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Exploring the relationship between Bitcoin price and network's hashrate within endogenous system

Jan Kubal [a], Ladislav Kristoufek [a,b,*]

[a] Institute of Economic Studies, Faculty of Social Sciences, Charles University Prague, Opletalova 26, 110 00 Prague, Czech Republic

[b] The Czech Academy of Sciences, Institute of Information Theory and Automation, Pod Vodarenskou vezi 4, 182 00 Prague, Czech Republic

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ABSTRACT

Bitcoin pricing mechanism is a complex system of interactions between factors that are not standard for traditional financial assets. Its understanding is essential for assessing specific topics, most prominently the interaction between Bitcoin price and network's hashrate as it directly translates into its power demand and consumption and thus also environmental implications. We examine an intertwined system of equations, controlling for various statistical caveats connected to such system, providing a coherent picture of the system dynamics and thus delivering the most rigorous and complex approach in explaining the pricing dynamics of the Bitcoin system up to date. We shown that the whole system is very well structured and delivers economically and logically sound results, pointing at the network security narrative in the Bitcoin price–hashrate nexus.

1. Introduction

Bitcoin is a decentralized payment network that emerged in 2009 (Nakamoto, 2008). It allows users to send and receive transactions with a high level of security. The unit of currency used in the network, also called bitcoin, has substantially risen in price since the inception of the network, as the popularity of Bitcoin experienced several booms. However, the price of Bitcoin remains extremely volatile compared to traditional assets (Aalborg et al., 2019).

The process of creation of new Bitcoin units, called mining, is conducted by computer hardware that has to solve a cryptographic problem in order to mine Bitcoin, and in return, the person running the hardware has a chance to receive a reward of a predetermined number of bitcoins. The more computing power a machine dedicates to mining, the higher the chance of receiving the reward there is. Therefore, the growth of Bitcoin price led to the development of a very competitive mining industry. One attempt of the mining hardware to resolve the mentioned cryptographic problem is called a hash. Based on this, the worldwide combined computing power dedicated to Bitcoin mining is called hashrate (i.e., how many hashes are being performed per unit of time in total). Since the price of a single bitcoin plays a major role in the profitability of mining, it would be reasonable to assume that a relation between the price and hashrate exists.

Here, we explore this relationship within a complex system of connections among the network as well as variables outside of it. Several authors have analyzed the factors affecting Bitcoin price. Among others, the hashrate was assumed to be an important technological factor that might have an effect on the price, however only a weak relationship was found (Kristoufek, 2015, 2020). On the other hand, the opposite relationship was identified, the price affecting the hashrate (Fantazzini & Kolodin, 2020; Kristoufek, 2020). Both directions of a causal effect are thus plausible, hashrate weakly affecting the price and the price strongly affecting the hashrate. In fact, the latter can be expected as the revenue of miners depends strongly on the price of Bitcoin. However, the studies provide mostly very simple analyses into the relationship without additional control variables as well as various methodological aspects, mostly the likely endogeneity, unaccounted for. We propose a system of equations covering different aspects of the Bitcoin market and possible interactions based on its economic foundations to deliver both more methodologically sound results as well as a more detailed description of interactions within the system.

The importance of understanding the dynamics of the system is at hand. It could help to improve the efficiency of investors in cryptocurrency markets, as well as assist governments and decision-makers with fair regulation. It should be also kept in mind that the total hashrate is one of the two driving factors of the total amount of electricity that is consumed by the Bitcoin network, the other factor being the mining efficiency. Therefore, if a strong influence of price, or some other factor, on the hashrate should be revealed, implications to the electricity consumption could be drawn from the price changes in the future.

* Corresponding author at: Institute of Economic Studies, Faculty of Social Sciences, Charles University Prague, Opletalova 26, 110 00 Prague, Czech Republic.
E-mail address: LK@fsv.cuni.cz (L. Kristoufek).

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The paper is structured as follows. Section 2 provides a detailed literature review of the Bitcoin mining process and of factors driving the price of Bitcoin and the network hashrate. Section 3 proposes the model setting and describes the process of collecting data. Section 4 presents the results of the analysis with a detailed validity discussion. Section 5 concludes and lays out avenues for future research.

2. Literature review

Bitcoin, created by Nakamoto (2008), is a decentralized network that allows users to conduct transactions safely over the internet without the need of a third party as a provider of trust. The process that allows the Bitcoin network to run is called mining, as it issues new bitcoins and releases them into circulation as a reward to miners for securing the network's operation. We provide a brief summary of the mining of Bitcoin, its history, mechanisms, and problems it faces, and further continue with a review of factors driving the price of Bitcoin and the total network hashrate.

2.1. Summary of the mining process and its evolution

Bitcoin is a type of digital asset. It can be held or traded over the internet, purely in a digital form. Transactions can be sent and received thanks to the decentralized network of nodes. The decentralization originates from the fact that there is no central authority allowing or denying rights, any user with proper hardware can become a node in a network or participate in Bitcoin mining. Transactions are being saved in the form of blocks into the blockchain, an online ledger, that is shared by all nodes. The mining is done by miners,[1] who run computers solving cryptographic problems as fast as possible, with the hope of being the first to find a solution to a problem that is specified by the Bitcoin algorithm. Only after this solution is found, a new block containing incoming transactions can be written into the blockchain and a miner who found it (and thus closed the block) is rewarded with a certain amount of bitcoins. The system is set so that, on average, a new block is added every ten minutes. This is ensured by a variable called Difficulty, which affects the likelihood of a miner to find a solution to the aforementioned problem. The Difficulty changes dynamically every 14 days according to the total computational power that miners expend, in order to keep the average of ten minutes per block.

The result of mining, similarly as in the mining of gold, is obtaining new units of the mined asset, therefore new bitcoins. These are created whenever a new block is found and the miner who closed it receives the bitcoins, together with transaction fees for the given block. From each sent transaction, a small fee is taken and paid to a miner who found the correct answer to the system algorithm task and thus closed the block. The amount of newly created bitcoins was initially set to 50 bitcoins per block, but the reward halves approximately every four years (every 210,000 blocks confirmed). Thus, after the first halving in 2012, miners received 25 bitcoins per a mined block instead of 50 and after 2016, the reward further halved to 12.5 bitcoins. Third halving in May 2020 further decreased the reward to 6.25 bitcoins per a block. This also means that there is a limited amount of bitcoins to be mined (21 million in total), as the reward will converge to 0 (Antonopoulos, 2014).

