AN ECONOMETRIC MODEL TO ESTIMATE THE VALUE OF A CRYPTOCURRENCY NETWORK. THE BITCOIN CASE

Research paper

Abbatemarco, Nico, SDA Bocconi School of Management, Milan, Italy, nico.abbatemarco@sdabocconi.it

De Rossi, Leonardo Maria, SDA Bocconi School of Management, Milan, Italy, leonardo.derossi@unibocconi.it

Salviotti, Gianluca, SDA Bocconi School of Management, Milan, Italy, gianluca.salviotti@sdabocconi.it

Abstract

A blockchain is, in its essence, an unchangeable, inviolable and transparent database distributed among a network's participants. Far from simply representing the latest innovation in ICT, blockchain could serve as a foundation for the development of new business models. Indeed, its distributed nature opens the door to the creation of a new economy characterized by greater decentralization, transparency, security and privacy. The most well-known example of blockchain is the digital currency (or cryptocurrency) Bitcoin, which aims to revolutionize the world of payments as we know it today. The remarkable appreciation of Bitcoin's value over the years has been examined by numerous studies, most of which trying to determine what are the drivers influencing its price. This study is intended to provide some economic prospects for the future of blockchain technology, with specific reference to Bitcoin. In particular, this paper is focused on identifying the costs and revenues that the Bitcoin network supports in order to ensure its operativity. On the basis of the results emerging from this analysis, the paper addresses further considerations about the nature of cryptocurrencies and the future trend of their prices.

Keywords: Blockchain, Bitcoin, Cryptocurrency, Distributed network

1 Introduction

The birth and the progressive spread of the Internet have represented some of the most important changes that human society has faced in the course of its existence. From a purely economic point of view, the internet has profoundly altered our reference systems by enabling extremely flexible and customized buying and selling paradigms, reducing payment lead-times, and introducing new business models that work on assets such as personal data and information (Angwin 2010, Lohr 2012, Boyd & Crawford 2012, Chen et al. 2012).

The ever-increasing level of global interconnection has created, over the last few years, the conditions for the development of a new technology that has the potential to further revolutionize business and economy models as we know them today: the blockchain. Defined the key to the development of the Internet of Value (Antonopoulos 2014, Mougayar 2016, Peters & Panayi 2016), as opposed to the Internet's first era conceived as the Internet of Information, blockchain is a technology that enables the decentralization of a long series of processes today centralized as well as peer-to-peer value exchange models.

Up to relatively recent times, blockchain has only been discussed in correlation with the most well-known project based on it, the digital currency (or cryptocurrency) Bitcoin (BTC). The Bitcoin protocol was born in January 2009 with the purpose of enabling the sending and receiving of user transactions on a network without the need for a central certification entity (Nakamoto 2008). Over time, a large number of users gathered around Bitcoin, so dedicated to the project to continue to develop and improve it in tune with its creator original will. The community plays a crucial role for the blockchain protocol ecosystems, as its participants, or more precisely a fraction of them (usually referred at as miners), perform the work previously carried out by a central entity. In exchange for their efforts, miners are rewarded by the emission of new cryptocurrencies units.

From an academic perspective, since 2011, Bitcoin has attracted a considerable amount of interest from the international community. Blockchain, as the underlying technology, is in fact in a very interesting convergence of complex themes involving, for example, economics, politics, game theory, cryptography (Catalini & Gans 2016, Reijers et al., 2016, Davidson et al., 2016).

The business community has also produced numerous studies on the subject (Bonneau et al. 2015, Beck & Müller-Bloch 2017, Lindman et al. 2017, Salviotti et al. 2018). In particular, some of these studies have focused on the identification of a number of "fundamental" factors at the basis of the price formation of a bitcoin. Compared to a traditional fiat currency, it is difficult to explain the trend of a cryptocurrency taking into account traditional macroeconomic factors suggested by classical theory (e.g. Mundell 1961, Mark 1995, Obstfeld 1996), since this new type of currency is not issued by any central entity and has, at least apparently, no underlying economy. The deflationary and therefore limited nature of cryptocurrencies has also led several authorities, such as the CFTC in the United States, to consider them a commodity or security rather than a currency in the strict sense, but this kind of explanation is not entirely satisfactory and leaves out some of the fundamental features of technology.

