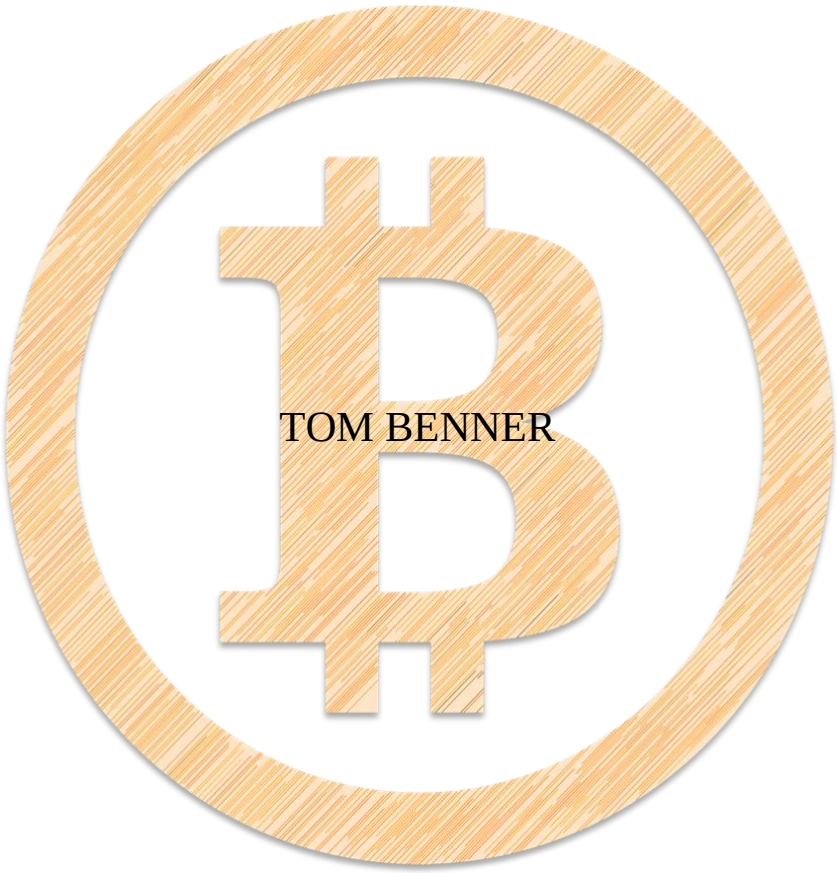
A Work Project presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

Bitcoin's Fundamental Value Drivers: An Empirical Analysis



TOM BENNER

Work project carried out under the supervision of:
(Emanuele Rizzo)

04-01-2021

Abstract

Bitcoin is a decentralized, self-sovereign digital currency that is not controlled by any state, bank, institution or individual. Despite being the best performing asset of the last decade, the technology is still not very well understood and previous literature has shown little consensus about the factors underlying its price formation. This paper aims to enhance the understanding of this new technology and analyze fundamental value drivers. We identified three key valuation models for Bitcoin based on (1) the energy consumption of the network, (2) the level of scarcity of the asset, and (3) the interplay between supply & demand for the digital currency.

Keywords: Bitcoin, Blockchain, Stock-to-Flow, Hash Rate, Mining Difficulty

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

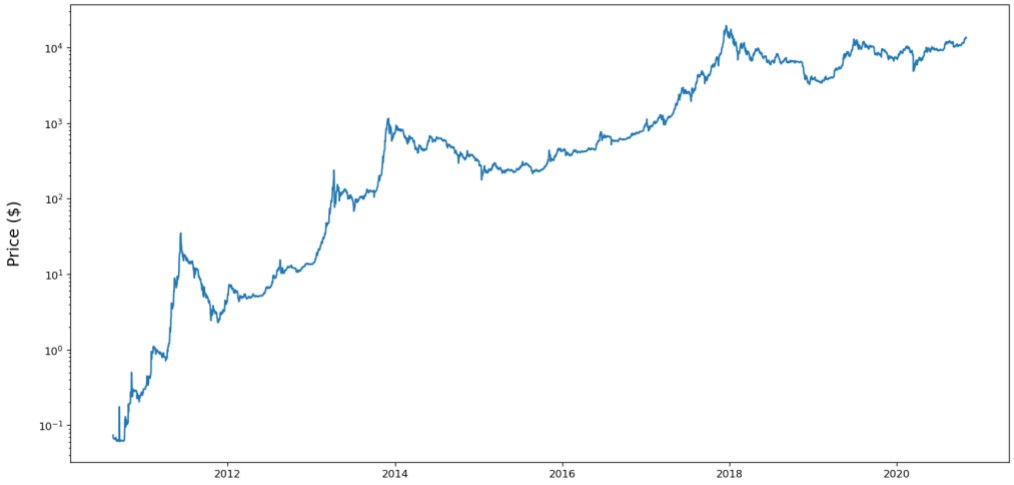
1. Introduction

On October 31st 2008, a pseudonymous character called Satoshi Nakamoto released a white paper proposing "Bitcoin" - a trustless, decentralized, peer-to-peer electronic cash system (Nakamoto, 2008). On January 3rd 2009, Satoshi Nakamoto mined the first ever block (genesis block) of the Bitcoin blockchain, making the concept of a self-sovereign digital monetary system a reality. 660,195 blocks later, or approximately 11 ½ years, Bitcoin has become the most powerful computing network in the world with a total computing power of 140 million terra hashes per second, reached a total network value of around $300 billion, an average daily transaction volume of $10 billion, and the first publicly listed companies adopting it as a cash substitute on their balance sheets. (November 14, 2020)

In its early days, in absence of a market and a price, Bitcoin was mainly used and produced by cryptography experts and was nothing else but a new tech-experiment. On October 5th 2009, 9 months after Bitcoin came into existence, a public sale was launched on the New Liberty Standard online forum quoting the first ever price for 1 Bitcoin at $0.00076. In February 2010, an online user called "dwdollar" established the world's first Bitcoin market and beginning of July 2010, after the first major update to the Bitcoin protocol by community developers, Bitcoin experienced its first ten-fold increase in its exchange value in just a matter of days, from $0.008 to $0.08 per Bitcoin. Shortly after, on July 17th, the MtGox Cryptocurrency exchange was launched and quickly became the most widely adopted exchange in the world for trading Bitcoin. After a few more updates to the core protocol, the Bitcoin exchange rate began to escalate, reaching $0.5 within a couple of months. On February 9th 2011, Bitcoin reached parity with the US dollar (1 Bitcoin = 1 Dollar) and only 4 months later, Bitcoin temporarily peaked at $31.91 before crashing by 94% in value. It took 601 days thereafter for the Bitcoin exchange rate to surpass the previous all-time high of $31.91. During this period, new

exchanges emerged, and new software updates were implemented, setting up a better infrastructure for future adoption.

Graph 1: Bitcoin Price



Graph 1 shows Bitcoin's price on a logarithmic scale from 18/08/2010 – 31/10/2020

In mid 2013, Bitcoin surpassed $100 for the first time and from then it took only half a year for one Bitcoin to reach $1,000, and the total network value to cross $10 billion for the first time. Shortly after Bitcoin reached this historic milestone, the MtGox exchange was allegedly hacked and 6% of the total circulating supply was stolen. Almost simultaneously, China, the country with the biggest adoption of Bitcoin at the time, banned the use of all cryptocurrencies. Both events put downward pressure on the price, resulting in yet another crash of 87% in the value of Bitcoin. This time, it took 720 days to reclaim the $1,000 mark. As before, during the bear market, the Bitcoin protocol was improved and newer, better infrastructure for buying, selling and transferring Bitcoin came into existence. Once Bitcoin surpassed $1,000 again in February 2017, the price went on an exponential trajectory until peaking at almost $20,000 on December 17th, marking the end of a retail driven buying frenzy that saw Bitcoin climb by more than 1,300% in a single year. Earlier in December, the world's biggest and most popular options trading market, the CBOE, introduced the first derivative products with Bitcoin as the underlying. After hitting the current all-time high of almost $20,000, Bitcoin once again entered

a severe multi-year bear market and bottomed at around $3,100, a decrease of 85%. Bitcoin is currently trading at around $16,000 (November 14, 2020), and is already 1,100 days into its recovery.

Throughout its lifetime, the mainstream media has declared Bitcoin dead 382 times, yet there have been only 17 days (out of a total 4355) where buying Bitcoin would not have been profitable as of now (November 14, 2020), measured in US dollars. In other words, the probability of being profitable if you had invested in Bitcoin at a random point in time of its existence is 99.6%. Moreover, the Bitcoin exchange rate measured in less favourable currencies such as the Turkish lira, Argentina peso, Brazilian real, and the Zimbabwean dollar is already reaching new all-time highs. Bitcoin is a foreign currency to every nation, every institution, and every individual. It creates an independent measure of universal value.

We believe that it is important to study and understand the fundamental value drivers of such an extraordinary and completely new financial invention. Previous literature identified models on the price of Bitcoin based on traditional financial factors, macroeconomic factors, and technological factors (e.g. Elie Bouri et al. 2018, Jamal Bouoiyour and Refk Selmi 2015). However, only a few academic studies focus on factors that are native to the Bitcoin protocol (e.g. Hayes 2018, Kjaerland et al. 2018). The purpose of this analysis is to fill this gap in the literature and construct statistical valuation models using Bitcoin-specific fundamental factors.

The next section is meant to familiarize the reader with fundamental concepts and mechanisms of the Bitcoin protocol. This will set the foundations for understanding the selection of the factors in the models discussed in Section 5.