The Bitcoin network came into existence on January 3, 2009, as the first block was mined by Satoshi Nakamoto. At first, standard CPUs from common (personal) computers were used for Bitcoin mining, but they were soon replaced by GPUs and in 2011 by FPGAs (Field Programmable Gate Arrays), as described by Narayanan et al. (2016). Each new generation of hardware progressed the efficiency of mining, however the largest step forward was the introduction of the first ASICs (Application-Specific Integrated Circuits) developed specifically for the needs of the mining of Bitcoin, at the end of 2013. It meant a large boost in the computing power, as well as in the efficiency of the electricity usage of mining units (Courtois et al., 2014). The computing power of a single hardware unit is expressed by how many hashes[2] per second it could perform when running on 100% of its capacity and its efficiency can be measured in J/Gh (joules per gigahash, how many joules of energy a machine consumes to perform 1 billion of hashes). The total computing power of the entire Bitcoin network is represented by hashrate, i.e., how many hashes per second are performed by all the mining machines combined. Hashrate is thus dependent on how much funds miners dedicate to Bitcoin mining. It is one of the two crucial pieces in determining the electricity consumption of the Bitcoin network. The other piece, however, the total efficiency of mining hardware, is not known and thus it can be only estimated.

As the popularity of Bitcoin grew, also its price and profitability of mining was rising, which attracted a large number of investors, seeking profits from selling mined bitcoins. This and the evolution of mining hardware led to professionalization of the mining industry. Miners transformed from the Bitcoin enthusiasts mining on their home computers to large mining farms, running numerous mining units in an industrial-like manner and seeking locations with the cheapest electricity (Blandin et al., 2020). This increase in the scale of mining inevitably led to an increase in the electricity consumed by the mining hardware, which became one of the main points in the criticism of Bitcoin. The problem of Bitcoin mining electricity consumption is complex from the normative perspective (is it justifiable to use so much energy to run the Bitcoin network?), as well as from the descriptive perspective (how much electricity is consumed by Bitcoin mining?). Despite that, there were only several attempts to answer these questions in the academic literature (De Vries, 2020; McCook, 2018; Rauchs et al., 2020; Stoll et al., 2019).

2.2. Drivers of the price of bitcoin

Identification of proper factors driving the price of Bitcoin and hashrate is crucial for the model/system construction. We thus provide a summary of studies identifying such variables and specifying their effects.

Kristoufek (2015) was among the first to study hashrate in relation to Bitcoin price. Application of the wavelet coherence analysis allowed to examine the correlation between price and various possible sources of price movements. The network hashrate was revealed to be positively correlated with price in the long-term. Later, Kristoufek (2020) examined the relationship of the Bitcoin price and the cost of mining (the cost of producing one bitcoin), similarly to Hayes (2017). The cost of mining was constructed from the total hashrate, an index of electricity prices and the best-available miner efficiency. This approach accounts only for operational costs of mining and neglects the capital expenditures via the fixed mark-up in the log–log specification of the estimated model. Results showed that the influence of the mining cost on the price is weak and present only in the short-run. On the other hand, the effect of the price on the mining cost was significant even in the long-run, with a shock in price being followed by an adjustment in mining cost, ranging from three months to one year. Bouoiyour and Selmi (2017) link Bitcoin price to various factors ranging from indicators of geopolitical situation up to technical parameters. Their importance seemed to differ according to overall market sentiment (bullish, neutral, or bearish), and among others, hashrate was found to have a positive causal relationship with price. Bhambhwani et al. (2019) examined the intrinsic value of several cryptoassets, including Bitcoin, stemming

[1] Somewhat confusingly, people owning or operating mining hardware are called miners, but the specialized hardware units used for mining are called miners as well.

[2] One hash can be seen as one attempt to submit an answer to a question posed by the Bitcoin network, and thus to close a block.

from their network hashrate and network size (adoption). They found evidence for a positive relationship of these two factors with Bitcoin's price and argued they should be included while assessing risk factors of cryptoassets investments. Mueller (2020) explored the price–hashrate relationship from the perspective of miners and the hardware they use. Similarly to Kristoufek (2020), they found a long run equilibrium relationship between the two variables, suggesting that hashrate should be used as (potentially non-linear) factor in cryptoassets pricing models.

Contrary to the previous, some authors also suggest that the price–hashrate relationship could be reverse. Kjærland et al. (2018) studied various factors with the goal of determining which of them are the drivers of Bitcoin price. In their analysis, the hashrate was found insignificant in explaining price changes, which was a contradictory finding compared to previous studies. Authors argue that most likely the price explains the hashrate, not the other way around. Fantazzini and Kolodin (2020) focused on the discrepancy between the results of Hayes (2017) and Kjærland et al. (2018) who both analyzed the relationship of the hashrate and price, but came to different results. While Kjærland et al. found hashrate to be insignificant in explaining the price movements and suggested the reverse effect, Hayes constructed the cost-of-production model (CPM) and argued that the "fair value" (production cost) is an important factor of Bitcoin's market price. Later, Hayes (2019) showed that the cost-of-production value of Bitcoin Granger-causes the price. To find what the relationship between price and hashrate is, Fantazzini and Kolodin (2020) used the hashrate directly, and alternatively the break-even cost of mining (computed by the CPM) as a proxy variable for the hashrate, in bivariate and multivariate models. The analysis showed that it is likely better to consider the hashrate directly rather than its proxy in the form of the cost of production while modeling its relationship with price. Also, similarly to Kjærland et al. (2018), Fantazzini and Kolodin (2020) found that the hashrate seemed to be driven by price, not the other way around.