The aim of this work is to better define the role of cryptocurrencies within the current economic landscape. In the study it is assumed that Bitcoin relies on a network of users willing to support actual fiat currency costs and receive digital currency profits in order to ensure its operativity: hence the purpose of verifying whether this production structure is comparable to the classical one of an industrial good. Therefore, a relationship has been found between the actual prices trend of Bitcoin and the estimated prices trend assuming the existence of such a structure.

2 Literature Review

Given the visibility gained over the years, it is normal that Bitcoin has attracted a lot of the attention from the academia. In particular, many studies were aimed at identifying the predictors for future fluctuations in its price.

The first contribution has been provided by Buchholz et al. (2012) that focused on the number of Bitcoin in circulation, number of daily transactions in Bitcoin, total daily volume of transactions in Bitcoin, and number of searches with query "Bitcoin" estimated through Google trends.

The following year, Kristoufek (2013), after discarding the hypothesis of existence of a real economy underlying Bitcoin, proposed a model to explain the elements of the speculative component in the formation of its price. Kristoufek started from the hypothesis that most of the variation in the price could be explained by the interest displayed (both in positive and negative sense) by the investors and that this could be retrieved through two proxies: the number of searches made on the search engine Google with "Bitcoin" as query (as already done in the previous study) and the number of unique visit on the Bitcoin page of Wikipedia. The conclusion drawn by Kristoufek in his study was that there is a significant bidirectional relationship between the price of a bitcoin and the number of searches made on both Wikipedia and Google. He also suggested the presence of a feedback mechanism increasing Bitcoin's volatility, pushing it higher than expected when its price was above its recent average and lower than expected in the opposite case. Eventually, Kristoufek concluded that the value of a bitcoin is purely based on speculation and he assumed a behavior very close to that of a bubble market, corroborating Buchholz's perspective.

Van Wijk (2013) proposed a study aimed at showing a relationship between Bitcoin's price and some macroeconomic variables, such as the Dow Jones Index, FTSE 100, the Euro/Dollar exchange rate, the Nikkei 225, the Dollar/Yen exchange rate, and the Brent, WTI and CMCI oil prices. Van Wijk's model highlighted a significant relationship between Bitcoin's price and Dow Jones Index both in the short and the long-term, and another one only in the long-term with the Euro/Dollar exchange rate and the WTI oil price.

The results of the studies of Buchholz et al. (2012), Kristoufek (2013) and Van Wijk (2013) have been subsequently analyzed and integrated by Ciaian et al. (2014). The authors analyzed Bitcoin's price trend in relation to demand/supply functions (number of Bitcoin in circulation, number of daily transactions, number of unique addresses used per day), investors' interest (number of searches on the Bitcoin Wikipedia page, number of new subscribers and new posts on bitcointalk[1]) and macroeconomic factors (DJ Index, WTI oil price). As a result of the analysis, previous hypotheses regarding the importance of classical fundamentals and investors' interest were confirmed. On the contrary, no statistically significant relationship was found with the macroeconomic factors exposed in Van Wijk's findings. Unlike Buchholz and Kristoufek, however, Ciaian et al. concluded that the speculative component of cryptocurrencies was not mandatorily leading to the formation of a market bubble but could have rather been physiological of the exponential adoption process of a new potentially disruptive technology such as blockchain.

In a subsequent study, Hayes (2015) finally tried to establish a connection between the price trend of Bitcoin and the economy underlying the protocol. As already mentioned in the introduction, the operativity of the Bitcoin protocol is ensured by the constant work of a group of users of its ecosystem (mining nodes or miners), which make use of more or less specific hardware devices in order to ensure that the protocol does not accept fraudulent transactions. Miners' work, which has a cost in terms of time and consumed electricity, is rewarded by the protocol itself by the emission of new bitcoins for each valid transaction block generated. Taking into account this mechanism, Hayes (2015) formulated a linear regression between the price of a bitcoin and the total computational power submitted by miners into the network (hashrate), concluding that a variation of the hashrate accounted for up to 80% of the price change of a bitcoin. In the second part of his study, Hayes developed a model to detect the marginal cost of production of a Bitcoin. The model consisted in a marginal cost function:

$$COST_{\$} = Hashrate_{hash/_{s}} * Efficiency_{J/_{hash}} * Electricity\ Price_{\$/_{\mathrm{kWh}}} \tag{1}$$

and a marginal profit function:

$$PRODUCT_{BTC} = Block\ Reward_{BTC} * Blocks\ generated \tag{2}$$

[1] The first and most popular forum among cryptocurrencies' enthusiasts.

such that, assuming the presence of efficient markets, their ratio should have been equal to the price of a bitcoin in equilibrium.

