under the assumption that the rate at which blocks are mined remains constant. For the purposes of relevancy, we also assumed that Bitcoin was being evaluated in US dollars (i.e., exchange rate is not considered). In terms of assumptions on a global scale, we assumed that Bitcoin was completely decentralized and was not subject to governing bodies or regulations. Finally, seasonality was not considered in the context of the models.

## Stock-to-Flow Model

To calculate the stock-to-flow of a commodity, one takes the total supply of that commodity and divides it by the annual production of the commodity. The number derived from this calculation is how many years it would take at the current production rate to match the current supply of that commodity. Therefore, higher values of stock-to-flow equate to a scarcer, and thus more valuable, commodity.

In his or her analysis, PlanB models the log of Bitcoin’s monthly price against the log of its stock-to-flow using ordinary least squares. PlanB finds a remarkable R-squared of 0.947. However, when repeating his or her analysis, we find that the assumptions of homoscedasticity and normality of residuals are violated in this model. To correct this, we found that modeling the month price of Bitcoin raised to the 0.08 power against the natural log of stock-to-flow to be a statistically sound descriptive model (Figure 1).

Chart, scatter chart

Description automatically generated

Figure 1 - Month price raised to the 0.08 power vs log of stock-to-flow

The R-squared of this model is 0.943 or, in other words, 94.3% of the variation in Bitcoin’s month price raised to the 0.08 power can be explained by the log of stock-to-flow. Therefore, we will move forward with the basis that the variation in Bitcoin’s market price of stock-to-flow can be explained by the variation in Bitcoin’s stock-to-flow calculation. This model broken down at the weekly level can be seen in Figure 2 below.

Chart, scatter chart

Description automatically generated

Figure 2 - Week price raised to the 0.12 power vs the log of Stock-to-Flow

## Modeling and Prediction Comparison

We trained five models to predict Bitcoin close price, each at the weekly and monthly level. For both time frames we considered the following models: simple moving average, linear regression, support vector machine, random forest, and neural network. Except for the simple moving average, the predictors included in each model for both timeframes were stock-to-flow (lagged 1 period), QQQ (lagged 1 period), NASDAQ (lagged 1 period), and average news sentiment (lagged 1 period). The models using monthly data had an additional variable, months until the next reward halving. The simple moving average uses only the Bitcoin close price and a rolling window using the previous 3 periods. We used the maximum likelihood approach of the box-cox transformation to transform our response variables to normality. We only considered the initial training set during our transformation and found raising the month price to the 0.08 power and the week price to the 0.12 power achieves normality. We transformed the stock-to-flow, QQQ and NASDAQ predictors by taking their natural logarithms to achieve normality.

The models were trained and evaluated using a form of dynamic evaluation. The method takes an iterative approach to train and evaluate the model over various time periods. The dynamic evaluation begins by training the model on a subset of the first 60 months for monthly or the first 241 weeks for weekly. The model is then used to predict the next period, and the results are saved. The process then repeats, and for each iteration, the window lengthens by one period to predict the next available data point. This is done until all points have been predicted. The saved predictions were used to calculate the RMSE, MAE, MAPE, and R-squared for each of the models (Figures 3 and 4). Table

Description automatically generated

Figure 3 - Model performance for monthly predictions

Table

Description automatically generated

Figure 4 - Model performance for weekly predictions

The simple moving average had the best performance based on all metrics for both the monthly and weekly models. This monthly simple moving average model had an RMSE of $6,054.99. As of December 8, 2021, Bitcoin’s market price was over $50,000, so this error is not unreasonable. Additionally, the R-squared was close to 86%. The weekly simple moving average had an RMSE of $2,727.54 and an R-squared of 96.5%. The next best model was the random forest model, but this model did not perform nearly as well. The RMSE for the monthly random forest was about $7,138.87 and the R-squared is 84%. The weekly random forest had an RMSE of $3,266.57 and an R-squared of 95.2%. It was hard to say whether the difference in performance between the simple moving average and random forest was significant.

## Data Collection & Preparation

We collected daily Bitcoin blockchain data that covers the time period from January 03, 2009 to October 29, 2021. The data comprises 707,315 blocks mined by Bitcoin miners. We used the fixed block reward to calculate the running total of Bitcoins in circulation. To account for lost coins, we filtered out approximately the first 3 million coins mined. After filtering those coins out, our data spanned from March 1, 2009 to October 29, 2021.

