How Will Bitcoin Move?

written by Hikmat Abdulazizov Hikmət Əbdüləzizov
Part 1 – Introduction, Literature Review and Data Description

This first part of this article consists of introductory information about Bitcoin, literature review, data descriptions and potential models to determine what we predict about Bitcoin's volatility (such as GARCH modeling for example) and value based on past data. Further parts will mainly be data analysis of the cryptocurrency, and thus predictions of future prices, returns or volatility. The creators of Bitcoin set up the digital currency in an effort to eliminate the need for trusted third parties to complete digital financial transactions. We here represent the ideas of Satoshi Nakamoto, the pseudonymous identity of the person/s behind Bitcoin, as presented in their white paper.

Trading online, Nakamoto asserts, has come to rely almost exclusively on financial institutions serving as trusted third parties to process electronic payments. While the system works well enough for most transactions, it still suffers from the inherent weaknesses of the trust-based model. Completely non-reversible transactions are not possible since financial institutions cannot avoid mediating disputes. The cost of mediation increases transaction costs, limiting the minimum practical transaction size and cutting off the possibility for small casual transactions, and thus there is a broader cost in the loss of ability to make non-reversible payments for non-reversible services. With the possibility of reversal, the need for trust spreads. Merchants must be wary of their customers, hassling them for more information than they would otherwise need. A certain percentage of fraud is accepted as unavoidable. These costs and payment uncertainties are avoided in person through the use of physical currency, but no mechanism yet exists, asserted Nakamoto in 2008, to make payments over a communications channel without a trusted party. What cryptocurrencies require is an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party. Transactions that are computationally impractical to reverse would protect sellers from fraud, and routine escrow mechanisms could easily be implemented to protect buyers (Nakamoto 2008).

Our modern economy, Nakamoto continues, relies heavily on digital means of payments. Trade in the form of e-commerce, for example, necessitates the usage of digital tokens. In a digital currency system, the means of payment is simply a string of bits. This poses a problem, as these strings of bits, like any other digital record, can easily be copied and re-used for payment. Essentially, a digital token can be counterfeited by using it twice; this is the so-called double-spending problem. Traditionally, this problem has been overcome by relying on a trusted third-party who manages for a fee a centralized ledger and transfers balances by crediting and debiting buyers and sellers' accounts. This third-party is often the issuer of the digital currency itself, one prominent example being PayPal, and the value of the currency derives from the fact that users trust the third-party to prohibit double-spending. Cryptocurrencies such as Bitcoin go a step further and remove the need for a trusted third-party. Instead, the creators of Bitcoin sought to address this problem by relying on a decentralized network of (possibly anonymous) validators to maintain and update copies of the ledger.

This necessitates that consensus between the validators is maintained about the correct record of transactions so that the users can be sure to receive and keep ownership of balances. But such a consensus ultimately requires that users do not double-spend the currency and that users can trust the validators to accurately update the ledger. How do cryptocurrencies such as Bitcoin tackle these challenges? Trust in the currency is based on a blockchain which ensures the distributed verification, updating and storage of the record of transaction histories. This is done by forming a blockchain. A block is a set of transactions that have been conducted between the users of the cryptocurrency. A chain is created from these blocks containing the history of past transactions that allows one to create a ledger where one can publicly verify the amount of balances or currency a user owns. Hence, a blockchain is like a book containing the ledger of all past transactions with a block being a new page recording all the current transactions.

From January 2017 through December, Bitcoin increased in value by 1270%, and the total cryptocurrency trading volume passed USD 5 billion a day. Interest from the mainstream media, regulators, the public and financial markets accelerated so much that some call this period Bitcoin’s “IPO moment.” During 2017, Bitcoin gained more focus from institutional money, hedge funds, and public funds. Its success culminated with the approval and introduction of Bitcoin derivatives.

Several authors have attempted to describe Bitcoin as a currency, stock, or asset. Yermack (2013) argues that Bitcoin appears to behave more similarly to a speculative store of value rather than a currency. Dwyer (2015), on the other hand, describes Bitcoin as an electronic currency that can be used to trade and can be stored in a personal balance sheet. Dwyer’s argument is supported by Polasik (2015), who adds that Bitcoin can operate as a medium of exchange alongside other payment technologies.

An increasing number of researchers have focused on the existence of a fundamental value of Bitcoin, and some have studied whether or not it is a bubble. Garcia (2014) finds that Bitcoin is a financial bubble because of the difference between the exchange rate and fundamental value of Bitcoin. He argues for a fundamental value given the cost of mining. Similarly, Hayes (2015, 2018) proposed a specific cost of production model for valuating Bitcoin. Additionally, Cheah and Fry (2015) conclude that Bitcoin is a speculative bubble and that the fundamental value of Bitcoin is zero.