In 2015, Kristoufek (2015) realized another study on this subject. His new analysis focused on the existing relationships between Bitcoin's price and five different variables. In addition to those analyzed in Kristoufek (2013), in his new work the following variables were considered: a trade-exchange ratio (designed to measure the use of Bitcoin as a currency for "real" use and not as a commodity), hashrate and difficulty[2] (proxies of the value of the hardware underlying the infrastructure), the Financial Stress Index (FSI, useful for measuring the degree of financial stress of the global economy), and the price of gold. The study confirmed the relevance of the investors' interest elements. However, Kristoufek came here to two other interesting conclusions. The first was that Bitcoin, unrelated to either FSI or gold, was not to be considered as a “safe haven” good; the second was that Bitcoin's value seemed not to be determined by pure speculation but supported by the growth of its real economy (the number of goods and services directly available in Bitcoin and the value of hardware underlying its infrastructure).

The Bouoiyour & Selmi (2015) study is linked to this last perspective. Bouoiyour & Selmi took into account several variables such as trade-exchange ratio, Bitcoin's monetary velocity, total daily volume in Bitcoin, hashrate, Google searches with “Bitcoin” as query, gold price and the Shanghai Stock Exchange Index (SI). Bouoiyour & Selmi came to the conclusion that although in the short-term Bitcoin trend resulted related to several variables (trade-exchange ratio, the total daily volume in Bitcoin and SI), in the long run its price seemed to be influenced above all by only one element, the hashrate.

Finally, Balcilar et al. (2017) tried to establish, through a non-parametric causality-in-quantiles test, a relationship between the prices trend of Bitcoin and the volume transacted daily on the main exchanges. However, the results showed that in no period of the observed conditional distribution the volume analysis allowed to make statistical predictions on Bitcoin’s future prices.

3 Econometric Approach

In the early years of blockchain technology, investors' interest was almost univocally considered to be the only significant proxy useful to determine the price trend related to a blockchain protocol. The predominance of this element led to the conclusion that the cryptocurrencies market was a very unstable one, subject to the formation of market bubbles.

However, recent studies focus on other variables, assuming that a more or less solid economy is emerging behind this new technology: in particular, the focus has moved on more technical elements, such as the costs sustained by the ecosystem members to ensure the survival and development of the protocol.

Hayes's (2015) study was the most relevant source of inspiration for this work. However, it was found that the first part of his research, which analyzes a linear regression between the price of a cryptocurrency and its hashrate, is most likely statistically invalid, as it considers non-stationary historical series. As stated in more than eighty years of statistical studies, a linear regression between two non-stationary series must be considered spurious and its results not significant (e.g. Yule 1926, Phillips 1986).

However, Hayes's intuition remains valid: in accordance with the common microeconomic assumptions of efficient markets, it should be possible to estimate the equilibrium price of a cryptocurrency by comparing the marginal costs and profits of the infrastructure that produces it.

Therefore, in line with what Hayes said in his study – and more generally with all the latest analysis produced on this argument – this paper aims to verify the existence of a significant production system underlying Bitcoin. The presence of this “infrastructure” will be assumed if there is a statistically significant long-term relationship between the actual prices trend of Bitcoin and the equilibrium prices trend.

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[2] The difficulty is a value linked to the hashrate and determined by the protocol to keep the generation time of a block into a certain range.

The equilibrium price trend has been estimated as follows:

Starting from what Hayes (2015) affirmed in his paper, i.e. the presence of:

- a daily marginal cost function designed to estimate the electrical costs of the hardware infrastructure underlying Bitcoin:

$$COST_{\$} = Electricity\ Cost_{\$} \ = H_{hash/_s} * EFF_{J/_{hash}} * CE_{\$/_{kWh}} * 24_{h/_{day}} \qquad (3)$$

  where H is hashrate (measured in hash per second), EFF the energy efficiency of the devices used by miners (measured in Joule per hash) and CE the cost of electricity (in USD per kilowatt/hour);