2. Technical Background

Bitcoin is thought of as being a digital/virtual form of value that leverages cryptography as its security measure to enable peer-to-peer transactions (Nakamoto, 2008). It is the first digital currency, also called "cryptocurrency", that was created and cannot be copied, forged or double-spent. The total supply of all Bitcoins that will ever be created is immutably fixed at 21 million. These unique properties make it the first form of digital scarcity known to mankind.

2.1 Blockchain

The underlying technology that enables the mining of Bitcoin (digital scarcity) is called "Blockchain". For the scope of this analysis, it is sufficient to understand that a Blockchain is a distributed ledger that records and maintains a history of transactions and uses a consensus algorithm to verify the recorded information.

The Bitcoin Blockchain is operated and secured by a global, decentralized web of nodes. A node is a device, like a computer, that acts as a data point in a larger network and is responsible for holding, distributing and verifying copies of the entire ledger. Currently, it is estimated that there are around 10,000 full nodes operating the Bitcoin network (November 14, 2020). The algorithm used by these nodes to reach consensus is called "Proof-of-Work" (PoW). The "work" that is being "proved" comes from the so-called "miners". Just like nodes, miners are computers and are an essential part to the Bitcoin network. Mining nodes are not actually responsible for verifying and maintaining the Blockchain but are responsible for processing transactions, bundle them in "blocks", and add them in chronological order to the previously mined blocks, creating a cryptographically linked chain. Thus, the name "Blockchain". A block is a data structure containing 1MB of information. On average, a block contains 1,600 transactions.

2.2 Bitcoin Mining & Hash Rate

In the mining process, to add a new block, a miner needs to solve a complex mathematical problem of the form: Given data *X*, find a number *n* such that the hash of *n* appended to *X* results in a number less than *Y*. Since the hash function used in the Bitcoin protocol (SHA-256) is cryptographically secure, it is impossible to run a program that can predict *n* such that the result will always be less than *Y*. Thus, the only way for miners to find a solution to this problem is by bruteforce. Each guess the mining nodes perform to find an input number *n* that satisfies the equation is a hash. Nowadays, mining devices can perform trillions of hashes per second. Nevertheless, the likelihood of solving the mathematical problem is infinitesimally small. The mathematical problem of Bitcoin's most recent block, as of November 2020, had a difficulty level of 19 trillion. That is, the chance of a single miner producing a hash of *n* below the target *Y* is 1 in 19 trillion. Once a miner has found a solution to the cryptographic puzzle and created a new block, the block is broadcasted to the network where full nodes verify its legitimacy. The first miner that is able to solve the cryptographic puzzle and creates a legitimate block receives a reward, paid in Bitcoin. The reward consists of two parts: a predetermined amount of Bitcoin from the network and the transaction fees that users pay for transacting on the network. That way, the Bitcoin protocol creates an economic incentive for miners to join the network and compete to verify transactions. Since greed is an integral part of human behaviour, operators of mining nodes will naturally try to increase their likelihood of receiving the block reward. However, since the solution to the mathematical problem is random, the only way to increase the likelihood of finding a solution is by increasing the computing power. This can be done through connecting more mining devices to the network or by improving the efficiency of existing mining devices. Through this game-theory like mechanism, Bitcoin creates competitive mining cycles in which mining operators increase their computing power to maximize profitability.

Another way of interpreting the hash rate (computing power) of the network is as a measure of security. Bitcoin is an open-source ledger that records information about the distribution of wealth of all participants. Hackers might try to falsify the stored information for their benefit, such as reversing previously confirmed transactions, double-spending coins or preventing certain transactions from being processed. Since the Bitcoin Blockchain utilizes the Proof-of-Work (PoW) consensus algorithm, to successfully attack Bitcoin, hackers would need at least 51% of the total hash rate. Thus, the higher the hash rate of the Bitcoin network, the more difficult it becomes for bad actors to take control of 51% of the computing power. Because it is unimaginably expensive to tamper with the protocol and sustain the attack for a longer period, the Bitcoin network incentivizes fair behaviour and creates a remarkable balance between acting in self-interest and benefiting the whole network and all participants.

2.3 Difficulty Adjustment

Embedded in the Bitcoin code is a functionality, called the difficulty adjustment, that ensures that new blocks are added to the chain at a constant rate. This rate is set to 10 minutes. This means that, on average, every 10 minutes a miner is rewarded with a certain amount of Bitcoin for verifying a block. This is necessary because mining devices are constantly being connected and disconnected from the network depending on the profitability of mining Bitcoin. Thus, it can happen that the rate at which new blocks are added is greater than or less than 10 minutes. To prevent this from happening for a longer period of time, the Bitcoin protocol automatically adjusts the difficulty of the cryptographic puzzle every 2016 blocks, or roughly every 2 weeks. Meaning that, if the average time to generate a block was below (above) 10 minutes, then the protocol makes Y smaller (larger) and thus increases (decreases) the difficulty of finding n. The Bitcoin protocol started at a mining difficulty of 1.

Bitcoin now had 322 difficulty adjustments and recently reached a record difficulty level of 19.31 trillion. The growth of the mining difficulty is very closely related to the growth of the total hash rate of the network but is much less volatile due to the 2-week adjustment period. In fact, the two variables have a Pearson-correlation of 0.9998. This is because the mining difficulty is a direct function of the total hash rate of the network. The higher the difficulty of mining, the safer the encrypted information stored in the blocks.

With the creation of Bitcoin, Satoshi Nakamoto found a way how we can utilize electricity to power a global settlement network, transforming energy into security.

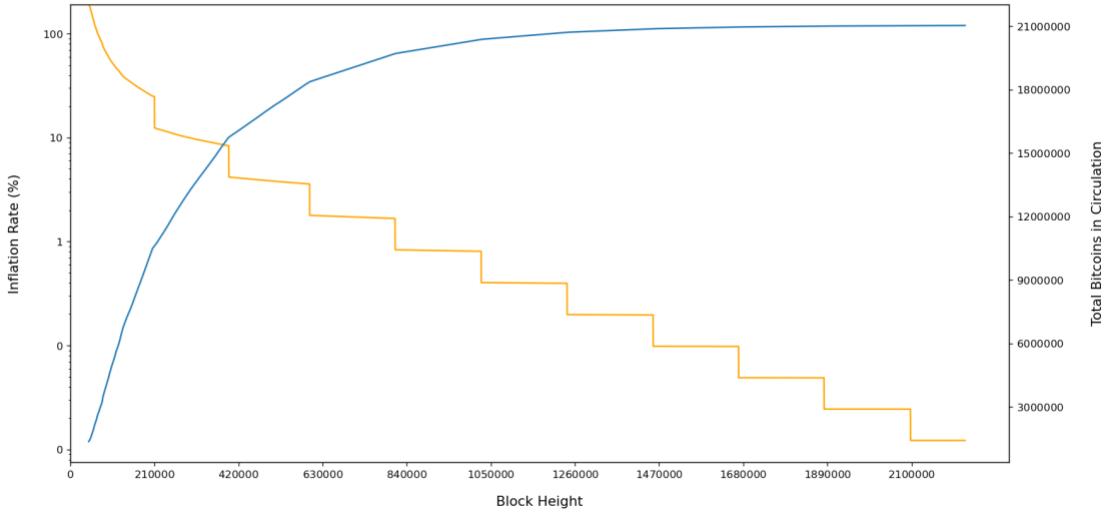
2.4 Bitcoin's Monetary Policy

The Bitcoin protocol has 2 main monetary policies embedded in its code - The Block Frequency and the Halving. The Block Frequency determines at which rate new Bitcoins will enter circulation. As mentioned before, the difficulty adjustment is the governing body that ensures a Block Frequency of 10 minutes. Thus, the full nodes are auditing and verifying the entire ledger every 10 minutes. This creates a constant and perfectly predictable rate of inflation.

The Halving determines how many new Bitcoins will enter circulation with every newly generated block and is divided into epochs of equal length. That is, the amount of newly issued Bitcoin is reduced by 50% every 210,000 blocks, or approximately every 4 years. This process will repeat itself until all 21 million Bitcoins have been mined (approximately by year 2140). Bitcoin has a total of 32 Halving cycles. Initially, when the Bitcoin network went live in 2009, the reward per block was 50 Bitcoins. The 3rd halving occurred on the 11th of March 2020 and cut the reward per block to 6.25 Bitcoin. The halving gives Bitcoin a deflationary characteristic and once all Bitcoins have been mined, Bitcoin becomes truly deflationary. Both policies are strictly governed and executed by the protocol itself, and the Bitcoin network has been up and

running uninterruptedly ever since inception. This creates a perfectly predictable monetary system, from now until 2140 and beyond:

Graph 2: Bitcoin‘s Monetary Policy



Graph 2 shows Bitcoin’s inflation rate per block (orange line) and Bitcoin’s total circulating supply (blue line). The graph shows Bitcoin’s monetary policy only for illustration purposes and is limited to the Block Height of 2,100,000, or the year 2048.

3. Literature Review

Bitcoin's rising popularity across the world accompanied with its rising price have resulted in a growing number of researchers studying various aspects of this new asset class, ranging from the privacy implications of such a digital currency (e.g. Androulaki 2013, Fergal 2012), over arbitrage trading strategies and predicting returns (e.g. Shynkevich 2020, Bistarelli et al. 2019, Balcilar 2017), to complex valuing techniques for decentralized networks (e.g. Pagnotta and Buraschi 2018, Brenig et al. 2018).

