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DOI: https://doi.org/10.1088/2632-072X/ad00f7

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Journal of Physics: Complexity

PAPER

Disorder unleashes panic in bitcoin dynamics

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Keywords: disorder, bitcoin, panic selling, blockchain

OPEN ACCESS

RECEIVED
25 May 2023

REVISED
4 October 2023

ACCEPTED FOR PUBLICATION
6 October 2023

PUBLISHED
17 October 2023

Abstract

The behaviour of Bitcoin owners is reflected in the structure and the number of bitcoin transactions encoded in the Blockchain. Likewise, the behaviour of Bitcoin traders is reflected in the formation of bullish and bearish trends in the crypto market. In light of these observations, we wonder if human behaviour underlies some relationship between the Blockchain and the crypto market. To address this question, we map the Blockchain to a spin-lattice problem, whose configurations form ordered and disordered patterns, representing the behaviour of Bitcoin owners. This novel approach allows us to obtain time series suitable to detect a causal relationship between the dynamics of the Blockchain and market trends of the Bitcoin and to find that disordered patterns in the Blockchain precede Bitcoin panic selling. Our results suggest that human behaviour underlying Blockchain evolution and the crypto market brings out a fascinating connection between disorder and panic in Bitcoin dynamics.

1. Introduction

Blockchain [1, 2] is a distributed ledger technology introduced by Nakamoto [1], rapidly expanding in many sectors of our society, the economy and industry. Among the several applications, cryptocurrencies such as Bitcoin represent the most successful ones. Bitcoin is a digital currency whose transactions get managed by a fully decentralised system that hinges on a blockchain. The latter has a data structure composed of a chain of blocks. Each block stores a set of transactions commonly verified by block creators termed *miners* in this context. Within the block size limit, the miners can receive an incentive to add as many transactions as possible. Nevertheless, the chain of blocks keeps growing no matter the amount of executed transactions since, in principle, even blocks with no transactions can be mined and added to the chain. Before proceeding, let us clarify the naming convention used in this work. Bitcoin (Uppercase) refers to the cryptocurrency (i.e. BTC), and Blockchain (Uppercase) refers to the blockchain underpinning BTC. Then, we use blockchain (lowercase) for referring to blockchains underpinning other cryptocurrencies. Cryptographic protocols protect the Blockchain from double-spending [3] and other risks. Remarkably, while fiat money requires third-party authorities, such as banks, to verify transactions, Blockchain does not need any additional authority. Over the years, many blockchains based on new tokens, such as Bitcoin, have been implemented. These tokens are also called cryptocurrencies, or cryptos, due to the underlying cryptographic mechanisms supporting and securing transactions. Nowadays, a crypto ecosystem [4–7] which includes, for instance, Ethereum (ETH), XRP (XRP), Cardano (ADA), Bitcoin Cash (BCH), Solana (SOL), Dogecoin (DOGE), Bitcoin Satoshi Vision (BSV), and many other tokens, continuously grows. Many cryptos of such an

ecosystem get exchanged in the crypto market, today accessible by several trading platforms. Like in financial markets, the crypto market shows positive (i.e. bullish) and negative (i.e. bearish) trends resulting from the behaviour of traders. In summary, the behaviour of Bitcoin users, i.e. wallet owners, traders, and so on, is relevant to the evolution of the Blockchain and the crypto market. Yet, several questions remain unanswered in this complex socio-technical system. Among these issues, we are interested in the following: Does human behaviour underlie some relevant relationship between the Blockchain and the crypto market? The goal of this investigation is to face this question. To this end, focusing on the most relevant and capitalised crypto, i.e. Bitcoin, we map the Blockchain to a spin model, which allows assessing and measuring interactions with the crypto market. Hypotheses on the nature and the existence of these interactions rely on the following observation. Namely, since Blockchain records the structure of Bitcoin transactions, any anomaly, such as high amounts of transactions or weird input/output transaction patterns, may underly some critical events relating to the market value of Bitcoin. For instance, the sudden emptying of wallets performed by transferring Bitcoin towards a limited number of wallets may reflect the need to increase control over them or to get ready for other unusual actions. Before moving to the details of the proposed model and related results, we remark that the Blockchain and cryptocurrencies constitute a modern and expanding research area. Just to cite a few, previous investigations studied the Bitcoin price dynamics [8–11], the crypto network of transactions [12–19], the predictive signals [20], using social data [21–24] and machine learning-based approaches [25, 26], and the interplay between the network of Bitcoin transactions and the crypto market [27].