- a marginal daily profit function designed to estimate the number of units per block:

$$PROFIT_{BTC} = Emission\ Reward_{BTC} = \mathrm{B}R_{BTC} * [\frac{3600\frac{s}{h} * 24\ \frac{h}{day}}{BT_s}] \qquad (4)$$

  where BR is the emission reward of new units of cryptocurrency per block and BT the time needed to generate a block;

then relying on the classical competitive market economic theories, the relationship between them must be equal to price under equilibrium conditions.

$$Equilibrium\ Price_{\$/_{BTC}} = \frac{COST_{\$}}{PROFIT_{BTC}} \qquad (5)$$

At a lower price than that of equilibrium, a miner would operate in loss and would be consequently forced out of the market; the removal of its devices from the network would lead to an increase in everyone's marginal profit (minor competition between miners for the emission reward) and consequently to the return of the system to the equilibrium. Conversely, a higher price than that of equilibrium would attract new miners into the market; the increase in the number of devices in the network would lead to a decrease in marginal profit (more competition for the emission reward) and therefore again to the return of the system in balance.

Though fundamentally correct, there are two elements missing in Hayes' formulations:

- on the cost side, Hayes considers irrelevant those of maintaining and updating miners' hardware. However, given the progressively higher cost of such equipment and the greater specificity that prevents it from being reused for other applications, this element can no longer be excluded in order to properly calculate the costs;
- on the profit side, Hayes does not consider that miners are rewarded not only through newly issued cryptocurrency units, but also through fees received for each transaction placed in a block. Given the progressive diminution of block-generated units (Bitcoin, as most of the cryptocurrencies, is deflationary), over time the entire validation work will be reimbursed only through fees; It is therefore wrong not to consider them.

The new equilibrium price estimation model is therefore based on:

- a cost function composed of a "Cost of Electricity" factor and a "Maintenance and Upkeep Cost" (MAN) factor:

$$NEW\ COST_{\$} = H_{hash/_s} * EFF_{J/_{hash}} * CE_{\$/_{kWh}} * 24_{h/_{day}} + MAN_{\$} \qquad (6)$$

- a profit function composed of a "Units obtained through emission reward" factor and a "Units obtained through fees" (FEES) factor:

$$NEW\ PROFIT_{BTC} = BR_{BTC} * \left[\frac{3600_{s/_h} * 24_{h/_{day}}}{BT_s}\right] + FEES_{BTC} \qquad (7)$$

As already explained, the relationship between these two elements should provide a valid estimate of the price of a cryptocurrency in equilibrium.

Once this model was estimated, a historical series of the past equilibrium states was built.

In order to verify the existence of a statistically significant long-term relationship between the estimated prices series and the actual prices one, we proceeded as follows.

Given the nature of the variables considered, there was a high probability that they were mutually interdependent. Lütkepohl & Krätzig (2004) state that the analysis of interdependencies between time series is subject to the endogenous problem. The solution proposed by the literature is to specify a Vector Auto Regressive model (VAR) that analyzes the causality between the two series estimated by the model.

However, Engle and Granger (1987) demonstrated the estimate of such a model in the presence of non-stationary variables (i.e. with mean and variance non-constant over time) can lead to erroneous model specification and hence to unconditional regressions (spurious regressions).

Intuition suggests that the price trend of a cryptocurrency and that of its estimated equilibrium prices are non-stationary time series, as there is a constant increase in their values over time.

Therefore, the first step in the analysis was to determine if the two series were stationary. We proceeded testing for the presence of a unit root through the Augmented Dickey-Fuller test.

Again, as stated by Engle and Granger (1987), the combination of two non-stationary series may be stationary; in this case, the two series are said to be co-integrated. This implies that there is a long-term relationship between them. It was therefore examined whether there was any cointegration between the two series.

To test whether or not there was cointegration, it was firstly determined the number of appropriate lags to be considered in the model, referring to the Akaike Information Criterion (AIC). Therefore, we determined if it was necessary to include in the model a time constant and a trend on the basis on what suggested by the Pantula's principle, as specified in Johansen (1995). Then, we verified the presence of cointegration through Johansen test for cointegration (Johansen & Juselius 1990) and determined the number of cointegration vectors on the basis of the eigenvalue and the trace test.

Finally, a Vector Error Correction (VEC) model for the co-integrated series was estimated, in order to indicate the rate of adjustment of its VAR-related model to its long-term balance.

Once the VEC model was determined, the correctness of the model was tested performing Lagrange's multiplier test for the presence of autocorrelation in the residues (Breusch & Pagan 1980) and the general model stability (Engle & Granger 1987).