The earliest literature studying Bitcoin mainly focused on building a high-level understanding of this completely new asset (e.g. Ron and Shamir 2013, Velde 2013, Kroll et al. 2013) and determining possible explanations for a non-zero valuation of the network (e.g. Grinberg, 2012; Barber et al., 2012; Lo and Wang 2014). After Bitcoin went through the first cycles of exponential price appreciation, the focus shifted from understanding the mechanisms behind the technology towards identifying fundamental factors that impact Bitcoin’s price

formation (e.g. Fink and Johann 2014, Garcia et al. 2014, Kondor et al. 2014, Bouoiyour and Selmi 2015). As Bitcoin continued to grow and a mature enough ecosystem of custodians, exchanges, brokerages, and financial institutions emerged, more academic literature shifted towards analyzing Bitcoin's abnormally high returns and how to take advantage of the immense volatility (e.g. Eisl et al. 2015, Pichl and Kaizoji 2017, Koutmos 2018, Panagiotidis et al. 2018). One noteworthy observation is that increased activity on social media platforms and google searches regarding terms related to "Bitcoin" have strong predictive power over the short-term price development and return structure of Bitcoin (e.g. Polasik et al. 2015, Geoirgoula et al. 2015, Aalborg et al 2019). Still, identifying fundamental factors, rather than predicting returns or building arbitrage strategies, has been the main focus in the literature studying Bitcoin. In this context, Kristoufek (2015) studied fundamental value drivers for Bitcoin but argued that due to Bitcoin's extraordinary and recurring periods of extreme price appreciations, Bitcoin's value is driven by different factors at different points in time.

Yermack (2013), Kristoufek (2013), and Cheah and Fry (2015) argue that Bitcoin has no intrinsic value and that its price is driven solely by speculative behavior. However, Jamal Bouoiyour et al. (2016) suggests that, although Bitcoin seems a speculative bubble, long-term fundamentals are likely major contributors to Bitcoin's price variations. Garcia et al. (2014) agrees on the speculative nature of Bitcoin but identifies the cost of mining as a fundamental value driver. Hayes (2015, 2018) supports the findings of a cost of production model for Bitcoin and finds that the hash rate of the network is a significant positive driver of Bitcoin's price. Following up on his findings, Bouoiyour and Selmi (2016), Sovbetov (2018), and Kjaerland et al. (2018) continued studying the positive effect of hash rate in their respective models. Other scholars, however, highlight more traditional factors, such as equity market indices (e.g. Estrada 2017, Kristoufek 2015, Bouoiyour and Selmi 2015), commodity prices (e.g. Bouri 2017, Bouri et al. 2018, Gronwald 2019), or currency exchange rates (e.g. Matkovskyy 2019, Jain et al. 2019, van Wijk 2013) as potential drivers of Bitcoin's price. In contrast, Ciaian et al. (2016)

found that macro-financial developments do not drive Bitcoin's price formation in the long-run, but that the price exhibits a strong relationship with supply and demand for the asset. Polasik et al. (2015) and Bouoiyour and Selmi (2015) find that higher transaction volume leads to higher prices, confirming the relationship between supply & demand and the value of Bitcoin.

As can be seen, different studies identify different value drivers over time, as alluded to by Kristoufek (2015). This is because, as of now, there is no unified interpretation in academics of what Bitcoin actually is. Since inception, Bitcoin has had a multitude of different narratives surrounding its functionality and vision, ranging from a worthless e-cash and a private, anonymous darknet currency to censorship resistant digital gold and a global reserve asset. Bitcoin's value is constrained by our understanding of it. As our understanding grows, its true fundamental value(s) will become clearer as we continue to approach equilibrium valuation. Until then, the price will be subject to immense volatility spurred by valuation models resulting from different interpretations of the technology.

4. Data and Methodology

4.1 Data

The goal of this analysis is to identify fundamental value drivers of Bitcoin. Since Bitcoin is a network, the dependent variable to be explained by the various models is the total market capitalization of Bitcoin. The value of a single Bitcoin can be derived from the network by dividing the total market capitalization by the circulating supply. The chosen factors are based on previous research, on the data availability, and on the technical and theoretical aspect of how the network operates. In particular, we further examine the causalities found by Kjaerland et al. (2018) regarding Bitcoin specific factors. Table 1 gives an overview of the selected variables, a short description, and the source from which the data were retrieved.

Table 1: Overview of the variables

Variable	Description	Type	Source
Bitcoin (BTC)	Total market cap of Bitcoin, measured in US Dollars	Dependent	Quandl
Hash Rate (H)	The estimated number of giga hashes per second the Bitcoin network is performing	Independent	Quandl
Difficulty (D)	Measure of the level of difficulty to find a hash below a given target to mine a block	Independent	Quandl
Transactions (T)	Total number of Bitcoin transactions per day	Independent	Quandl
Active Wallets (W)	Number of unique Bitcoin addresses used per day	Independent	Quandl
Trading Volume (V)	An estimate of the total USD trade volume on exchanges	Independent	Quandl
Stock-to-Flow (S2F)	Total circulating supply of Bitcoin divided by yearly production	Independent	Quandl

The original data are daily rates for all variables. In addition, since Bitcoin had no measurable monetary value for roughly its first two years of existence, the data set ranges from 18/08/2010 to 31/10/2020, a total period of 3,727 days. Note that, unlike traditional assets, Bitcoin is traded every day of the week. The data are gathered on the 01/11/2020.

We apply a logarithmic transformation to all variables, including the dependent variable. This is necessary because Bitcoin's total market cap spans 10 orders of magnitude (from $10 to over $100bn), and the independent variables show a similar growth pattern (see charts in section A1 in the Appendix). Without the log transformation, the OLS method would not be able to capture any meaningful linear relationship between the factors and the market value of Bitcoin. In addition, we modify the daily data into weekly averages to avoid potential issues with autocorrelation. Although previous literature suggests significant relationship between some traditional factors and the price of Bitcoin, such as the S&P500 or the CBOE Volatility Index (VIX) (e.g. Lopez-Cabarcos et al. 2019, Estrada 2017), this paper solely examines Bitcoin specific fundamentals.

4.2 Methodology/Research Design

The above listed independent variables can be categorized in three different types of factors: Energy factors (H & D), Scarcity factors (S2F), and Supply & Demand factors (T, W & V). Section A2 in the Appendix shows the scatter plots between Bitcoin's market cap and the various factors. In all cases, there seems to be a clear relationship between the market value and the selected variables. The nature of this relationship will be discussed in the next section. As Kristoufek (2015) noted, "because of the dynamic nature of Bitcoin and its rapid price fluctuations, it is logical that the drivers behind the price will vary over time." Thus, we propose three different valuation models based on the characteristics of the selected variables that can help explain the growth in Bitcoin's market value over time. Nevertheless, future research is needed to support, add, and/or disprove some of the factors discussed in this research.

4.3 Regression Model

The analyses of the different valuation models are carried out through a single factor log-log OLS regression. Each model is of the form:

$$\Delta ln(BTC_t) = \alpha + \beta * \Delta ln(X_{t-1}) + e_t, \quad (1)$$

where X is representative of the six variables that are being tested. To measure the impact of changes in the variables on today's market value of Bitcoin, we regress Bitcoin's market value against the independent variables with a one period lag, X_{t-1}. This study includes factors that can numerically depict different growth patterns of the network and serve as reference points for a fair value of the asset. These growth patterns are based on increasing energy consumption, increasing scarcity, and increasing demand. Relevant summary statistics

for all regressions can be found in section A4 in the Appendix. Section A3 in the Appendix shows the graphs of all valuation models that were tested.

The next section will discuss each of the three categories labelled in section 4.2 on its own, summarize the findings, identify fundamental value drivers of the network, explain the rationale behind the results, and discuss some limitations for each approach.

5. Bitcoin's Valuation Models

5.1 Bitcoin's Energy Valuation

Hypothesis 1 (H1): Bitcoin's market capitalization can be explained by the amount of energy spent to support the network.

A study by Gail Tveberg (2015) found that the increase in global energy consumption can almost perfectly explain (R-squared = 99.07%) the increase in world GDP from 1965 to 2015. In fact, most things in our lives are closely connected to the consumption or transformation of energy; manufacturing products, transportation of any kind, cooking, purifying water, or simply walking down a street all require energy. Energy is the common denominator of all assets. That is especially true for Bitcoin: The only way to issue new Bitcoin is by putting in more energy. The mechanism that makes it possible for economic agents (miners) to transform electricity (energy) into monetary value is the Proof-of-Work algorithm. In a sense, the PoW algorithm establishes a direct connection between Bitcoin and energy, the ultimate form of value.

As long as the marginal return from burning a kWh of electricity through PoW is greater than the marginal return of selling that same kWh to the grid, miners are incentivized to keep

mining, and new miners are incentivized to keep joining the network to compete for Bitcoins. Exactly when this equilibrium will establish itself and the PoW premium equals 0 is impossible to predict. At maturity, the Bitcoin network will consume exactly as much energy as people draw perceived utility from it.