Unlike earlier studies, Corbet (2017) found that there is no clear evidence of a bubble in Bitcoin. While these authors discuss whether Bitcoin is a bubble or not, Bouri (2017) found that Bitcoin could be used as an effective diversifier and, in some periods, also display safe-haven and hedge properties. Some studies have been dedicated to determining the factors that drive the price of Bitcoin. Bouoiyour and Selmi (2015) argue that long-term fundamentals are likely to be major contributors to Bitcoin price variations. Among others, they also found technical factors to be a positive driver of Bitcoin prices. Specifically, Georgoula (2015) and Hayes (2015) found the technical factor Hashrate to be a significant positive price driver. Bouoiyour and Selmi (2016), Garcia (2014), Kristoufek (2015) have all used Hashrate as a variable in their respective models.

Other scholars also argue for the significance of fundamental factors such as exchange-trade, equity market indices, currency exchange rates, commodity prices, and transaction volume. In contrast to Bouoiyour and Selmi (2015), Polasik (2015) states that an increase in the transaction volume will lead to higher prices and that global economic factors do not seem to be an important driver. Ciaian (2016) also found that supply and demand factors have strong impacts on price and that standard economic currency models can partly explain price fluctuations.

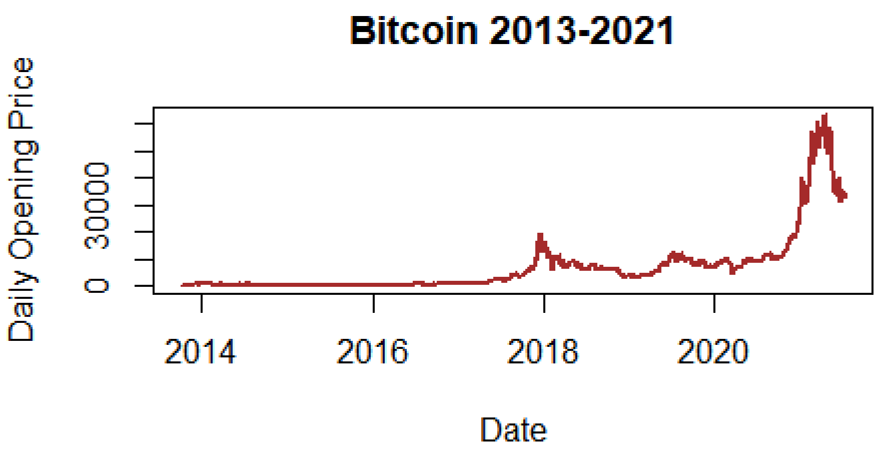
Kristoufek (2013, 2015) analyzed the frequency of online searches for Bitcoin, found them to be a good proxy for interest and popularity, and discovered that the relationship between the price of Bitcoin and online popularity is bidirectional. Ciaian (2016) also found a positive relationship between Wikipedia searches and Bitcoin. Others argue along the same lines as Kristoufek in that it is primarily popularity and investor attractiveness Others argue along the same lines as Kristoufek in that it is primarily popularity and investor attractiveness that drive price movements (Bouoiyour 2016).

Regarding the volatility, in order to control for homoscedasticity, we test the unconditional variance of the regression. Breaking this assumption means that the Gauss–Markov theorem does not hold and that the OLS estimators are not BLUE. Even though the unconditional variance is stable, the conditional variance may not be constant over time. Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model that recognizes the difference between unconditional and conditional variance and lets the conditional variance change over time as a function of previous periods' error terms. This technique has the ability to capture the effect of volatility clustering, but it requires a model with a relatively long lag structure, which makes estimation difficult. To make this task easier, Bollerslev (1986) proposed the GARCH model that enables a reduction in the number of parameters by imposing nonlinear restrictions. The GARCH model can predict unconditional variance and requires fewer parameters. In a GARCH model, the most recent observations have greater impacts on the predicted volatility.