Apart from hashrate, also other factors related to the Bitcoin network were studied in the literature. Kristoufek (2015) showed positive correlation of price and Bitcoin money supply and negative correlation with price level. Further, Kristoufek (2019) expanded upon their research of fundamentals of Bitcoin network by constructing a price level index for the Bitcoin market (computed as the total transaction volume divided by the number of transactions). A cointegration relationship was found between the implied and observed Bitcoin price time series, suggesting a long-term equilibrium relationship between Bitcoin price and its price dynamics implied from baseline economic models. Ciaian et al. (2016) examined several groups of Bitcoin price drivers, showing that the number of transactions and the number of addresses in the network had a significant positive impact on the price, while the total number of bitcoins in circulation was significantly negative. Additionally, they argued that their predecessors neglected an important factor, being that the drivers were analyzed separately and the interaction between them was not accounted for. This might have resulted in overstressing the importance of some factors. Kjærland et al. (2018) showed the transaction volume to have a negative impact on price (although only in the second half of the dataset), in line with traditional supply and demand theory. This was further supported by Fantazzini and Kolodin (2020), who also suggested inclusion of total transaction fees paid in the Bitcoin network into the model. Wheatley et al. (2019), similarly to Bhambhwani et al. (2019), stressed the importance of size of the network while examining the price. In particular, the number of active addresses was an important factor of the total Bitcoin market capitalization.

It was repeatedly shown that one of the key factors while modeling the Bitcoin price is the public attention that Bitcoin receives. Kristoufek (2013) introduced such type of research in Bitcoin-related literature by using the Google Trends and Wikipedia queries data. Their results revealed a strong, bidirectional relationship, i.e., not only the increase in price could be explained by the increase in public attention, but also more public attention was caused by the rising price of Bitcoin. Moreover, when the sentiment was negative, the bidirectional relationship existed as well, but with a negative sign, leading to both positive and negative feedback loops. Similarly, Garcia et al. (2014) discovered two feedback cycles that might drive the price of Bitcoin, being fueled by the search volume and word of mouth (social media activity) or amount of users. Kristoufek (2015) found a long-run positive correlation between price and Bitcoin-related search volumes from Google and Wikipedia. The number of new posts on the online forum Bitcointalk.org[3] was shown to have a significant positive impact on the price as well (Ciaian et al., 2016). Additionally, the public attention in form of the search statistics for the term "Bitcoin" from Google Trends seemed to have a significant positive relationship with Bitcoin price in the research of Fantazzini and Kolodin (2020) and Kjærland et al. (2018).

Also other economic factors were examined in terms of Bitcoin price, their explanatory power however seemed to vary. Ciaian et al. (2016) studied the effect of factors representing global macroeconomic situation (oil prices and the Dow Jones Industrial Average index) on Bitcoin price. Neither of those were significant in the long-run, implying that global financial development has little to no impact on the price of Bitcoin. In a similar vein, Kristoufek (2015) found no correlation of price with the gold prices, neither with the Financial Stress Index. Contrary, Kjærland et al. (2018) showed the S&P500 index to be significant in explaining price changes, and the VIX index was significant on a sub-sample of data (years 2017 and 2018); the gold and oil prices were insignificant. Fantazzini and Kolodin (2020) provided similar results.

3. Methodology and data

3.1. Model proposal

As laid out above, there is strong evidence of a relationship between the Bitcoin price and the network hashrate. According to Ciaian et al. (2016), the inclusion of multiple factors from various areas and their simultaneous analysis improved their results greatly. Results of Fantazzini and Kolodin (2020), Kjærland et al. (2018), Kristoufek (2015, 2020) and Mueller (2020) indicate both directions of causal effect between the price and hashrate being plausible. Thus a system of equations could be constructed, with the Bitcoin price and the hashrate both being dependent variables and also included (among others) as explanatory variables transversely, in order to account for potential endogeneity.

Aiming to explain changes in Bitcoin price and in the network hashrate, the selection of the explanatory variables is affected firstly by the logic and rules that drive the Bitcoin network, and secondly by the data availability, as some of the variables are not accessible, because it would be hard or even impossible to measure them. In some cases, an explanatory variable can be assumed exogenous, as its values are determined solely by the forces that come outside of the Bitcoin system or are predetermined within the system. However, there are variables that could be able to explain some of the variance in the price or the hashrate, and simultaneously might be at least partially affected by the forces already contained in the system, thus being endogenous. Apart from the Bitcoin price and hashrate itself, we also assume the network congestion (which we measure by the total transaction fees paid in BTC), and interest and attention directed towards Bitcoin (which we measure by the Google searches for queries Bitcoin or BTC) to be endogenous. Among these four, there can be several endogenous connections as e.g. network congestion can be due to increased attention and thus use of the network can rise, leading to increases the price. This in turn motivates miners to attribute more

[3] https://bitcointalk.org/.

of the computational power to the system as mining becomes more profitable both due to increasing Bitcoin price but also due to high fees which resulted from higher congestion. The system is thus evidently complex and highly intertwined. Our baseline system of equation is the following one:

$$\begin{aligned}\log\left(price_t\right) = \alpha_1 &+ \beta_1 \log\left(hashrate_t\right) + \beta_2 \log\left(addresses_t\right)\\ &+ \beta_3 \log\left(price\_level_t\right) + \beta_4 \log\left(M2_t\right)\\ &+ \beta_5 \log\left(search\_volume_t\right) + \beta_6 \log\left(transaction\_fees_t\right)\\ &+ \beta_7 \log\left(exchange\_ratio_t\right) + \beta_8 \log\left(S\&P500_t\right) + \epsilon_{1t}\end{aligned} \tag{1}$$

$$\begin{aligned}\log\left(hashrate_t\right) = \alpha_2 &+ \beta_9 \log\left(price_{t-1}\right) + \beta_{10} \log\left(addresses_t\right)\\ &+ \beta_{11} \log\left(efficiency_t\right) + \beta_{12} \log\left(transaction\_fees_t\right)\\ &+ \beta_{13} reward\_phase_t + \epsilon_{2t}\end{aligned} \tag{2}$$

$$\begin{aligned}\log\left(transaction\_fees_t\right) = \alpha_3 &+ \beta_{14} \log\left(price_t\right) + \beta_{15} \log\left(addresses_t\right)\\ &+ \beta_{16} \log\left(search\_volume_t\right)\\ &+ \beta_{17} \log\left(exchange\_ratio_t\right) + \epsilon_{3t}\end{aligned} \tag{3}$$

$$\log\left(search\_volume_t\right) = \alpha_4 + \beta_{18} \log\left(price_t\right) + \beta_{19} \log\left(sigma_t\right) + \epsilon_{4t} \tag{4}$$

where $t = 1 \dots T$ is a time index, α_1, α_2, α_3 and α_4 are intercepts, β_j for $j \in \{1, \dots, 19\}$ are the coefficients of the explanatory variables and $\{\epsilon_{1t}\}$, $\{\epsilon_{2t}\}$, $\{\epsilon_{3t}\}$ and $\{\epsilon_{4t}\}$ are the error terms. The logic behind the system structure follows.