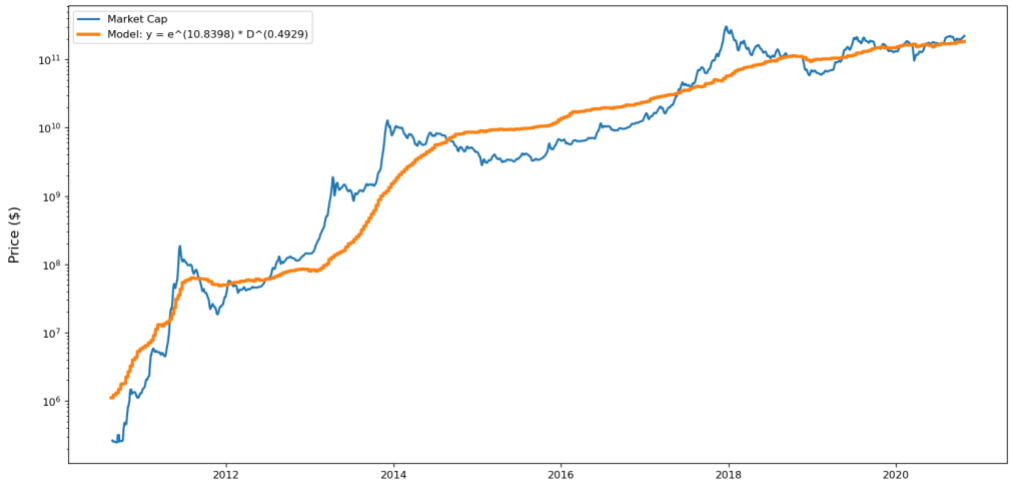
According to the Cost-of-production theory of value, an increase in the cost of producing any object will lead to an increase in the price of the underlying (Smith 1776). In the context of Bitcoin, the cost of production is equal to the amount of energy spent to verify transactions. Since Bitcoin has an exponentially decreasing inflation rate, under constant conditions, more energy is required over time to produce the same amount of Bitcoin as today. Thus, ceteris paribus, mining Bitcoin becomes more energy-expensive over time. Following up on this theory, Adam S. Hayes (2015, 2018) established empirical evidence of a cost of production model for the fair value of Bitcoin. He determined that the marginal cost of production in terms of US dollar plays an important role in explaining Bitcoin's price, suggesting that even though bubbles occur, prices will tend to this bound and not collapse to zero. However, because of the highly competitive nature of the Bitcoin mining industry, Bitcoin miners naturally migrate towards using sustainable energy sources to remain profitable. A report by the Cambridge Center for Alternative Finance (CCAF) estimates that 76% of Bitcoin miners already rely on renewable energy sources, which accounts for approximately 40% of the total energy consumption of the Bitcoin network. Renewable energy sources lower the marginal cost of production, which, according to Hayes' theory, should lower the fair value of Bitcoin. Thus, to prevent a paradoxical outcome of decreasing fair value of a network while its utility is growing, it seems more applicable to measure the cost of producing Bitcoin in terms of raw energy used instead of its US dollar equivalent.

In this context, Charles Edwards (2019) proposed an energy model where the fair value of Bitcoin can be represented as a function of the Joules of energy spent to produce it, instead

of the US dollar equivalent of the energy spent. While his model has good predictive power (R-squared = 80%), it is highly dependent on the estimated energy efficiency of over 150 different mining devices, which leaves room for errors and inconsistencies.

To avoid arbitrary inputs to our model, this analysis uses the mining difficulty as the factor representing energy value. The mining difficulty is non-arbitrary as it is controlled and recorded by the Bitcoin protocol itself and is easily verifiable. Moreover, as mentioned in section 2.3, it is a direct function of the total hashing power of the network, thereby being a good proxy for Bitcoin's energy consumption. Lastly, it is one of the most integral parts of the Bitcoin protocol: it ensures a constant rate of inflation, regardless of how much energy is spent to mine Bitcoins. Graph 4 below shows the result of the estimated model:

Graph 3: Bitcoin Market Cap vs. Difficulty Model



Graph 3 shows Bitcoin's market cap (blue) and the projected fair value of the energy model using the mining difficulty as independent variable. The y-axis is on a logarithmic scale.

The model is statistically significant and has an R-squared of 94%. Thus, we do not reject *H1*. The equation that best fits the model is given by:

$$ln(BTC_t) = 10.8398 + 0.4929 * ln(D_{t-1}) \quad (2)$$

This means that, for a 1% increase in the difficulty of mining Bitcoin, we would expect a 0.4929% increase in the total market value of the Bitcoin network. Bitcoin has had 322 difficulty adjustments as of now and the average percentage increase in the mining difficulty

was 0.84%. This means that, every 2 weeks, we would expect the Bitcoin market cap to increase by 0.41%. The model predicts a price per Bitcoin of $10,000 at the current difficulty level compared to the $13,816 at which Bitcoin actually closed the month of October. Using Bitcoin's total hash power of the network yields slightly better results (R-squared = 94.2%). However, in contrast to mining difficulty, the total hash rate of the network is only an estimate of its true value by comparing the number of blocks that were mined in the last 24 hours with how many blocks were expected given the current difficulty level. Thus, the slightly better predictive power of the hash rate factor is offset by increased uncertainty. Summary statistics of the regression can be found in section A4.1 of the Appendix.

5.1.1 Limitations of the Energy Model

Although mining difficulty seems to give an accurate fair value model for Bitcoins market capitalization, it is doubtful that the level of mining difficulty on its own is a leading factor. An increase in the amount of energy that the network consumes, which leads to a higher mining difficulty, is a result of increased mining competition. Mining competition increases when the profitability of deploying mining devices to the network increases. The profitability of mining increases when the price per Bitcoin increases. The price per Bitcoin increases when demand for holding it increases. Neither previous literature nor this analysis was able to establish proof that increased energy consumption of the Bitcoin network drives demand for holding Bitcoin. Rather, other factors impact the demand for Bitcoin, which drives price upwards and encourages miners to join the network. Thus, we believe that the causality between the observed factors is such that Bitcoins market value drives mining difficulty, and not vice versa. That being said, the difficulty model can serve as an indicator of extreme price deviations from a fair value. If Bitcoins market value is well above/below the suggested fair value, a temporary trend reversal can be expected.

5.2 Bitcoin's Scarcity Valuation

Hypothesis 2 (H2): Bitcoins market capitalization is dependent on its level of scarcity.

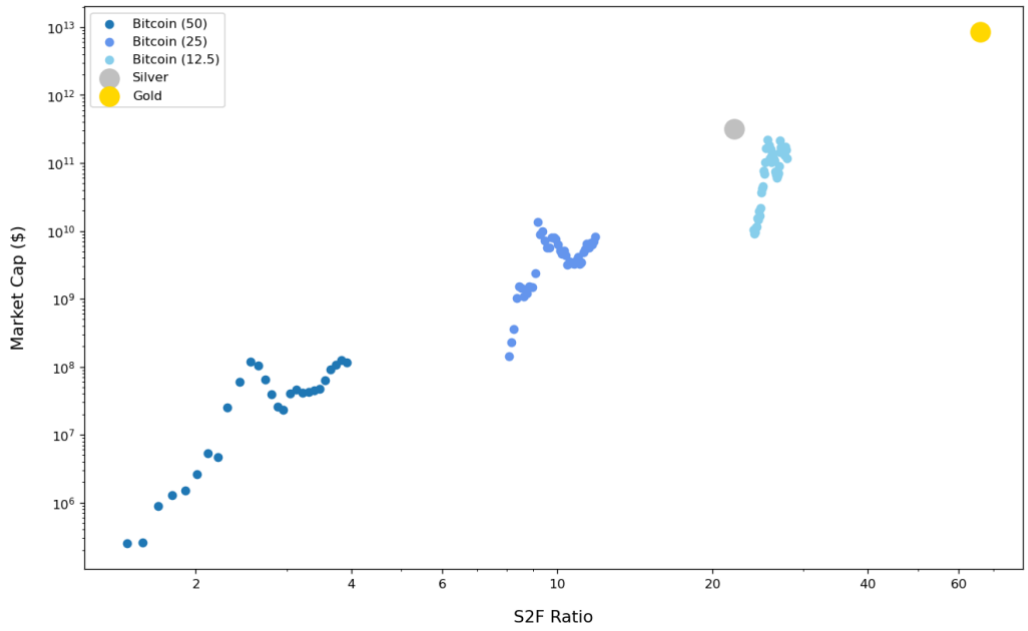
Scarcity is when the means to fulfil ends are limited and costly. Scarcity sits at the foundation of economic theory: The allocation of limited resources to fulfil unlimited wants (Matthaei 1984). Scarcity requires people to make decisions about how to allocate resources efficiently. Most prices of any good or service in an economy are a direct function of the perceived scarcity, also referred to as relative scarcity. Since money is a way of allocating resources, a monetary good that is scarce, also referred to as "hard" money (e.g. gold), encourages the efficient allocation of resources. The scarcer the money, the more efficiently will resources be allocated.

In his book, "The Bitcoin Standard", Saifedean Ammous defines scarcity in terms of the stock-to-flow (S2F) ratio. The S2F ratio is a measure of scarcity based on how much of a commodity is already in circulation (stock) versus how much of that commodity is newly entering circulation every year (flow). It tells us how many years are required, at the current production rate, in order to produce what's in the current stock. Saifedean argues that goods with a high S2F ratio, e.g gold and Bitcoin, are considerably different from consumable commodities such as nickel, copper or zinc because a high S2F ratio translates into a low price elasticity of supply and adds a monetary premium to the price of the commodity. The latter is because the possession of scarce things conveys a feeling of personal distinctiveness or uniqueness (Brock 1968). In fact, the only 2 assets that have stood the test of time as money are gold and silver. These are also the only assets, besides Bitcoin, with a S2F ratio which is significantly greater than 1. Gold has a S2F ratio of 66 and silver a ratio of around 22. The Bitcoin network currently has approximately 18.515 million Bitcoins in circulation and a yearly inflation of 328,500 new Bitcoins. This translates into a S2F value of around 56. However,

Bitcoin's deflationary characteristics will only make it scarcer over time and by 2024, after the 4th halving, Bitcoin will become the scarcest asset on the planet with an estimated S2F of around 120. In a free market society, when there are multiple assets competing to become a form of money, the money which has the highest S2F ratio usually wins. This is because people will always choose the store of value that inflates the slowest (Davidson 1978, Kicks 1989).