We also collected data for the market price of Bitcoin in US dollars. Our price data covers the period from July 17, 2010 to October 29, 2020. We only considered the closing price of Bitcoin each day. Daily price data is not available from March 1, 2009 to July 16, 2010, so we estimated what the market price would have been if traded on an exchange using the available historical context of those transactions. Specifically, in October 2009, 5,050 coins were sold for $5 (Wright, 2020) and on May 22, 2010 10,000 coins were exchanged for two large pizzas (or $41) from Papa John’s (The Rise and Fall of Bitcoin, 2011).

To explore the potential effects of external variables, we collected additional data to use as predictors. The additional data includes daily level QQQ, NASDAQ, and news sentiment index measures. QQQ and NASDAQ were collected from Yahoo Finance (Yahoo Finance, n.d.). The news sentiment index attempts to provide a daily score for US economic sentiment by analyzing various articles from major US newspapers (Federal Reserve Bank of San Francisco, n.d.).

After gathering all the data at a daily level, we performed two aggregations – one at a weekly level and one at a monthly level. For the weekly aggregations (Figure 7), we determined the week price of Bitcoin to be the closing market price at the end of day each Saturday. Similarly, the closing market price at the end of day each Friday was used for QQQ and NASDAQ. The flow for each week was calculated as the number of new Bitcoins minted during the week, and the stock was simply the total number of Bitcoins in circulation at the end of each week. The news sentiment index was aggregated as a weekly average.

Chart, histogram

Description automatically generated

Figure 5 - Bitcoin week price: predicted vs actual. Line plotted on log scale.

For the monthly aggregation (Figure 8), the market price of Bitcoin, QQQ, and NASDAQ were determined to be their respective close price on the last day of each month. The stock was determined to be the number of new Bitcoins minted during the month, and the supply was the total number of Bitcoins circulating at the end of the last day of each month. Finally, the news sentiment index was aggregated as a monthly average.

Chart, histogram

Description automatically generated

Figure 6 - Bitcoin month price: predicted vs actual. Lines plotted on log scale.

Our Bitcoin, stock, and news sentiment data were not known before the predictions were made. To account for this, each of these time dependent predictors was lagged one period. This meant each variable that would be unknown was either lagged one week or one month depending on the level of aggregation. This allowed our models to make predictions one period into the future.

# Conclusions

To predict the future price of Bitcoin, we concluded that a simple moving average using 3 periods back was the optimal model. This model was superior most likely due to its ability to handle intense volatility because of its memoryless property. We confirmed there was still a very significant relationship between Bitcoin’s scarcity and its market value. Building upon the simple linear regression approach that was attempted by PlanB, we discovered that the fit could be improved with a transformation that took the natural log of stock-to-flow and raised the monthly price to the 0.08 power. Using that relationship and other external predictors, random forests performed almost as well as the simple moving average in both time aggregations. The linear regression models and support vector machines were not able to predict as well. sedwa. Overall, weekly predictions were preferred over monthly predictions, depending on the goals.

# Limitations & Future Research

There are a few limitations of the model that were identified. This model did not take into consideration the seasonal aspect of investment trends. Moving forward, seasonality could be a feature to consider for model improvement. Other discrepancies included the influence of governmental agencies in different countries and their impact on investment behavior at a global scale. This limitation drew the scope of this study to an evaluation of the behavior of Bitcoin in the United States primarily. This study was also limited by the implementation of the same aspects with respect to different cryptocurrencies. For example, each coin had a particular process that influenced price increases and decreases like particular mining processes and differing minting technologies. This might suggest that the malleability of this study to different coins would more than likely be ineffective in making accurate predictions. The final limitation was the total number of Bitcoins. Because there is a finite total, this study would have to be reconducted under different circumstances once all Bitcoins have been minted into circulation and the mining process of that currency culminates.