Price equation Eq. (1) explores the building blocks of Bitcoin price – $\{price_t\}$. The relationship with the total network hashrate, depicted by $\{hashrate_t\}$, is one of the main questions of the current research and builds on the above-reviewed previous research. Following Wheatley et al. (2019), we assume the price depends on the technology utility. We represent the network usage with several variables covering different parts of the dynamics—number of active addresses ($\{addresses_t\}$), network congestion ($\{transaction\_fees_t\}$), and ratio between traded volume on centralized exchanges and on-chain volume ($\{exchange\_ratio_t\}$). As Bitcoin is often claimed to be a currency or directly money, its implied price level may play a role in explaining its price dynamics as well (Kristoufek, 2019). $\{price\_level_t\}$ is defined as the ratio between the sum of all on-chain transfers and number of transfers for the given time period, thus practically a BTC price of an average transfer. The price action of the last few years suggests that Bitcoin reacts to the injections of the monetary base as well as to the stock market dynamics. We thus also include the M2 monetary aggregate ($\{M2_t\}$) and the Standard & Poor's 500 stock index ($\{S\&P500_t\}$). The public attention towards Bitcoin was captured by $\{search\_volume_t\}$, which represents the Google search data for terms BTC or Bitcoin. The public attention measured by internet searches has been shown to well represent the price runs and busts and thus also well represents possible bubble dynamics (Garcia et al., 2014; Kjærland et al., 2018; Kristoufek, 2013).

Hashrate equation Eq. (2) describes the relation of hashrate to its explanatory factors. The Bitcoin price and the transaction fees are clearly linked to the total hashrate, as miners' revenue is formed by the price of a single bitcoin, by the number of bitcoins awarded per block, and by transaction fees. As the adjustment of hashrate can be lagged behind Bitcoin price, we include the lagged price. The number of bitcoins awarded per block are algorithmically determined for each mining era/phase ($\{reward\_phase_t\}$) which obviously motivates miners to take part in the market. Another variables that might be able to capture the changes in the hashrate are the number of active addresses, and the efficiency of the mining hardware ($\{efficiency_t\}$) as more efficient hardware enables miners to output more computing power for the same amount of electricity, thus effectively increasing hashrate.

Transaction fees equation The transaction fees are driven by the demand for completing transactions as fast as possible. This need consists of factors explored by Eq. (3) – price, active users, and public interest. A sudden change in Bitcoin price might motivate users to send transactions more than usual,[4] thus increasing transaction fees. The number of active addresses influences the transaction fees directly as more active users lead to higher competition for a space in a block (which is limited), and in turn increases the fees. The search volume could have a similar effect as the number of active addresses. The more people are interested in Bitcoin, the more potential users exist, and thus the higher demand for the transactions completed there might be.

Search volume equation Finally, Eq. (4) describes the assumed dynamics of investors' attention. The price bubbles and bursts are often driven by retail investors entering the market to engage in the ongoing price action. $\{price_t\}$ is thus an obvious candidate for a good explanatory variable. We also add uncertainty to the equation as a volatile market can attract attention to the market. Uncertainty is measured by daily volatility $\{sigma_t\}$.

Table 1 shows that the variables cover a wide array of ranges and scales so that the logarithmic representation of most of the variables is reasonable for more efficient interpretation as it leads to the elasticity specification for most pairs of variables. Most variables are somewhat skewed (mostly right tail) and there are several variables with a rather high excess kurtosis (transaction fees and search volume, i.e., two of our four assumed endogenous variables), which gives the logarithmic transformation a more solid ground. There are several additional variables in the table that serve as possible extra instruments for the eventual estimation (as we eventually use the two-stage least squares – 2SLS or TSLS – as the estimation method). These cover the Bitcoin supply ($\{supply_t\}$), and net and raw transfer values in BTC ($\{net\_transfer\_value_t\}$ and $\{transfer\_value_t\}$). Note that we do not opt for any further transformations, most notably first-differencing any of the series, as we are interested in the long-run relationship among variables. This poses some additional requirements on statistical testing, which is provided in the respective sections. We follow with a detailed description of the dataset.

3.2. Dataset construction

This section describes the collection of data, their sources, and also the way some of the variables were constructed. The dataset covers the time span from 4 January 2016 to 31 January 2022 at weekly frequency, giving 318 observations in total. The time frequency is dictated by the monetary base M2 that is available only at weekly frequency. All other variables are then taken as averages over the last seven days (for Bitcoin-related variables) or over the last five days (for S&P500). The description was split into three subsections, the first of which being formed by variables easily available thanks to the blockchain data, the second group is formed by mining equipment data, and the third group for variables from various other sources. Table 2 gives a review of the data sources.

[4] Typically, the transaction fees spike when there are extreme growths or falls in the price, as many users want to buy or sell Bitcoins as fast as possible.

Table 1
Descriptive statistics.