Graph 5 shows the relationship between the monthly Stock-to-Flow ratio and the respective market capitalization of Bitcoin, silver, and gold. In this graph, Bitcoin is split into 3 "sub-assets". Each sub-asset represents a different halving cycle of Bitcoin. Before the first halving, Bitcoin had a S2F between 0.5 and 4. After the first halving, Bitcoins S2F increased to around 12, and after the second halving to around 26. Every time a halving occurs, Bitcoin's S2F approximately doubles. Note that the most recent halving cycle that started in May 2020 with 6.25 as the new block reward is not yet depicted on the graph. Moreover, we used the theoretical values for Bitcoins S2F ratio, rather than the actual ones. The actual values can differ from what is to be expected given a block frequency of 10 minutes and a halving every 210,000 blocks. This is due to frequent and highly volatile increases/decreases in the hash rate of Bitcoin.

Graph 4: Stock-to-Flow Ratio vs. Market Cap



Graph 4 shows the S2F ratio of Bitcoin, gold, and silver and their respective market capitalization. Both axes are on a logarithmic scale.

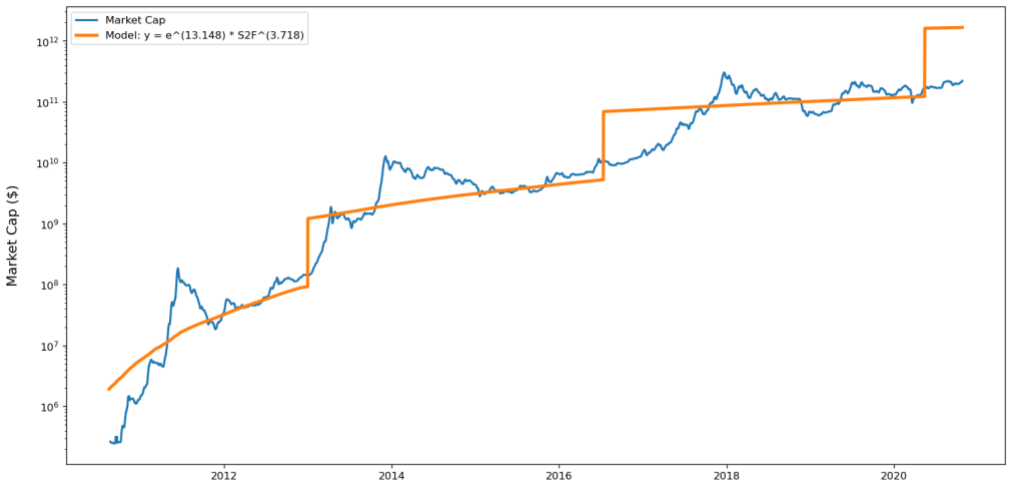
There seems to be a clear linear relationship between the Stock-to-Flow Ratio and the market cap of the respective assets. Notice that both data points for gold and silver are closely aligned with the Bitcoin values for S2F. This adds confidence to the validity of the S2F model. In fact, the line that best fits this model is given by:

$$ln(BTC_t) = 13.148 + 3.718 * ln(S2F_{t-1}) \quad (3)$$

The model is statistically significant and has an explanatory power of 93.2%. Therefore, the likelihood that the relationship between the S2F ratio and market value is caused by chance is close to zero. The level of scarcity seems to be a dominant driving force of Bitcoin's market value. We do not reject *H2*. Relevant summary statistics can be found in section A4.3.

Since Bitcoins S2F ratio increased to around 56 after the halving in May 2020, the model would predict an increase in Bitcoins valuation of around 800%. This would put the Bitcoin network at a $1.66 trillion valuation, which translates to an estimated price per Bitcoin of $89,800. Graph 6 below shows the projected model value using the S2F factor and the actual market value of Bitcoin.

Graph 5: Bitcoin Market Cap vs. S2F Model



Graph 5 shows Bitcoin's market cap (blue) and the projected fair value of the scarcity model using the theoretical Stock-to-Flow Ratio as independent variable.

It can be seen from the graph that Bitcoin's market value adjusts to the new level of scarcity with a lag, then proceeds to overshoot the predicted value by the model before

correcting down and approaching fair value. Depending on how the market value of Bitcoin reacts to the latest increase in the level of scarcity, the next months will either add validity to the model or disprove its significance.

5.2.1 Limitations of the Scarcity Model

There are some inconsistencies in the S2F model. Firstly, if all Bitcoin miners were to suddenly stop mining, no new blocks would be created, and no transactions would be sent through the network, making Bitcoin useless. However, in such an event, the S2F model would predict a market value for Bitcoin of infinity. Secondly, according to this model, every halving, the Bitcoin S2F ratio roughly doubles and the market value increases by a factor of 10. This cannot go on forever because eventually adoption matures and there is only so much wealth to be absorbed by the network. By then, the scarcity of Bitcoin, including its absolute limit of 21 million coins and exponentially decreasing inflation rate, will be priced in before they occur, in accordance with the efficient market hypothesis (Fama 1960). Lastly, this model does not account for potentially permanently lost Bitcoins, including the 1 million Bitcoins held by Satoshi Nakamoto.

5.3 Bitcoin's Supply & Demand Valuation

Hypothesis 3 (H3): As a decentralized monetary system with a fixed supply schedule, Bitcoin's network value is determined by the activity on the demand side.

Since Bitcoin is not issued by a central bank, government, or commercial bank, Bitcoin is not subject to standard economic theories of price formation such as future cash-flow models,

purchasing power parity, or uncovered interest rate parity (Kristoufek 2013). As a result, Bitcoin's value in the marketplace is determined by the interaction between supply and demand (Ciaian et al. 2016, Bouoiyour et al. 2016). The supply of Bitcoin determines its scarcity in the market and is a function of (1) the number of units in circulation and (2) the current inflation rate per block. The inelasticity of Bitcoin's predetermined monetary policy makes its supply side 100% deterministic. A rise in demand cannot result in an increase in the rate at which Bitcoins are being issued. Thus, the deciding factor for determining Bitcoin's exchange value is the demand side. The demand of Bitcoin is mainly determined by transaction volume on exchanges as a speculative asset, on OTC desks as a medium of exchange, and by companies adopting it as a reserve asset on their balance sheets. Another difference to most traditional assets is that Bitcoin is not restricted to trading hours, similar to the Forex market. Bitcoin can be traded 24-hours a day, 7 days a week on hundreds of different exchanges in all major currency pairs in the world. Over the long-run, this unlimited access to liquidity should make Bitcoin's price reflect its true value as closely as possible. In the short-run however, this can cause immense volatility as different countries, institutions and individuals are trying to price a completely new asset all at the same time.

In total, we were able to identify three variables that represent an estimation of the activity on the demand side. The variables are (1) the daily number of transactions on the network, (2) the number of unique Bitcoin addresses actively transferring funds in a given day, and (3) the estimated daily US Dollar trading volume on exchanges. All 3 variables are transformed into 20-day moving averages to smooth out the immense volatility. Summary statistics can be found in the appendix section A4.4 to A4.6. Results show that the market capitalization of Bitcoin is highly correlated with all 3 selected variables. However, the US Dollar trading volume has by far the highest R-squared (97.7%). Getting rid of extreme outliers and using interpolation to replace the values, the US Dollar trading volume has a R-squared of 98.3%. The corresponding OLS-regression equation is:

$$\ln(BTC_t) = 3.8171 + 1.0320 * \ln(V_{t-1}) \quad (4)$$

The beta coefficient of trading volume has a value very close to 1. In a log-log OLS regression, this implies that for a 1% change in either direction in the trading volume, the market cap of Bitcoin will almost move proportionally. In the total 3,727-day period that is analyzed, Bitcoin had 1,850 days (49.6%) where the day-to-day change in trading volume was positive. However, the average daily change was +12.6%. Both facts imply that Bitcoin has been in a strong upward trend during its existence and that Bitcoin's returns are strongly asymmetrically skewed to the upside.

Additionally, the number of active wallets per day and total number of transactions per day are also highly positively correlated to market value with an R-squared of 92.4% and 89.4%, respectively. These findings are in accordance with previous literature (Koutmos 2018, Kondor et al. 2014). We do not reject *H3*. Our results suggest that an increasing number of active wallets and transactions per day increase the market value. This implies that network participants are net buyers. In other words, an increasing number of transactions means an increasing number of buyers, and an increasing number of wallets translates into an increasing number of investors accumulating and holding Bitcoin. As more wallets are created, more Bitcoins will be taken out of the circulating supply.

5.3.1 Limitations of the Supply & Demand Model

Although trading volume has an extraordinarily high explanatory power over the historic market value of Bitcoin, the Bitcoin market is in its infancy and prices are subject to market manipulation (Gandal et al. 2018; Peterson 2020). At a total market value of $300bn, high volume trades have a much stronger impact on the overall price than in traditional, mature markets. As bitcoin ownership matures, market participants should have less of an ability to

move the market at will. Moreover, it has been proven that less regulated exchanges and derivative platforms engage in wash trading, which corrupts the actual US Dollar trading volume by taking "fake" trades into account (e.g. Cong et al. 2020, Aloosh and Li 2019). Lastly, it is noteworthy that the development of a yield curve for Bitcoin as collateral is slowly emerging on other decentralized, blockchain-based application layers like Ethereum. Such developments could introduce additional valuation techniques to the price discovery of Bitcoin.