4 Data

As highlighted in the previous paragraph, it was necessary to determine the value of seven variables to formulate the equilibrium price estimation model:

- for the emission reward: BR and BT;
- for the electrical costs: H, EFF and CE;
- for the maintenance costs: MAN;
- for the fees: FEES.

With regard to the data needed for the calculation of variables, a series of publicly accessible databases or sources have been consulted. Given the wide availability of data and in order to make the model as statistically significant as possible, we opted for a selection of daily observations. As for the observations starting date, we have chosen the first for which all the necessary data was available: November 11th, 2013. Last observation date is September 5th, 2017, for a total of 1395 observations.

Regarding the emission reward, BRBTC is constant over time: the initial reward was 50 BTC per generated block, an amount that halves every 210,000 blocks (about four years). In mathematical terms, the reward per block is given by a geometric progression:

$$BR_n = BR_1 * \frac{1}{2}^{n-1} \tag{8}$$

where BR1 is equal to 50 and n increases by 1 every 210,000 blocks;

As for the time needed to generate a block (BT), it is regulated by the following equation:

$$BT_s = \frac{D * 2^{32}}{H} \tag{9}$$

where 232 is a protocol constant that indicates the probability of finding the correct hash to generate a new block in a second.

Regarding the values of EFF, EC, MAN and FEES, no public estimates were available. Consequently, some assumptions as adherent to the empirical reality as possible were formulated:

- Cost of Electricity (CE). In order to estimate the cost of electricity consumed by a blockchain protocol, we used as proxies the average cost of energy for a US/European consumer (CEwest – 17.5 USD cents) and a Chinese industrial consumer (CEest – 4 USD cents). Assuming such estimates, a linear function was formulated with values ranging from 13.5 USD cents (0.7 * CEwest + 0.3 * CEest) at the end of 2013 to 6.7 USD cents (0.2 * CEwest + 0.8 * CEest) at the end of 2017;
- Energy efficiency of hardware (EFF). No estimate was available regarding the whole Bitcoin network's hardware level of energy efficiency. However, it was possible to trace that of the single hardware component level of energy efficiency. Given the relatively small number of device types and their relative homogeneity, a function was formulated to approximate the energy efficiency level through the following steps:
    - Division of the observation period in semesters;
    - For each semester, determination of a miner hardware sample;
    - Starting from a fair distribution of the overall network hashrate (33% for each of the three most efficient devices at day one), estimate of the hashrate distribution assuming a percentage of adoption of the latest equipment of 0.5% daily and, in a proportional way, a reduction of the most outdated equipment;
    - On the basis of the distribution calculated in the previous step, estimate of the number of devices used per day;
    - Calculation of the overall energy efficiency of the network as the product of the matrix between the energy efficiency of each device and the number of devices used daily.
- Hardware maintenance cost (MAN). For this element, which approximates the cost of maintenance and continual renewal of the mining equipment park, no prior reference literature was found, nor any publicly available estimate. The only thing that was possible to track was the price of the single hardware component. Similarly to what was proposed to estimate costs in the field of cloud computing by Li et al. (2009), we chose to use as a proxy to estimate the maintenance cost the daily amortization of the individual hardware components. Given, as in the previous case, the conditions of a small number of device types and their relative homogeneity, we proceeded to formulate a function approximating the cost of hardware maintenance as follows:
    - Estimate of the amortization rate of the single device. This value was calculated by dividing the price for the lifespan of a device (2,880 days for a GPU device and 540 for an ASIC device). In addition, we assumed the presence of an accelerated market growth phase (when hardware growth in the previous semester> 100%), during which the lifespan of a device is considered halved (due to the expectation of a miner to return from the investment in less time);

- Given the number of devices used daily calculated previously, estimate of the network maintenance cost as the product of the matrix between the amortization of each device and the number of devices used daily.

- Fees received (FEES). Fees received daily by miners have been calculated as the average daily fee per transaction (MFEE) and number of daily transactions (NOTR).

BR and BT formulas have been extracted directly from the protocol code source, hosted on https://github.com/bitcoin. CE values have been obtained by Wikipedia (https://en.wikipedia.org/wiki/Electricity_pricing), while data relatives to the miners distribution worldwide from Blockchain.info (https://blockchain.info). The specifics of mining equipment have been obtained from Bitcoin Wiki (https://en.bitcoin.it/wiki) and Crypto Junction (https://cryptojunction.com), while the average daily fee and the number of daily transaction from the website BitInfoCharts (https://bitinfocharts.com).