Variable	Mean	Median	Minimum	Maximum	SD	Skewness	ex. kurtosis
price	13 369	7429	377	64 868	16 696	1.66	1.45
hashrate	6.42×10^7	4.69×10^7	7.82×10^5	1.97×10^8	5.78×10^7	0.46	−1.19
transaction_fees	0.00035	0.00022	0.00004	0.00303	0.0004	2.85	10.29
search_volume	0.81	0.61	0.15	7.67	0.73	4.10	28.01
addresses	757 940	722 590	386 590	1 234 100	189 660	0.42	−0.58
efficiency	0.11	0.05	0.03	0.50	0.11	2.02	3.20
reward_phase	2.23	2.00	1.00	3.00	0.59	−0.10	−0.44
exchange_ratio	5.49	3.22	0.22	27.22	5.89	1.60	2.37
M2	15 675	14 394	12 412	21 750	2822.90	0.86	−0.75
net_transfer_value	65.87	69.00	22.63	145.76	24.10	0.15	−0.75
price_level	0.50	0.42	0.19	1.47	0.23	1.13	0.88
sigma	0.03	0.02	0.00	0.12	0.02	1.62	3.78
S&P500	2978	2803	1865	4766	742	0.83	−0.22
supply	1.74×10^7	1.75×10^7	1.50×10^7	1.89×10^7	1.12×10^6	−0.31	−1.14
transfer_value	320 980	277 880	140 070	738 770	113 560	0.96	0.34

Table 2
Data sources.

Variable	Ticker	Source
price	PriceUSD	CoinMetrics.io
hashrate	HashRate	CoinMetrics.io
transaction_fees	FeeMeanNtv	CoinMetrics.io
search_volume	BTC + Bitcoin	Google Trends
addresses	AdrActCnt	CoinMetrics.io
efficiency	*manual*	various sources
reward_phase	*manual*	Bitcoinblockhalf.com
exchange_ratio	*manual*	CoinMetrics.io + CoinMarketCap
M2	WM2NS	St. Louis Fed
net_transfer_value	NVTAdj	CoinMetrics.io
price_level	*manual*	CoinMetrics.io
sigma	*manual*	CoinMarketCap
S&P500	GSPC	Yahoo Finance
supply	SplyCur	CoinMetrics.io
transfer_value	TxTfrValAdjNtv	CoinMetrics.io

3.2.1. Blockchain variables

As mentioned before, blockchain technology is unique for its unprecedented data availability, as information on every transaction is being saved into the blockchain. This allows for the analysis of many variables that would be hard to measure otherwise. We use the data aggregator CoinMetrics.io which provides detailed description of each variable as well as large and deep datasets for many other cryptoassets. Bitcoin price is given in USD and is a volume-weighted average over the exchanges. The total network hashrate is measured in terahashes per second (an average number of terahashes per second the network was performing in the last 24 h) and is estimated from the number of mined blocks and the difficulty. The number of active addresses shows the number of unique addresses that were active on the blockchain on a given day, i.e., they received or sent Bitcoin. The total transaction fees, measured in Bitcoin, express the total number of bitcoins that were paid to miners as transaction fees in one day. The total circulating supply of Bitcoin indicates how many bitcoins were issued up to the given date. The net transfer value is parallel to the velocity of money in the equation of exchange and the transfer value gives the total value of all successful transfers in BTC. The dates of the halving events were retrieved from Bitcoinblockhalf.com.[5] The price level of Bitcoin was constructed in line with the economic theory described by Kristoufek (2019) as a ratio of the total transaction volume and the number of transactions.

3.2.2. Mining efficiency data

As mentioned before, it is not known exactly which hardware units are being used for mining and the total mining efficiency (combined energy efficiency of all miners deployed in the network) thus cannot be computed with high confidence. In the relevant literature, a theoretical optimum of the mining efficiency was computed and used (all miners using the best available hardware at a time), as well as the worst feasible efficiency (all miners mining at break-even costs). Some of the researchers used the data from the IPO filings of mining hardware producers in order to approximate the number of sold units, thus estimate the real mining efficiency and Bitcoin electricity consumption (Stoll et al., 2019). As the usefulness of the information from the IPO files declines with time (because new and more efficient mining units are being produced, which were not accounted in the files), this analysis makes use of a simplified method of choosing the mix of the most efficient available ASICs at each point in time. The technical specification of ASICs, as well as the dates of their release to the market, were taken from a list constructed by Zade and Myklebost (2018) and from Asicminervalue.com,[6] where all the necessary information is available. Additionally, data on release dates and efficiencies were further validated against other websites[7] listing the mining hardware.

Three options for the energy efficiency were created: the efficiency of the best available ASIC, simple arithmetic mean of efficiencies of the three best available ASICs, and of the five best available ASICs in time. From these three alternatives, the most appropriate one was selected by using a comparison with the estimated electricity consumption computed by the CBECI.[8] The CBECI electricity consumption was used as a benchmark because the methodology used in this estimate is well described and robust, but it uses data that is not publicly available. Additionally, the estimate is continuous through time, which makes the comparison possible. As for the comparison itself, three versions of the electricity consumption were computed based on the three scenarios for the mining efficiency. Then, using the Root Mean Square Error (RMSE), they were compared to the CBECI electricity consumption estimate and a series with the smallest RMSE value was selected. Based on this approach, the arithmetic mean of the five most efficient ASICs was chosen to be used in further analysis.

3.2.3. Other data

The remaining variables to be described are the USD money supply, S&P500, uncertainty, exchange ratio, and the Google Trends data.

The USD money supply is published by the Fed weekly as the trend-adjusted or the not-adjusted M1 and M2. During the examined period, the composition of the M1 was changed, which made it not directly comparable to its older values, thus the not-adjusted M2 was used in

5 https://www.bitcoinblockhalf.com/.

6 https://www.asicminervalue.com/efficiency/sha-256.

7 https://cryptomining.tools/compare, https://en.bitcoin.it/wiki/Mining-hardware-comparison, https://www.bitcoinmining.com/bitcoin-mining-hardware/.

8 See Rauchs et al. (2020) or https://cbeci.org/.

the analysis. The S&P500 index has been obtained from Yahoo Finance and the Monday weekly averages are being used. For the uncertainty sigma, we estimate the daily volatility using the Garman and Klass (1980) estimator.

The Google Trends[9] statistics was often used as a sign of public interest in Bitcoin. Therefore, the search data for the term "bitcoin"[10] or "BTC" downloaded from Google Trends were used as one of the variables. Data has been downloaded at daily frequency, each time five times with an added random alphanumeric string to force a re-sample of the Google database, and averaged. Eventually the two series for "BTC" and "bitcoin" are weighted together with a weight based on comparison of average searches of the two terms over the whole sample period. As the daily data on Google Trends can be downloaded only for periods of several months, these have been chained together via an overlapping month.