6. Conclusion & Discussion

The recent increase in corporate and institutional investor adoption of Bitcoin has spurred newfound interest in this completely new asset. This paper aims to provide a better understanding of the fundamental values underlying Bitcoin's price dynamics. To do so, this paper lays out the theoretical and empirical analyses of three different valuation models for a fair market value of Bitcoin. The determinants include the interplay between supply and demand, the total energy consumption of the network, and the ever-increasing level of scarcity of Bitcoin. Our empirical results support the idea that there are indeed long-term Bitcoin specific factors outside of our traditional system that can explain the rising value of Bitcoin as an alternative monetary network. We find that the increasing level of scarcity of Bitcoin seems to be the dominant driving force in Bitcoin's price discovery as a monetary network. The absolute and verifiable scarcity of Bitcoin attracts demand from investors, which sets the exchange rate in the marketplace. Due to its limited supply, the increasing demand for Bitcoin drives the market value upwards, which attracts miners and ultimately leads to an increase in the energy consumption of the network. In this context, it would be interesting for future research to examine whether Bitcoin follows a 4-year cycle as implied by the S2F model, or if Bitcoin follows traditional theory and exhibits diminishing returns with lengthening cycles as

the market matures. Moreover, there are undoubtedly latent variables that this analysis did not encompass. Besides the technical factors that were analyzed in this paper, Bitcoin also has intangible, less quantifiable attributes as money that give rise for a non-zero value, such as censorship resistance, decentralization and incorruptibility. Future research is needed to incorporate such variables in possible valuation models for Bitcoin and assess their significance as fundamental value drivers.

Bitcoin is arguably the biggest financial innovation in recent history; a decentralized, trust-less, self-sovereign monetary network initiating the separation of money and state. Milton Friedman, one of the most renowned economists of the 20th century, foresaw that Bitcoin, or something similar, would inevitably be developed and that it would bring about great advancements in modern civilization. “The one thing that’s missing, but that will soon be developed, is a reliable e-cash, a method whereby on the Internet you can transfer funds from A to B, without A knowing B or B knowing A.” - Friedman 1999.

Bitcoin is disrupting the central banking industry and redefines what money is; Money is a belief system, a psychological construct, a technology that has no definite form. Similar to language, money takes on an important role in human civilization. While language is facilitating cooperation through the distribution of information, money is doing so by regulating trade and allocation of capital. The better our language, the more efficiently will information be distributed and understood. The better our money, the more efficiently will resources be allocated, and value be produced. In its purest form, money is a tool to store the energy (time & effort) that was spent to produce something of value. Spending money is a way to redeem that stored energy at a later point in time. Inherently, people would choose that kind of money which can store the energy earned in the most efficient way over time without power loss. Bitcoin offers a way to transform the energy earned into information of encrypted blocks and store it on a digital ledger, backed by the biggest computing network in the world. Money is information and Bitcoin is the most efficient way to store that information.

7. Bibliography

Aalborg, Halvor Aarhus, Peter Molnar, John Erik de Vries. 2018. “What can explain the price, volatility and trading volume of Bitcoin?” *Finance Research Letters.*

Aloosh, Arash, and Jiasun Li. 2019. “Direct Evidence of Bitcoin Wash Trading” *SSRN.*

Androulaki, Elli, Ghassan O. Karame, Marc Roeschlin, Tobias Scherer, Srdjan Capkun. 2013. “Evaluating User Privacy in Bitcoin.” *International Conference on Financial Cryptography and Data Security.*

Balcilar, Mehmet, Elie Bouri, Rangan Gupta, and David Roubaud. 2017. “Can volume predict Bitcoin returns and volatility? A quantiles-based approach.” *Economic Modelling.*

Barber, Simon, Xavier Boyen, Elaine Shi, Ersin Uzun. 2012. “Bitter to Better - How to Make Bitcoin a Better Currency.” *International Conference on Financial Cryptography and Data Security.*

Becker, Jörg, Dominic Breuker, Tobias Heide, Justus Holler, Hans Peter Rauer, and Rainer

Bistarelli, Stefano, Alessandra Cretarola, Gianna Figà-Talamanca, and Marco Patacca. 2019. “Model-based arbitrage in multi-exchange models for Bitcoin price dynamics.” *Digital Finance.*

Bouoiyour, Jamal, Refk Selmi, Aviral Kumar Tiwari, Olaolu Richard Olayeni. 2016. “What drives Bitcoin price?”. *Economics Bulletin*.

Bouoiyour, Jamal, and Refk Selmi. 2015. “What Does Bitcoin Look Like?” *Annals of Economics and Finance.*

Bouri, Elie, Naji Jalkh,Peter Molnár, and David Roubaud. 2017. “Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven?” *Applied Economics*.

Bouri, Elie, Rangan Gupta, Amine Lahiani, and Muhammad Shahbaz. 2018. “Testing for asymmetric nonlinear short- and long-run relationships between bitcoin, aggregate commodity and gold price.” *Resources Policy.*

Brenig, Christian, Jonas Schwarz, and Nadine Rückenhäuser. 2016. “Value of Decentralized Consensus Systems - Evaluation Framework.” *Research Papers.*

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, Tyler Moore. 2015. “Bitcoin: Economics, Technology, and Governance.” *Journal of Economic Perspectives.*

Böhme. 2013. “Can we afford Integrity by Proof-of-Work? Scenarios Inspired by the Bitcoin Currency.” In *The Economics of information Security and Privacy,* 135-156, Berlin: Springer.

Ciaian, Pavel, Miroslava Rajcaniova, and d’Artis Kancs. 2015. “The economics of BitCoin price formation.” *Applied Economics.*

Cong, Lin William, Xi Li, Ke Tang, Yang Yang. 2020. “Crypto Wash Trading.” *SSRN.*

Davidson, Paul. 1972. *Money and the Real World.*

Eisl, Alexander, Stephan M. Gasser, Karl Weinmayer. 2015. “ Caveat Emptor: Does Bitcoin Improve Portfolio Diversification?” *SSRN.*

Estrada, Julio Cesar Soldevilla. 2017. “Analyzing Bitcoin Price Volatility.” *University of California.*

Fama, Eugene F. 1960. “Efficient Markets Hypothesis.” *Journal of Finance.*

Fink, Christopher, and Thomas Johann. 2014. “Bitcoin Markets.” *SSRN.*

Gandal, Neil, JT Hamrick, Tyler Moore, and Tali Oberman. 2018. “Price manipulation in the Bitcoin ecosystem.” *Journal of Monetary Economics.*

Garcia, Favid, Claudio J. Tessone, Pavlin Mavrodiev, and Nicolas Perony. 2014. “The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy.” *Journal of the Royal Society Interface.*

Geoffrey Lightfoot. 2015. “Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry”. *International Journal of Electronic Commerce.*

Georgoula, Ifgeneia, Demitrios Pournarakis, Christos Bilankos, Dionisios Sotiropoulos, George M. Giaglis. 2015. “using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices.” *SSRN.*

Grinberg, Reuben. 2012. “Bitcoin: An innovative Alternative Digital Currency.” *Hastings Science and Technology Law Journal.*

Gronwald, Marc. 2019. “Is Bitcoin a Commodity? On price jumps, demand shocks, and certainty of supply.” *Journal of International Money and Finance.*

Hayes, Adam S. 2015. “Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin.” *Telematics and Informatics.*

Hayes, Adam S. 2015. “Bitcoin price and its marginal cost of production: support for a fundamental value.” *Applied Economic Letters.*

Hicks, John. 1989. *A Market Theory of Money.*

Jain, Pankaj K., Thomas H. McInish, and Jonathan L. Miller. 2019. “Insights from bitcoin trading.” *Financial Management.*

Kjaerland, Frode, Aras Khazal, Erlend A. Krogstad, Frans B. G. Nordstrom, and Are Oust. 2018. “An Analysis of Bitcoin’s Price Dynamics.” *Journal of Risk and Financial Management.*

Kondor, Daniel, Márton Pósfai, István Csabai, and Gábor Vattay. 2014. “Do the Rich Get Richer? An Empirical Analysis of the Bitcoin Transaction Network.” *PLoS ONE.*

Koutmos, Dimitrios. 2018. “Bitcoin returns and transaction activity.” *Economic Letters.*

Kristoufek, Ladislav. 2015. “What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis”. *PLoS ONE.*

Kristoufek, Ladislav. 2013. “BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era.” *Scientific Reports.*

Kroll, Joshua A, Ian C. Davey, E. Felten. 2013. “The economics of Bitcoin Mining, or Bitcoin in the Presence of Adversaries.” *Journal of Public and International Affairs.*

López-Cabarcos, M. Ángeles, Ada M.Pérez-Pico, Juan Piñeiro-Chousa, and Aleksandar Šević. 2019. “Bitcoin volatility, stock market and investor sentiment. Are they connected?” *Finance Research Letters.*

Matkovskyy, Roman, and Akanksha Jalan. 2019. “From financial markets to Bitcoin markets: A fresh look at the contagion effect.” *Finance Research Letters.*

Matthaei, Julie. 1984. “Rethinking Scarcity: Neoclassicism, NeoMalthusianism, and NeoManrsm.” *Sage.*

Nakamoto, Satoshi. 2008. “Bitcoin: a peer-to-peer electronic cash system.” *Available online:* https://bitcoin.org/bitcoin.pdf (accessed on 5 October 2020).