2. From data to model

Datasets used in this investigation refer to a time interval from 2012 to 2022, including about 518643 blocks and 730662636 transactions. Blockchain data can be accessed at [28] and crypto market data at [29]. Blockchain data describe blocks and contain Bitcoin transactions and other parameters such as the Timestamp and the Blockheight. For instance, the Timestamp corresponds to the time a block gets 'mined' (i.e. generated), whereas the Blockheight identifies the position of a block along the chain. As above-mentioned, we define a spin model by mapping blocks to vectors (see also [30]). In particular, we consider the following parameters: the number of transactions, the number of inputs, and the number of outputs per block. The number of transactions per block has a self-explanatory meaning, while the other parameters, which refer to the structure of transactions [2], need further details. To this end, we describe a simple transaction between Alice and Bob. Alice owns 3 BTC, collected from previous transactions, and wants to send 2.5 BTC to Bob. She previously received: 1.0 BTC, 0.35 BTC, 0.45 BTC, 0.9 BTC, and 0.3 BTC, each constituting an 'unspent transaction output' (UTXO) for a motivation later clarified. To send 2.5 BTC to Bob, she has to compose a transaction using a combination of UTXOs, e.g. choosing 1.0 BTC, 0.9 BTC, 0.45 BTC, and 0.35 BTC, whose summation equals 2.7 BTC. The chosen UTXOs constitute the inputs of the new transaction. Then, noting that the UTXO summation is greater than the amount of Bitcoin Alice wants to send to Bob, the transaction has two outputs. The first output is addressed to Bob's wallet (i.e. 2.5 BTC), while the other is to Alice's wallet (i.e. 0.2). These two outputs, in turn, become UTXOs that the respective receivers (i.e. Bob and Alice) can use for future transactions. Detailed information about the microstructure of the Blockchain, i.e. the content of its blocks, can be accessed by anyone, albeit the Bitcoin owners' identity remains preserved. Since every action in the crypto market (outside centralized exchanges, i.e. crypto trading platforms) is recorded in the Blockchain, it might be possible to extract partial information about agents' sentiments. In particular, anomalies in the transaction structure could reflect, as observed before, relevant market instabilities.

Coming back to our model, using three parameters, each block gets represented by a 3-dimensional normalised vector

$$\mathbf{B} = \frac{(\text{transactions}, \text{inputs}, \text{outputs})}{\|\mathbf{B}\|} \tag{1}$$

—see plot (A) in figure 1, and the Blockchain gets mapped to a one-dimensional lattice. The resulting structure resembles an n-vector model [31] with $n = 3$. Now, we highlight that the content of blocks cannot change over time, as the Blockchain is an immutable ledger. That entails spin vectors are *quenched* variables of the proposed model, namely never change state, albeit the chain grows as new spins add over time. For the sake of clarity, new spin vectors added to the chain cannot change the spin chain configuration. In summary, the Blockchain does not evolve as the well-known classical spin models. However, that does not prevent defining a Hamiltonian-like function (to which we refer to just as Hamiltonian for simplicity), for instance, by fixing an instant of time to consider a limited number of spin vectors. In addition, we may assume that the spin configuration we observe at a given time represents an equilibrium configuration obtained at some

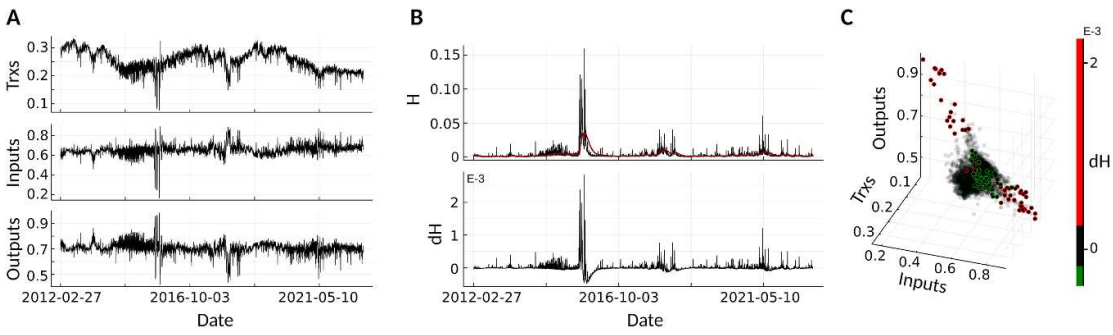

Figure 1. Blockchain evolution. (A) Time evolution of components of the normalized daily block state. (B) Local Hamiltonian (H) and the time derivative of its moving average (dH). The small fluctuations indicate blocks are usually very similar to each other. In July 2015, a clear peak shows up. (C) Phase space of the Blockchain. Each point represents the state of one daily block, associated with dH on a colour basis (above 98.5—below 1.5 percentile). Rapid increases in H (high values of dH) mostly correspond to days with unbalanced inputs-outputs components. Fast relaxations of H are restricted to the post Flood Attack period.

temperature. In general, the Hamiltonian of a spin model minimises at low temperatures as ordered spin patterns emerge. Similarly, it increases its value at high temperatures as disordered spin patterns show up.