As a careful reader certainly noticed, the dataset does not contain electricity price. This is due to at least four reasons. First, the electricity price is available at monthly frequency at best, possibly limiting the whole analysis. Second, even if it were available at weekly frequency, its nature and structure would be hardly useful. Electricity prices are often available as aggregates over a certain (sub)population like households or industry, in addition often only in a specific country. However, the times when one could mine bitcoins for retail prices is long gone and much of the current mining business runs either on renewables or on company-specific contracts or both. The index prices would thus be hardly useful. Third, there are no official statistics about distribution of the Bitcoin miners among countries, making an average electricity price even more complicated. And fourth and in the end, these index electricity prices are often only very mildly variable, making their usefulness very limited even if we forgot about the previous three points.[11]

4. Results and discussion

4.1. Final model and statistical validity

As mentioned several times above, the Bitcoin pricing system is a system of interactions between and among many variables. We assume that some of the variables are bidirectionally causal, i.e., endogenous withing the system. Specifically, our system is built on the premise that Bitcoin price, its network hashrate, transaction fees representing the network congestion, and interest in or attention about Bitcoin are such endogenous variables. The instrumental variables approach is thus at hand. Hausman (1978) test leads to the 2SLS approach against the standard least squares estimation (test statistic of 129.4 and p-value $\ll 0.01$.). 3SLS including possible common shocks to the system of equations is not suggested here as the estimated covariance matrix of system residuals is not positive semi-definite. We thus stick to the 2SLS procedure.

Selecting a proper specification of the final estimation procedure, i.e., identifying the included exogenous variables and instrumental variables, is not an easy feat in such an interconnected system. We approach this by building on the original system specification as outlined in Section 3.1 and combining it with testing for weak instruments (Stock et al., 2002) and actual exogeneity of the instruments via the Sargan's J-test test (Hansen, 1982; Sargan, 1958). Table 3 summarizes the final system specification and Table 4 presents the associated

Table 3
Final system specification—endogenous, exogenous, and instrumental variables.

Type	price	hashrate	transaction_fees	search_volume
Endogenous	hashrate search_volume	$price_{-1}$ transaction_fees	price search_volume	price
Exogenous	SP500	efficiency exchange_ratio addresses	addresses	sigma addresses
Instruments	addresses supply M2 sigma exchange_ratio	supply transfers exchange_ratio SP500	reward_phase efficiency SP500 sigma transfers	M2

statistical tests. Wu-Hausman test (Greene, 2003) is added to ensure that the assumed endogenous variables are in fact endogenous within the system. If there are two right-hand side endogenous variables in the given equation, there are two tests for weak instruments, one for each right-hand side endogenous variable. For a system equation to be valid, we want to reject the null hypothesis for the weak instruments model (reject that the instruments are weak), reject the null hypothesis for the Wu-Hausman test (reject that the variables are not endogenous), and not to reject the null hypothesis of the Sargan's J-test (the null hypothesis states that the exogenous variables are in fact exogenous within the system). We see this ideal combination for the price, hashrate, and transaction fees equation, while for the search volume equation, the Sargan's test is on the edge. Nevertheless, the main aim here is to explore the relationship between the price and hashrate so this borderline results for the search volume equation does not affect the results for the other three equations.

Table 6 presents the estimated system. Before we turn to actual reporting and interpretation of the results, we must focus on statistical validity of the estimates. Table 5 summarizes the necessary tests. For each equation in the system, we test the residuals for stationarity, heteroskedasticity, and autocorrelation. We reject unit roots for all equations based on the Augmented Dickey–Fuller test (Fuller, 1996) and Phillips–Perron test (Phillips & Perron, 1988), and we do not reject stationarity via the KPSS test (Kwiatkowski et al., 1992). Such a result is essential as it allows to use the variables specification in their levels or log-levels. The residuals of practically all equations are heteroskedastic (Breusch & Pagan, 1979) and have non-zero autocorrelation (Durbin & Watson, 1971) with the only exception of the search volume equation not showing signs of heteroskedasticity. We thus use the heteroskedasticity and autocorrelation consistent (HAC) standard errors (MacKinnon & White, 1985).

4.2. Discussion

Table 6 reports the results of the 2SLS estimation together with the HAC standard errors and respective t-statistics and p-values. We now go through the results equation-by-equation and discuss the implications.

Bitcoin price dynamics is driven by hashrate, search volume and the S&P500 stock index. All three variables have a positive effect on the price, statistically significant at all conventional levels. The strongest effect is reported for the stock index, with the elasticity of 2.26. Bitcoin thus very strongly reacts to the changes in the stock market, which has been mostly evident in reaction to the Covid-19 pandemic when Bitcoin mostly followed the stock markets, both up and down, reacting to the monetary injections of most central banks. The monetary base M2 itself remains as an instrument and is not part of the final equation as it is highly correlated with the stock index ($\rho = 0.95$) but still serves as a strong instrument. Search volume, standardly representing the retail interest in the cryptoassets market, shows almost perfect unity elasticity (we do not reject the null hypothesis of the unity elasticity). The retail interest thus strongly drives the Bitcoin

[9] https://trends.google.com/.

[10] Google Trends search engine does not differentiate between lowercase and capital letters, therefore the search statistics for the terms "bitcoin" and "Bitcoin" are the same.

[11] Our preliminary analysis on monthly data confirmed the suspicions and electricity price we were able to construct, within our capabilities keeping the limiting factors in mind, was one of the first variables in the system to be eliminated.

Table 4
Final system testing—instruments, exogeneity, endogeneity.

Test *(value [p-value])*	price	hashrate	transaction_fees	search_volume
Weak instruments	573.16 [≪0.01] 42.39 [≪0.01]	95.82 [≪0.01] 45.49 [≪0.01]	278.88 [≪0.01] 29.59 [≪0.01]	129.33 [≪0.01]
Wu–Hausman	86.97 [≪0.01]	205.20 [≪0.01]	97.54 [≪0.01]	26.82 [≪0.01]
Sargan	5.30 [0.26]	3.153 [0.21]	3.74 [0.44]	4.23 [0.04]

Table 5
Tests for stationarity, autocorrelation and heteroskedasticity.