Pagnotta, Emiliano, Andrea Buraschi. 2018. “An Equilibrium Valuation of Bitcoin and Decentralized Network Assets.” *SSRN.*

Panagiotidis, Theodore, Thanasis Stengos, and Orestis Vravosinos. 2018. “On the determinants of bitcoin returns: A LASSO approach. *Finance Research Letters.*

Pichl, Lukas, and Taisei Kaizoji. 2017. “Volatility Analysis of Bitcoin Price Time Series”. *Quantitative Finance and Economics.*

Polasik, Michal, Anna Iwona Piotrowska, Tomasz Piotr Wisniewski, Radoslaw Kotkowski, and Peterson, Timothy. 2020. “To the Moon: A history of Bitcoin Price Manipulation.” *SSRN.*

Reid, Fergal, and Martin Harrigan. 2012. “An Analysis of Anonymity in the Bitcoin System.” In *Security and Privacy in Social Networks*, 197-223. New York: Springer.

Ron, Dorit, and Adi Shamir. 2013. “Quantitative Analysis of the Full Bitcoin Transaction Graph.” *International Conference on Financial Cryptography and Data Security.*

Shynkevich, Andrei. 2020. “Bitcoin arbitrage.” *Finance Research Letters.*

Smith, Adam. 1776. *The Wealth of Nations.* London: W. Strahan and T. Cadell.

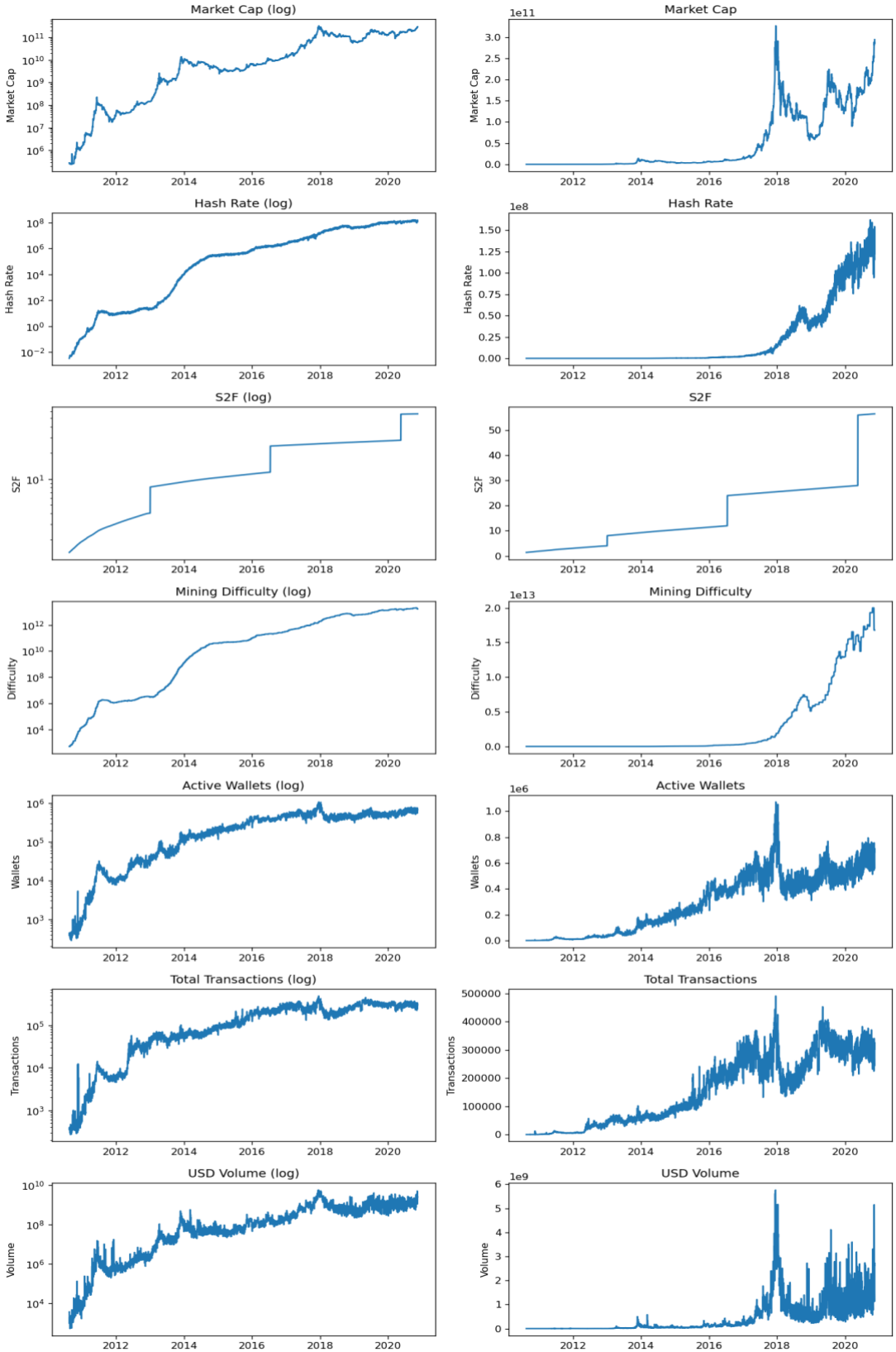
van Wijk, Dennis. 2013. “What can be expected from the Bitcoin?” *Erasmus Universiteit Rotterdam.*

Velde, Francois R. 2013. “Bitcoin: A primer.” *Chicago Fed Letter.*

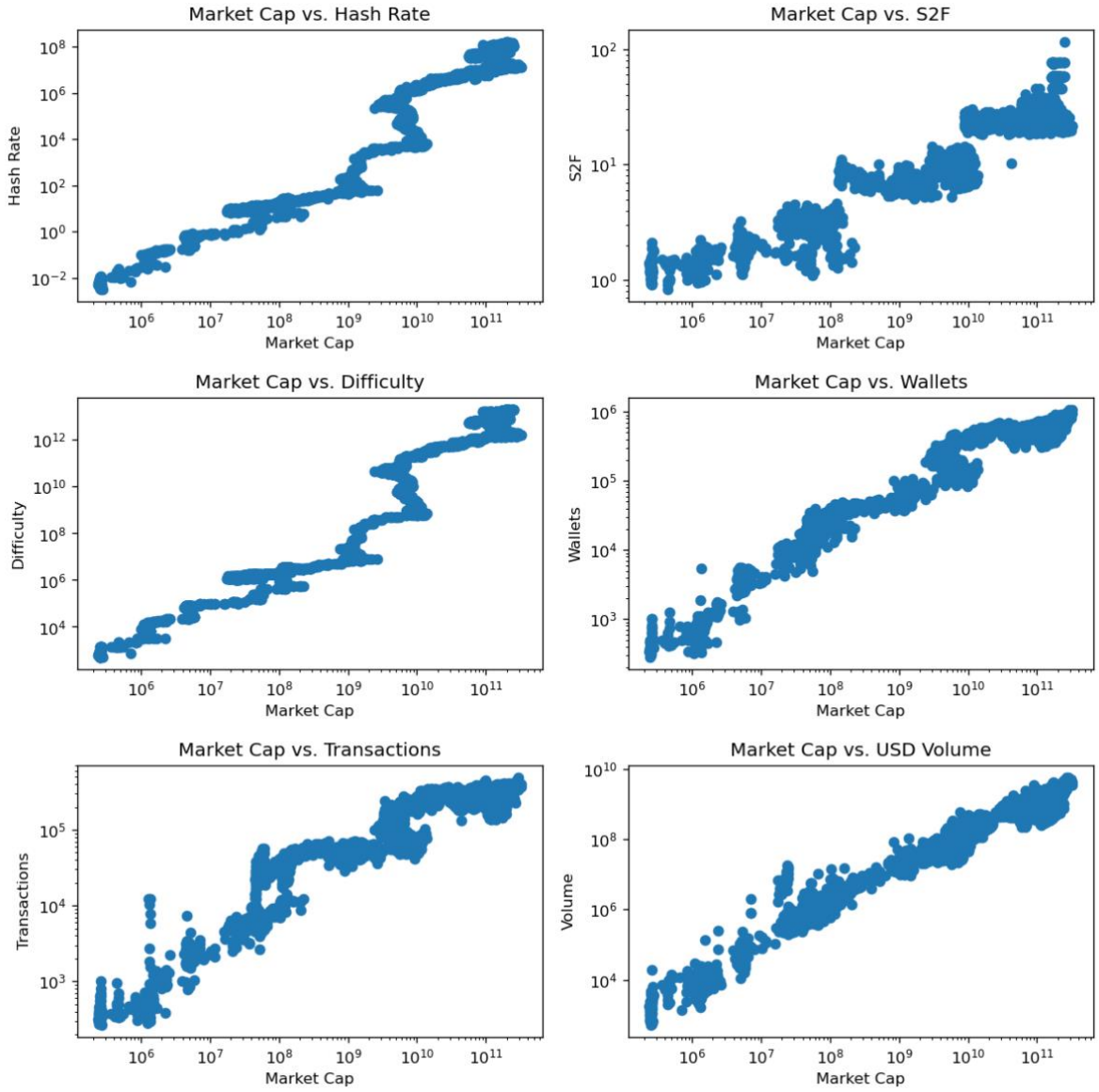
Yermack, David. 2013. “Is Bitcoin a Real Currency? An economic appraisal”. *National Bureau of Economic Research.*