# Works Cited

Bambrough, B. (2021, October 23). *Crypto Price Prediction: Bitcoin Forecast To Hit $5 Million As Price Soars Through 2021.* Retrieved from forbes.com: https://www.forbes.com/sites/billybambrough/2021/10/23/crypto-price-prediction-bitcoin-forecast-to-hit-5-million-as-price-soars-through-2021/?sh=15437eda75e6

*Bitcoin.* (2021, December 3). Retrieved from wikipedia.com: https://en.wikipedia.org/wiki/Bitcoin

Chavez-dreyfuss, G. (2021, October 25). *Cryptocurrencies post record inflows in latest week -CoinShares data.* Retrieved from reuters.com: https://www.reuters.com/technology/cryptocurrencies-post-record-inflows-latest-week-coinshares-data-2021-10-25/

Editorial Board. (2021, March 15). *Crypto's Rising. So are the Stakes for Governments Everywhere.* Retrieved 10 2021, from Bloomberg.com: https://www.bloomberg.com/opinion/articles/2021-03-15/cryptocurrencies-are-rising-so-are-the-stakes-for-governments

Edwards, J. (2021, November 30). *Bitcoin's Price History.* Retrieved from investopedia.com: https://www.investopedia.com/articles/forex/121815/bitcoins-price-history.asp#:~:text=Bitcoin%20first%20started%20trading%20from,per%20coin%20in%20July%202010.)

Federal Reserve Bank of San Francisco. (n.d.). *Daily News Sentiment Index*. Retrieved from frbsf.org: https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/

HM Revenue & Customs. (2018, December 19). *Check if you need to pay tax when you sell cryptoassets*. Retrieved from gov.uk: https://www.gov.uk/guidance/check-if-you-need-to-pay-tax-when-you-sell-cryptoassets

Hong, E. (2021, November 30). *How Does Bitcoin Mining Work.* Retrieved from investopedia.com: https://www.investopedia.com/tech/how-does-bitcoin-mining-work/

Huang, J.-Z., Huang, W., & Ni, J. (2018, November 22). *Predicting Bitcoin Returns Using High-Dimensional Technical Indicators.* Retrieved from sciencedirect.com: https://www.sciencedirect.com/science/article/pii/S2405918818300928

McNally, S. (2016, August 22). *Predicting the price of Bitcoin using Machine Learning*. Retrieved from http://norma.ncirl.ie: http://norma.ncirl.ie/2496/1/seanmcnally.pdf

NPR. (2021, September 25). *China Makes Cryptocurrency Illegal.* Retrieved 12 2021, from npr.com: https://www.npr.org/2021/09/25/1040669103/china-makes-cryptocurrency-illegal

PlanB. (2019, March 22). *Modeling Bitcoin Value with Scarcity*. Retrieved from medium.com: https://medium.com/@100trillionUSD/modeling-bitcoins-value-with-scarcity-91fa0fc03e25

Securities and Exchange Commission. (2017, January 31). *SEC Issues Investigative Report Concluding DAO Tokens, a Digital Asset, Were Securities*. Retrieved from sec.gov: https://www.sec.gov/news/press-release/2017-131

Shalvey, K. (2021, October 31). *A Coinbase user lost $11.6 million in under 10 minutes after falling for a fake-notification scam, the US Attorneys Office said.* Retrieved 10 2021, from msn.com: https://www.msn.com/en-us/money/news/a-coinbase-user-lost-11-6-million-in-under-10-minutes-after-falling-for-a-fake-notification-scam-the-us-attorneys-office-said/ar-AAQ9qai

Statista. (2021, November 3). *Number Crypto Coins Tokens.* Retrieved from statista.com: https://www.statista.com/statistics/863917/number-crypto-coins-tokens/

*The Rise and Fall of Bitcoin.* (2011, November 23). Retrieved from wired.com: https://www.wired.com/2011/11/mf-bitcoin/

US Commodity Futures Trading Commission. (2019, December). Retrieved from ctfc.gov: https://www.cftc.gov/sites/default/files/2019-12/oceo\_bitcoinbasics0218.pdf

US Department of the Treasury. (2021, October 15). *Frequently Asked Questions*. Retrieved from treasury.gov: https://home.treasury.gov/policy-issues/financial-sanctions/faqs/topic/1626

Wright, T. (2020, December 20). *Early Bitcoin dev misses out on $1.3B after selling too soon.* Retrieved from cointelegraph.com: https://cointelegraph.com/news/early-bitcoin-dev-misses-out-on-1-3b-after-selling-too-soon

Yahoo Finance. (n.d.). *Yahoo Finance*. Retrieved from yahoo.com: https://finance.yahoo.com/quote/