Test *(value [p-value])*	price	hashrate	transaction_fees	search_volume
	Stationarity			
ADF	−6.26 [≪0.01]	−3.19 [≪0.01]	−6.46 [≪0.01]	−5.62 [≪0.01]
PP	−63.6 [≪0.01]	−79.2 [≪0.01]	−62.4 [≪0.01]	−50.8 [≪0.01]
KPSS	0.0871 [≫ 0.10]	0.0950 [≫ 0.10]	0.0422 [≫ 0.10]	0.0742 [≫ 0.10]
	Heteroskedasticity			
BP	62.288 [≪0.01]	64.250 [≪0.01]	70.469 [≪0.01]	4.1293 [0.2478]
	Autocorrelation			
DW	0.3893 [≪0.01]	0.0995 [≪0.01]	0.3915 [≪0.01]	0.4820 [≪0.01]

price, contributing to its swingy behavior and dynamics, amplifying the bull and bear markets. The estimated elasticity between hashrate and Bitcoin price is reported at 0.22. Interpretation of such estimate, and mainly its direction, i.e., from hashrate to price, calls for understanding the perception of the Bitcoin network hashrate within the system. From the basal perspective, hashrate is the amount of computational power miners/validators are contributing towards the network, competing for the mining rewards and fees. However, the network hashrate is often seen as a measure of security of the network. Why security? Because higher hashrate means that a potential attacker who would want to overtake blocks formation needs to attribute more of their hashing power, and thus money, into doing so. Higher hashrate thus means lower likelihood of such attack successfully happening. Thus security. From this perspective, the positive effect of hashrate on Bitcoin price makes perfect sense. Overall, the three variables explain 94% of the Bitcoin price dynamics while meeting all standard statistical/testing criteria, making the results very solidly founded. Interestingly, the final equation form for price is rather minimalistic when compared to the starting specification, yet still the coefficient of determination is this high. The other variables thus apparently carry similar information, at least with respect to price.

There are three statistically significant variables (at the 90% level) for the hashrate equation—addresses, efficiency, and transaction fees. The most straightforward interpretation comes for the efficiency—it is measured in J/GH so that decreasing the absolute value of the variable means improvement in efficiency so the elasticity estimated at −1.09 is expected with respect to the sign. The more efficient the mining equipment is, the more computational power can be supplied to the network's functioning. The more active users come, the more hashing power is needed to ensure proper functioning of the network but also the more fees are collected (both hypothetically but also empirically as is documented in the fees equation later) which motivates miners to participate. The fees themselves as a separate variable have negative effect on the hashrate which is a bit puzzling as higher fees should motivate miners to compete for them more. However, if we take transaction fees as a measure of network congestion, we can see how a congested network is associated with an insufficient network power albeit not necessarily in a causal manner. Importantly, the effect of price is found to be statistically insignificant. Even though one might expect to see a positive relationship (Kristoufek, 2020) as higher price means motivation to participate in the mining market either for higher profits or for miners that had not been profitable before, it more reflects towards the previously expanded notion of hashrate as a sign

Table 6
Final system results.

	$\hat{\beta}_j$	SE	*t-statistic*	*p-value*
Price equation				
Intercept	−12.5895	1.8763	−6.7096	≪0.01
log(hashrate)	0.2173	0.0340	6.3919	≪0.01
log(search_volume)	0.9750	0.0730	13.3527	≪0.01
log(S&P500)	2.2603	0.2803	8.0630	≪0.01
Hashrate equation				
Intercept	−73.4578	46.3181	−1.5859	0.1138
log(price$_{-1}$)	−0.6312	0.5639	−1.1193	0.2634
log(addresses)	6.0315	3.3958	1.7762	0.0787
log(efficiency)	−1.0878	0.5789	−1.8790	0.0612
reward_phase2	0.3829	0.7703	0.4971	0.6195
reward_phase3	−0.0461	0.8052	−0.0573	0.9545
log(transaction_fees)	−1.3604	0.6407	−2.1232	0.0345
Fees equation				
Intercept	−35.2564	7.6436	−5.6125	≪0.01
log(price)	−1.5965	0.1380	−11.5699	≪0.01
log(addresses)	3.0936	0.5598	5.5262	≪0.01
log(search_volume)	2.3556	0.3630	6.4900	≪0.01
Searches equation				
Intercept	−12.5985	4.5724	−2.7553	0.0062
log(price)	0.1617	0.0736	2.1977	0.0287
log(addresses)	0.8809	0.3767	2.3385	0.0200
log(sigma)	0.3126	0.0788	3.9691	≪0.01
	R^2		Adj. R^2	
Price eq.:	0.943		0.943	
Hashrate eq.:	0.780		0.776	
Fees eq.:	0.193		0.185	
Search eq.:	0.727		0.724	
Num. obs. (total)		318		

or measure of network's security. The price does not affect this. This also goes in hand with the price–hashrate relationship observed in the examined period 2016–2022 where hashrate quite consistently grows but price undergoes a much more erratic dynamics. Also, the China Bitcoin mining ban in July and August 2021 certainly contributed, even though it eventually remained an on-the-paper ban as the Chinese miners activity has grown considerably since. However, getting official or at least somewhat reliable statistics on such activities is practically impossible. Overall, the variations in hashrate are very well explained by the given factors with the adjusted coefficient of determination of 0.78.