5 Results

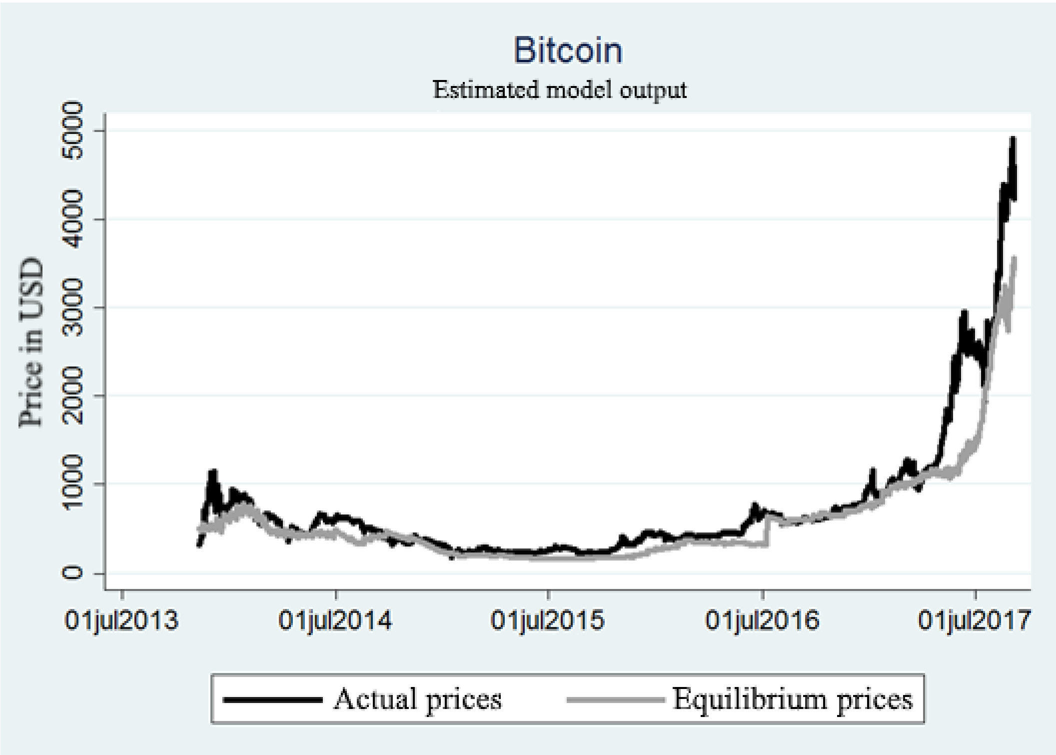

Figure 1. Bitcoin equilibrium model output.

As shown by the chart, the equilibrium prices trend almost resembles that of the actual prices during all the observation period, with a significant detachment starting from the beginning of 2017.

From a statistical point of view, as expected, the estimated equilibrium prices series and the actual prices series were found to be non-stationary once subjected to the Augmented-Dickey Fuller test, even at a logarithmic transformation level.

Therefore, a possible cointegration between the two series was tested. First, the number of lags was determined by using the Akaike Information Criterion. The number of lags selected was 7.

Once the lags were determined, Johansen tests were performed to verify the presence of cointegration; the p-values of both eigenvalue and trace tests were less than 5% for r = 1, leading us to the rejection the null hypothesis of absence of cointegration and to the assumption of presence of a cointegrating vector.

On the basis of the cointegration test results, a Vector Error Correction model was elaborated. The model thus obtained was statistically significant. From the VEC results, a double long-term relationship between the actual prices trend of Bitcoin and the estimated prices trend emerged, such that, in the first 7 days after a price increase of 1 %:

- the actual price drops (the first difference of the actual price lagged by seven periods has a statistically significant negative coefficient);
- the estimated price rises (the first difference of the estimated price lagged by seven periods has a statistically significant positive coefficient).

The coefficient of the cointegration vector was statistically significant with a negative value of -0.813. This implies that the complete transmission is approximately 81.3%, i.e. an increase of 1% of the actual price leads to a permanent increase in the estimated price of 0.813% in seven days.