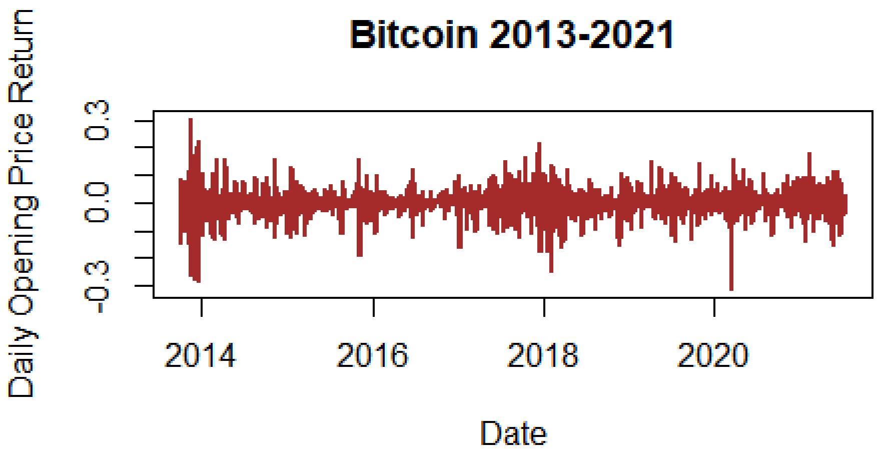
Data Description and Potential Methodology

We have six kinds of Bitcoin data on hand. Each has different frequency and structure. First, we have daily Bitcoin data from 1 October 2013till 14 July 2021. This data has 2.843 observations. In this data set, we have open and closing price, daily high and low values. It is good to have this kind of data since it shows almost all movement of Bitcoin so far. Let's look at the daily open price more closely and carefully. Moreover, it is useful to have these kind of variables because we can use spread values to determine future values of the price (or average daily price).

Graph 1. Historical Daily Bitcoin Prices



Graph 2. Historical Daily Bitcoin Returns



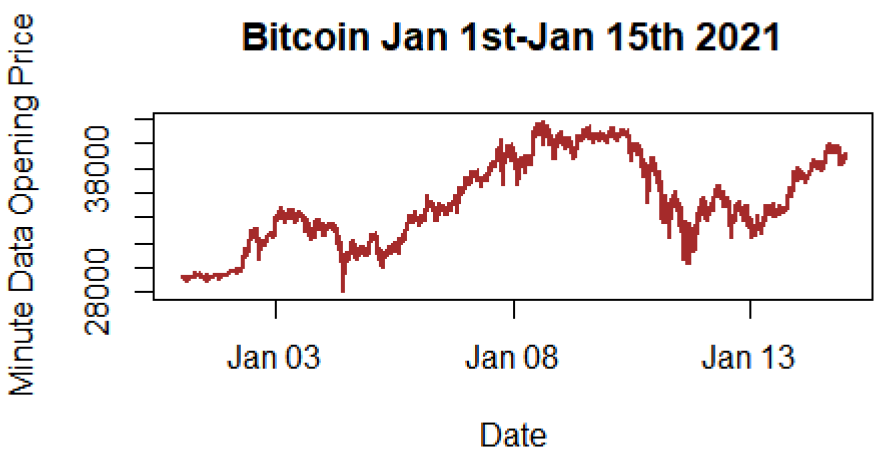
The first graph shows an upward trend with sharp declines and the second graph shows some kind of volatility clustering. Prices can be estimated and predicted with ARIMA type models and volatility (risk) of returns could be predicted via GARCH mechanisms.

Table 1. Summary Statistics of Daily Prices

Minimum	1st Quantile	Median	Mean	3rd Quantile	Maximum
108.6	470.2	3412.7	7105.5	8796.2	63562.7

The second type of data bulk has four data sets for the first 15 days of January 2021 depending on their recorded frequency: minute, 5-minute, 30-minute, 1 hour. Besides open, close, high, low prices it also has trading volume, which is great to have as it might be quite predictive. Below are graphs and summary statistics of those data sets. In order to save space, we only show graphs of minute data and skip the others to the appendix since they just look alike with only frequency difference. These data are important since we can predict a minute later, 5 minutes later, etc. Data sets respectively have 20.154, 4.033, 673, 337 points of observation.