8. Appendix

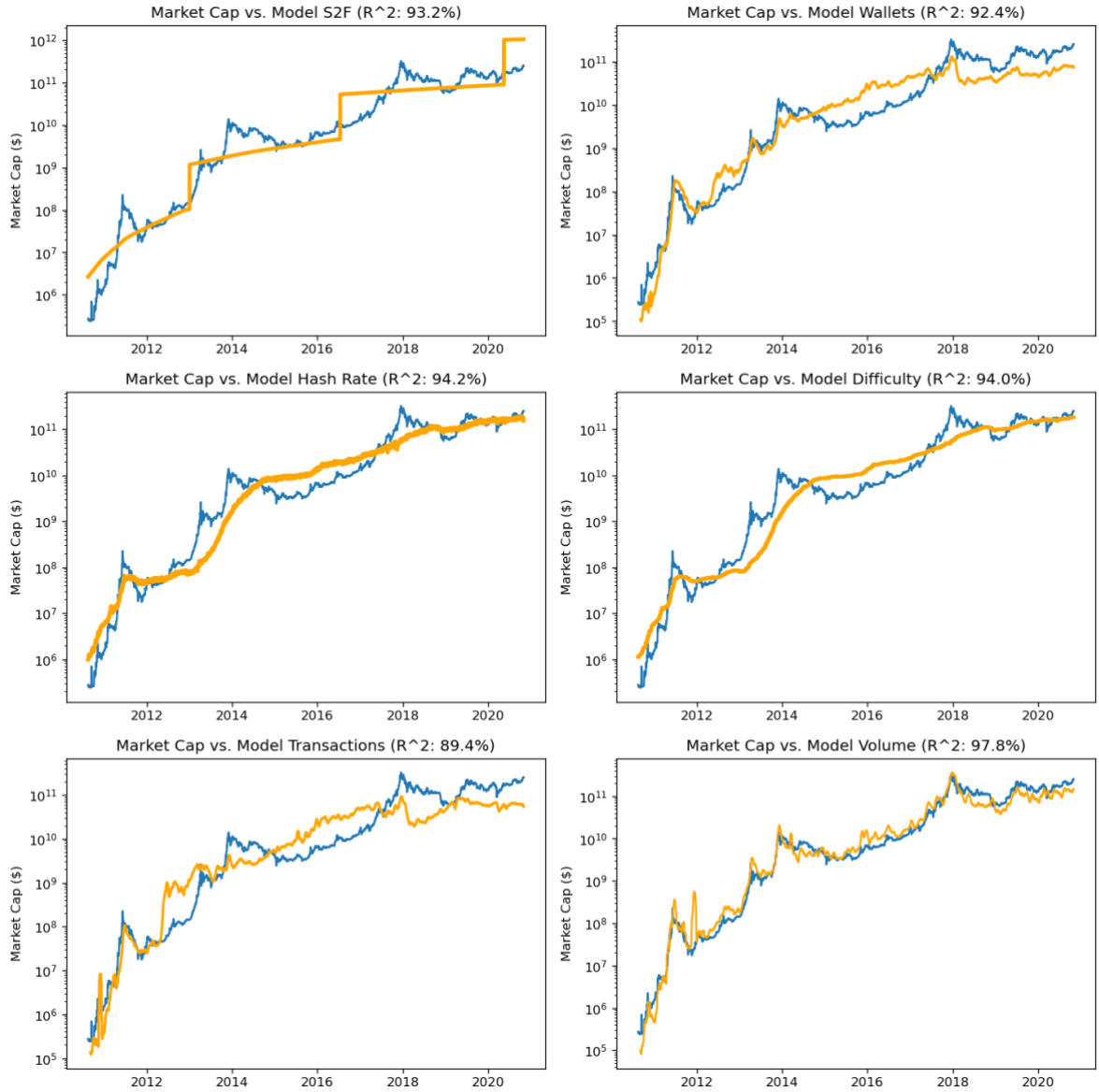
Appendix A1: Graphs of all selected variables (left side log transformation)



Appendix A2: Scatter plots of Bitcoins market value and each independent variable



Appendix A3: Projected fair value of Bitcoin by each factor model



Appendix A4: Short summary statistics of the regression for each variable

OLS-regression					
Variable	**R^2**	**p-value**	**Coefficient**	**Standard Error**	**t-statistic**
Volume	0.987	0.000	1.0356	0.003	403.055
Hash Rate	0.942	0.000	0.496	0.002	245.079
Difficulty	0.94	0.000	0.4925	0.002	240.876
S2F	0.932	0.000	3.718	0.017	210.312
Wallets	0.924	0.000	1.8074	0.009	212.243
Transactions	0.894	0.000	1.9381	0.011	176.95

Appendix A4.1: Summary statistics for the mining difficulty factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.940
Model:	OLS	**Adj. R-squared:**	0.940
Method:	Least Squares	**F-statistic:**	5.68E+04
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3706	**Log-Likelihood:**	-4582.6
Df Model:	1	**AIC:**	9169
Covariance Type:	nonrobust	**BIC:**	9182

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	10.9059	0.049	222.184	0	10.81	11.002
Log Difficulty	0.4904	0.002	238.41	0	0.486	0.494

Omnibus:	180.075	**Durbin-Watson:**	0.001
Prob(Omnibus):	0	**Jarque-Bera (JB):**	206.164
Skew:	0.575	**Prob(JB):**	1.71E-45
Kurtosis:	3.118	**Cond. No.**	85.8

Appendix A4.2: Summary statistics for the hash rate factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.942
Model:	OLS	**Adj. R-squared:**	0.942
Method:	Least Squares	**F-statistic:**	5.89E+04
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3.71E+03	**Log-Likelihood:**	-4521.2
Df Model:	1	**AIC:**	9046
Covariance Type:	nonrobust	**BIC:**	9059

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	16.6443	0.026	631.417	0	16.593	16.696
Log Hash Rate	0.4939	0.002	242.646	0	0.49	0.498

Omnibus:	161.759	**Durbin-Watson:**	0.006
Prob(Omnibus):	0	**Jarque-Bera (JB):**	182.453
Skew:	0.538	**Prob(JB):**	2.40E-40
Kurtosis:	3.147	**Cond. No.**	25.5

Appendix A4.3: Summary statistics for the S2F factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.932
Model:	OLS	**Adj. R-squared:**	0.932
Method:	Least Squares	**F-statistic:**	4.39E+04
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3706	**Log-Likelihood:**	-5029.2
Df Model:	1	**AIC:**	1.01E+04
Covariance Type:	nonrobust	**BIC:**	1.01E+04

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	13.6291	0.043	313.441	0	13.544	13.714
Log S2F theoretical	3.4792	0.017	209.471	0	3.447	3.512

Omnibus:	225.302	**Durbin-Watson:**	0.006
Prob(Omnibus):	0	**Jarque-Bera (JB):**	267.261
Skew:	-0.656	**Prob(JB):**	9.23E-59
Kurtosis:	2.898	**Cond. No.**	8.33

Appendix A4.4: Summary statistics for the USD trading volume factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.987
Model:	OLS	**Adj. R-squared:**	0.987
Method:	Least Squares	**F-statistic:**	1.63E+05
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3706	**Log-Likelihood:**	-2710.9
Df Model:	1	**AIC:**	5426
Covariance Type:	nonrobust	**BIC:**	5438

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	3.7361	0.046	80.498	0	3.645	3.827
Log Volume 20D	1.0356	0.003	403.055	0	1.031	1.041

Omnibus:	908.249	**Durbin-Watson:**	0.01
Prob(Omnibus):	0	**Jarque-Bera (JB):**	5562.301
Skew:	-1.021	**Prob(JB):**	0
Kurtosis:	8.642	**Cond. No.**	102

Appendix A4.5: Summary statistics for the active wallets factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.924
Model:	OLS	**Adj. R-squared:**	0.924
Method:	Least Squares	**F-statistic:**	4.51E+04
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3706	**Log-Likelihood:**	-4984.2
Df Model:	1	**AIC:**	9.97E+03
Covariance Type:	nonrobust	**BIC:**	9.99E+03

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.8517	0.101	8.394	0	0.653	1.051
Log Wallets 20D	1.8074	0.009	212.243	0	1.791	1.824

Omnibus:	98089.438	**Durbin-Watson:**	0.001
Prob(Omnibus):	0	**Jarque-Bera (JB):**	293.769
Skew:	-0.137	**Prob(JB):**	1.62E-64
Kurtosis:	1.648	**Cond. No.**	79.9

Appendix A4.5: Summary statistics for the USD trading volume factor regression

Dep. Variable:	Log Market Cap 7D	**R-squared:**	0.894
Model:	OLS	**Adj. R-squared:**	0.894
Method:	Least Squares	**F-statistic:**	3.13E+04
No. Observations:	3708	**Prob (F-statistic):**	0
Df Residuals:	3706	**Log-Likelihood:**	-5597.8
Df Model:	1	**AIC:**	1.12E+04
Covariance Type:	nonrobust	**BIC:**	1.12E+04

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.3367	0.125	2.704	0.007	0.093	0.581
Log Transactions 20D	1.9381	0.011	176.95	0	1.917	1.96

Omnibus:	740.785	**Durbin-Watson:**	0.002
Prob(Omnibus):	0	**Jarque-Bera (JB):**	213.931
Skew:	-0.341	**Prob(JB):**	3.51E-47
Kurtosis:	2.042	**Cond. No.**	79.3