6 Conclusions

The blockchain technology is the cornerstone of a new economic cooperation paradigm characterized by greater decentralization, transparency, security and privacy; a paradigm aimed at incorporating every trust-related concept – such as governance, accountability and risk – at a technological level, enabling the creation of a trustless and secure network without the need of intermediaries.

To date, cryptocurrencies represent the most widespread and relevant declination of this new technology. Following Catalini & Gans (2016) perspective we corroborate the importance of a broad and public network as a key factor for a cryptocurrency's success. As already happened with banknotes, also in the case the affirmation of this new type of money will depend not so much on the underlying technological breakthrough as on the acceptance of a network that makes use of it.

Given their decentralized nature, cryptocurrencies need that a part of their network carry out tasks typical of a central entity (primarily, the emission of new coins and the validation of transactions). In particular, we suggest the existence of a stable production infrastructure for Bitcoin; existence confirmed by the presence of a long-term relationship between the actual Bitcoin prices trend and that of its equilibrium prices estimated assuming such infrastructure.

Asserting that a blockchain protocol has a dedicated hardware infrastructure with cost and profit functions comparable to that of a normal production facility could have a huge impact both on the economical and the legal framework of this new technology.

The existence of such a system of price formation, in fact, makes:

- on the one hand, difficult to consider the price as a value based solely on hype and speculation;
- on the other hand, given the hybrid nature of a cryptocurrency of commodity and digital currency, easy to think of the first function as overwhelming compared to the second.

Bitcoin has created a new trusted, disintermediated and secure way of storing value. In fact, to date Bitcoin users prefer to retain bitcoins rather than exchanging them; the "store of value" function is much more pronounced than that of "mean of exchange". To assert that Bitcoin and other protocols are "digital gold" is not at all out of place, neither theoretically nor practically.

From a practical point of view, the proposed model could be used for predictive purposes. Its application would enable investors interested in this new technology to identify in advance the reaction of the markets after some specific types of exogenous shocks, such as the halving of units generated per block. After applying the developed model, at the beginning of September, we predicted that the price of Bitcoin would have increased from 4500$ to 8000$ by the end of the year. As of today – 27th November 2017 - Bitcoin has reached the all-time-high price of 9630$.

We believe that the difference between the estimated and the actual price can be justified taking into consideration some different kind of elements. In fact, although the market self-regulation mechanism seems logical from an empirical point of view, it is fair to point out that:

- is very likely that elements such as the greater acceptance of cryptocurrencies at a legal level, greater network diffusion, the birth and development of increasingly user-friendly cryptocurrencies wallets, are in the long-term Bitcoin price' driving forces;
- the market capitalization of Bitcoin remains very limited compared to the size of the global economy[3] - thus it could be easily influenced in an artificial way by some of the most involved actors in the ecosystem to maintain profitable the mining activity.

Even in this case, we believe that the marginal cost model would continue to provide a good indication of the minimum equilibrium price. This means that the model would not rule out the presence of speculative movements that interact with pricing mechanisms nor underestimate some of the most important elements of adoption as currency of a protocol (user confidence, ease of use, flexibility).

Given the adherence of the model to the empirical reality, further researches could be conducted applying the model presented in this study to other similar blockchain protocols.

[3] Bitcoin's market capitalization is 92 billion USD against the over 70 trillion estimated for the global stock market and the over 650 for the derivatives market.

7 Appendix

Period	Type	Model
1s 2012	GPU	AMD 7900
2s 2012	FPGA	X5000
1s 2013	FPGA	X6500
2s 2013	ASIC	Avalon 1
1q 2014	ASIC	Bitmain S1
2q 2014	ASIC	Bitmain S2
3q 2014	ASIC	Bitmain S3
4q 2014	ASIC	Bitmain S4
1s 2015	ASIC	Bitmain S5
2s 2015	ASIC	Bitmain S5+
1s 2016	ASIC	Bitmain S7
2s 2016	ASIC	Bitmain S9
1s 2017	ASIC	Bitmain S9

Table 1. Sample of devices used for Bitcoin mining.

Dickey-Fuller test for unit root Number of obs = 1394

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	0.667	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9892

Dickey-Fuller test for unit root Number of obs = 1394

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	0.824	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9920

Table 2. Results of the Augmented Dickey-Fuller test.