The fees equation is quite straightforward. We have three solidly significant variables—price, addresses, and search volume. As the fees can be seen as a measure of network congestion, it makes sense that addresses and search volume play an important role. The higher the usage and the higher the retail investors activity, the higher the network congestion. The negative effect of price is slightly counter-intuitive but it needs to be remembered that the fees are reported in BTC here so the negative coefficient mostly suggests that the market participants are not willing to pay disproportionally more for their transactions. This is not shocking for Bitcoin as such because the speed of transactions, or better the urge to be in the first coming block, is often not as urgent as for e.g. the Ethereum network where the speed of transaction in making a trade in an automated market maker decentralized exchange is of great importance as the transaction can be front-run or not executed because the exchange price could have changed during the waiting period, leading to not transacting but losing the fees. This shall be an interesting avenue of research for the smart contract cryptoassets. Even though we arrived at three significant variables explaining fees, the overall explanatory power of the model is considerably lower than for the previous two equations with the coefficient of determination at 0.19. The dominant technical reason for this is the fact that fees are mostly mean-reverting. Even though this is not necessarily automatically given by the protocol, an inspection of the data shows a clear picture. Either way, the relatively low R^2 suggests there might be more to the dynamics of this variable. As the fees or network congestion are not the main aim of the current research, we leave a more detailed discussion of this phenomenon for later work.

Google searches have been a standard explanatory variable for Bitcoin price or returns since the very beginnings of the quantitative research into the cryptoasset (Garcia et al., 2014; Kristoufek, 2013). However, its potential endogeneity has been mostly left out since. Here, we show that they clearly are endogenous to Bitcoin price as they both explain the price (the price equation) but are also explained by it (the current searches equation). Although, the effect of the price on attention is much lower than the other way around (elasticity of 0.16 vs. 0.98, respectively), yet still we observe a positive feedback loop between the two variables highlighting amplification of rapid market movements. In addition to price boosting the attention, we find the number of active addresses and sigma to play an important role in explaining the dynamics of this last endogenous variable, both with a positive sign. The number of active addresses is quite expected but it is interesting to see that a more volatile market attracts attention. Note that we do not and cannot distinguish between positive and negative attention with Google search queries (unless we analyze more specific queries but this can again serve as a good starting point for more detailed studies into the specific crypto-related searches). Note that both the addresses and sigma are good instruments in the price equation, only highlighting coherence of this system of equations describing the complex dynamics of the Bitcoin system. The search equation again shows a high explanatory power of the independent variables with R^2 of 0.72.

As a robustness check, we have rerun the analysis with alternative endogenous variables—Bitcoin market capitalization in place of price, mean difficulty in place of hashrate, fees in USD rather than in BTC, and Wikipedia page visits instead of Google searches. The results remain qualitatively very similar, only the searches equation with the Wikipedia views is considerably weaker as is quite expected. In the early studies of Bitcoin dynamics (Garcia et al., 2014; Kristoufek, 2013), Wikipedia views have been successfully used as the market participants were mostly in the exploratory phase. However, the current use of social media has completely changed the playing field and Wikipedia is hardly used in the cryptoassets community. The detailed results of this robustness check are available upon request.

Putting the results of all four equations together, we can summarize the results in the following points. First and mostly general, the system of equations we present is statistically very solid with high coefficients of determination, passing all necessary statistical tests, and yielding economically interesting and sound results. Second and now more specifically, the Bitcoin price strongly follows the stock market with the retail-driven price action superimposed onto the basic dynamics that is also solidly built on the network's security. Third, the system hashrate is mostly driven by its increasing size and efficiency of the mining equipment. Fourth, the network congestion is expectedly driven by the number of active users, including the retail investors. And fifth, the retail interest is driven by booming price as well as volatility. When put together, these findings are not shocking. This might be taken as a bad thing but in reality, it shows that the Bitcoin market or system does not behave haphazardly or chaotically but it rather follows the logic of its building blocks and architecture.

5. Conclusions

The main motivation of the current research was to identify the factors driving the price of Bitcoin and the total hashrate of the Bitcoin network and to explore the mutual relationship of these two variables. For this purpose, a system of equations was built, with the aim of including explanatory variables that would be able to capture the dynamics of the examined relationship. The assumed and later confirmed endogeneity led us to the two-stage least squares estimation with all its intricacies. This way, we have delivered the most rigorous and complex approach in explaining the pricing dynamics of the Bitcoin system up to date. In the process, we have shown that the whole system is very well structured and actually delivers economically and logically sound results, which is not usually expected for the cryptoassets systems. By showing that many of the relevant variables are in fact endogenous poses higher expectations on future studies dealing with Bitcoin price and hashrate, and in effect also on the environment-oriented studies examining the future of Bitcoin proof-of-work basis. The evidence for the price–hashrate nexus is mostly within the security narrative. The security of the network represented by the hashrate provided by the miners is reflected in increasing Bitcoin price. The increasing price does not lead to further increases in the hashrate, profit as such thus does not seem to be the main driver in this case. This is well reflected in the fact that large mining pools usually cash out their bitcoins only during large market corrections or so called "capitulation". In a way, mining could be seen as a cheaper long-term investment into Bitcoin without actually needing to buy it directly, at least within the results we find here.

Apart from the empirical results as such, we have hinted various opportunities for future research along the way. In addition to an obvious one in the relationship of Bitcoin and stock market price dynamics, which has been long studied, there are several new ones. First, the transaction fees, either as a representation of the network congestion or as such, deserve a more detailed treatment. We expect more interesting stories in the smart contract protocols such as Ethereum where the urgency for transactions being pushed through is much higher, mostly with the decentralized exchanges in mind. Second, the number of active users is an important variable in three out of four of our equations. As there are various ways how to look at these (e.g. exchanges, large wallets), it invites for deeper investigation. Third, the role of (retail) investors' attention is evidently important and its apparent endogeneity poses additional challenges to numerous studies utilizing them. Also, exploring the alternative sources of retail investors' interest in the market could be explored in more detail, specifically Telegram and Discord groups dynamics, as it is likely that the role of Google, similarly to the Wikipedia's fate in the crypto-community, will be fading even more. And fourth, the complexity of relationships calls for utilizing these in price and returns forecasting, either in standard trading strategies studies (even though the frequency might be limiting there) or in environmental studies focusing on mining, albeit these would need to lead to scenario studies rather than actual forecasting, at least partially. Overall, we present a robust study of Bitcoin system dynamics that opens various avenues for better understanding this fascinating, yet still mostly unexplored playing field of modern finance.

CRediT authorship contribution statement

Jan Kubal: Formal analysis, Methodology, Writing – original draft. **Ladislav Kristoufek:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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