Graph 3. Historical Minute Bitcoin Data



Graph 4. Historical Minute Bitcoin Returns

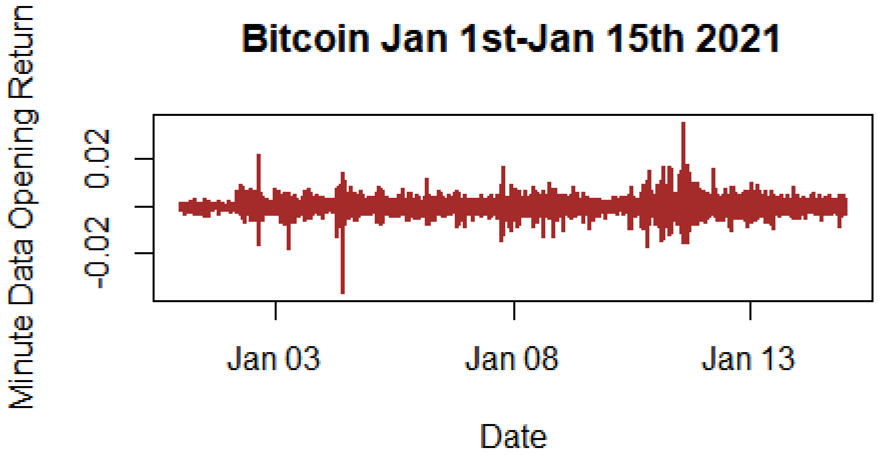
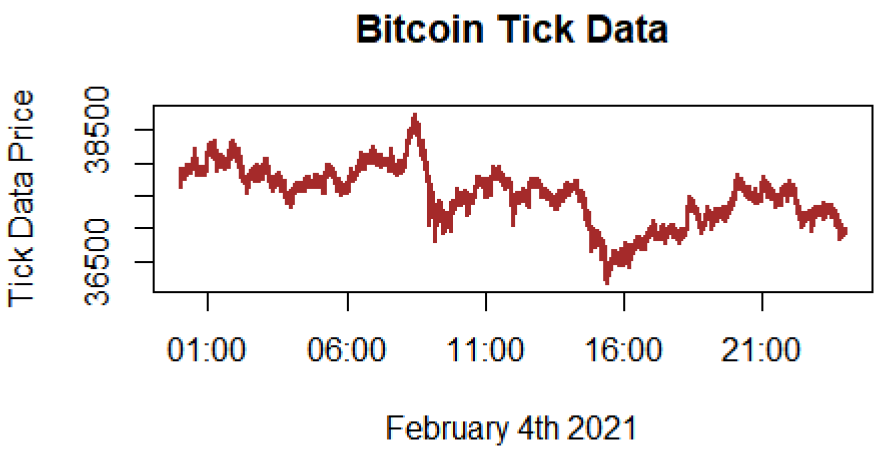


Table 2. Summary Statistics of Minute Prices

Minimum	1st Quantile	Median	Mean	3rd Quantile	Maximum
27998	32672	34685	35253	38422	41916

The last type of data are the most interesting: tick data. The data has records for each transaction occurred in milliseconds (almost all activity of Bitcoin). This data has volume and price variables and consists of 701.661 observations for just one day (4 February 2021), which is quite rich.

Graph 5. Historical Bitcoin Tick Data



Graph 6. Historical Returns of Bitcoin Tick Data

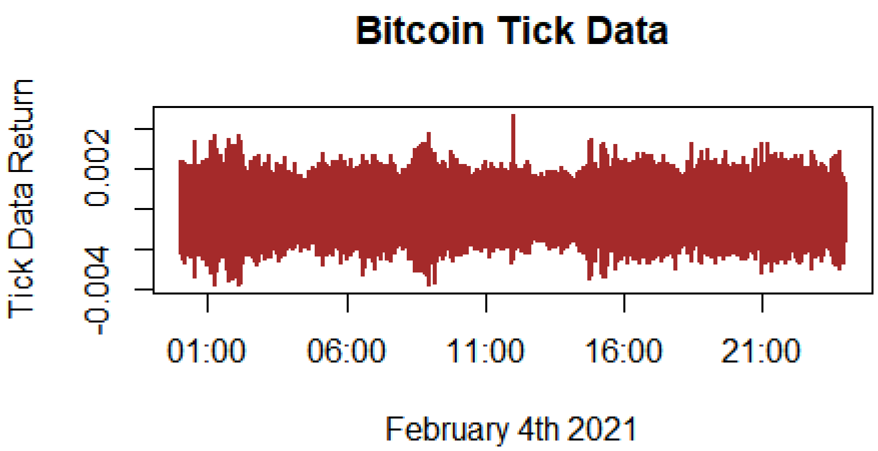


Table 3. Summary Statistics of Tick Prices

Minimum	1st Quantile	Median	Mean	3rd Quantile	Maximum
36147	37152	37488	37524	37846	38769

For returns of tick data, we could use more rigorous methodology rather than GARCH framework. We might try GARCH but our data is not an equidistant time-series anymore. That is why we should rather use penalized and conventional logistic models for predicting return movements. We can use more than a down-up approach and predict many categories under multinomial logistic regressions. If we have computing power and can estimate 100 categories, for example, the regression would yield a quantile prediction for a millisecond later return, which is very intriguing. One more methodology would be to find potential scaling laws in tick data as in foreign exchange or stock prices. The last two methodologies would be a great tool for algorithmic trading.

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