Selection-order criteria
Sample: 21nov2013 - 05sep2017 Number of obs = 1385

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1000.79				.00081	-1.4423	-1.43947	-1.43474
1	7508.85	13016	4	0.000	6.8e-08	-10.8344	-10.826*	-10.8118*
2	7513.68	9.659	4	0.047	6.7e-08	-10.8356	-10.8215	-10.7979
3	7518.93	10.494	4	0.033	6.7e-08	-10.8374	-10.8177	-10.7845
4	7525.21	12.571	4	0.014	6.7e-08	-10.8407	-10.8153	-10.7727
5	7528.46	6.4996	4	0.165	6.7e-08	-10.8397	-10.8086	-10.7565
6	7534.73	12.537	4	0.014	6.7e-08	-10.8429	-10.8062	-10.7447
7	7540.39	11.308	4	0.023	6.7e-08*	-10.8453*	-10.8029	-10.732

Table 3. Lag selection criteria.

Johansen tests for cointegration
Trend: constant Number of obs = 1388
Sample: 18nov2013 - 05sep2017 Lags = 7

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	26	6851.8308	.	36.6219	15.41
1	29	6870.0583	0.02845	0.1670*	3.76
2	30	6870.1418	0.00013		

Table 4. Results of the Johansen tests for cointegration.

Vector error-correction model

Sample:	18nov2013 - 05sep2017	Number of obs =	1,388
		AIC =	-10.77275
Log likelihood =	7505.287	HQIC =	-10.73184
Det(Sigma_ml) =	6.89e-08	SBIC =	-10.66336

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_logP	14	.018064	0.0248	34.98251	0.0015
D_logPE	14	.014701	0.0459	66.09808	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_logP						
_ce1						
L1.	-.0107906	.0052329	-2.06	0.039	-.0210469	-.0005342
logP						
LD.	-.0140194	.0272032	-0.52	0.606	-.0673367	.0392979
L2D.	-.057607	.0272045	-2.12	0.034	-.1109267	-.0042872
L3D.	-.0075638	.0272453	-0.28	0.781	-.0609635	.0458359
L4D.	.0659258	.0272154	2.42	0.015	.0125846	.119267
L5D.	.0441143	.0271382	1.63	0.104	-.0090757	.0973043
L6D.	.0787412	.0271451	2.90	0.004	.0255378	.1319446
logPE						
LD.	-.0262414	.0325179	-0.81	0.420	-.0899752	.0374925
L2D.	.069625	.0325109	2.14	0.032	.0059047	.1333452
L3D.	-.0245824	.0326161	-0.75	0.451	-.0885089	.039344
L4D.	.0138848	.0325642	0.43	0.670	-.0499398	.0777095
L5D.	.0501151	.0325232	1.54	0.123	-.0136292	.1138595
L6D.	-.0030065	.032503	-0.09	0.926	-.0667111	.0606982
_cons	.0007875	.0004981	1.58	0.114	-.0001887	.0017638
D_logPE						
_ce1						
L1.	.0239396	.0042587	5.62	0.000	.0155927	.0322865
logP						
LD.	.0364028	.0221386	1.64	0.100	-.0069881	.0797936
L2D.	-.0042142	.0221396	-0.19	0.849	-.047607	.0391787
L3D.	-.0762785	.0221728	-3.44	0.001	-.1197364	-.0328205
L4D.	-.0219453	.0221485	-0.99	0.322	-.0653555	.021465
L5D.	-.0569352	.0220857	-2.58	0.010	-.1002225	-.013648
L6D.	.0000371	.0220913	0.00	0.999	-.043261	.0433353
logPE						
LD.	-.0509923	.0264638	-1.93	0.054	-.1028604	.0008758
L2D.	-.0660632	.0264581	-2.50	0.013	-.1179202	-.0142062
L3D.	-.0400152	.0265438	-1.51	0.132	-.09204	.0120096
L4D.	-.0404027	.0265015	-1.52	0.127	-.0923446	.0115393
L5D.	-.038149	.0264681	-1.44	0.149	-.0900256	.0137276
L6D.	-.0423157	.0264517	-1.60	0.110	-.09416	.0095286
_cons	.000355	.0004054	0.88	0.381	-.0004395	.0011495

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	251.3083	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
logP	1	.	.	.	.	.
logPE	-.8131226	.0512924	-15.85	0.000	-.9136538	-.7125915
_cons	-.5771716	.	.	.	.	.

Table 5. Vector Error Correction model.

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