As detailed below, the formation of ordered and disordered spin patterns offers valuable information to analyse the evolution of the Blockchain. Then, the Hamiltonian of the obtained spin model (see also [32]) reads

$$H(\mathbf{B};T) = \sum_{i,j} J_{i,j}\left(1 - \left(\mathbf{B}_i^{\intercal}\mathbf{B}_j\right)\right) \tag{2}$$

with $J_{i,j}$ interaction weight whose value is set to 0 if $i > j$, and $\mathbf{B}_i$ spin vector corresponding to the ith block of the chain (the index i represents the Blockheight and goes from 0 to T). The scalar products in equation (2) get close to 1 when consecutive vectors, i.e. blocks, are similar, otherwise get close to 0. Note that the scalar product usually can range from -1 to $+1$. However, according to the range of values of the selected block parameters, the scalar product can span the interval $[0, +1]$. Eventually, to include long-range interactions in the Hamiltonian, whose amplitude decays with the distance $J_{t-k,t} \sim e^{-\frac{k}{\tau}}$, equation (2) gets re-written as follows:

$$H(\mathbf{B};T) = \sum_{t=0}^{T} 1 - \sum_{k=1}^{t} \frac{e^{-\frac{k}{\tau}}}{Z_t}\mathbf{B}_{t-k}^{\intercal}\mathbf{B}_t \tag{3}$$

with $Z_t = \sum_{k=1}^{t} e^{-\frac{k}{\tau}}$. In doing so, each block interacts with all previous ones. However, the exponential term weights the interactions between blocks, decaying over long distances. Such a decay gets controlled by the parameter τ. Using the single components which sum over in equation (3), we obtain a collection of spin configurations that form ordered and disordered patterns. Lastly, we emphasise that the formation of ordered and disordered patterns in the 3-vector model can get exploited for studying the relationships between the Blockchain and trends of Bitcoin in the crypto market.

3. Results

The Hamiltonian defined in (3) can be decomposed in single contributions $H(\mathbf{B};T) = \sum_{t=0}^{T} H_t(\mathbf{B})$ forming a time series, to which we refer to as H. The latter, shown on the top of plot (B) in figure 1, gets computed by setting a τ small enough to include only significant long-range interactions limited to the previous 90 days. In addition, after applying an exponential moving average to H, we compute its time derivative. The resulting time series, i.e. dH, is shown at the bottom of plot (B) in figure 1. Interestingly, signals in figure 1 have a prominent peak temporally located around July 2015. After looking for the possible sources of such a peak, we found it corresponds to the *Flood* attack [33], a stress test performed to the Bitcoin network.

Rapid fluctuations in H seem to correspond to blocks with an unbalanced number of inputs relative to the number of transactions and outputs (see plot (C) in figure 1). In particular, the area identified by a low number of outputs and a high number of inputs could correspond to the emptying of wallets in the whole network, suggesting an attitude of concern for the future value of the crypto or even market manipulations.

Both H and dH can get used for studying causal relationships with the crypto market and related phenomena. To this end, we focus on the *BTC*/*USD* ratio (i.e. Bitcoin in American Dollars) and work on the

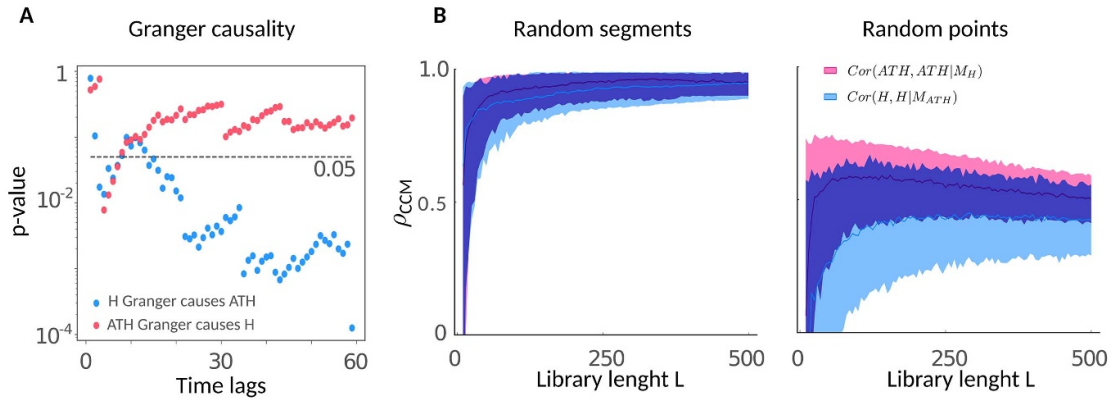

Figure 2. Causality test between H and ATH. (A) The p-value for Granger causality (using F-test) is shown as a function of time lags used in the fit. Increasing the knowledge of the past of H in forecasting ATH leads to higher significance in the test (always below $p = 0.05$), whereas the opposite is found when trying to forecast H using ATH. (B) The results of the CCM test for the same variables. The convergence to an asymptotic value of the reconstruction of the variables, increasing the library length, indicates causal relation in both directions. The test was performed, for each L, using 400 random points or contiguous segments. The straight lines are median values, and the error is computed with the 95th percentile.

time series composed of samples of the percentual drawdown from the All-Time-High of the BTC/USD ratio. Notably, these samples equal 1 every time Bitcoin overcomes its previous historical maximum:

$$\mathrm{ATH}(t) = \frac{\mathrm{Price}(t)}{\max_{t'<t}\{\mathrm{Price}(t')\}}. \tag{4}$$

Accordingly, the time series related to the BTC/USD ratio, which we refer to as ATH, and H have the same range. To study the causal relationship between the Blockchain and the crypto market, we use only the H time series, as H and dH are strongly related. However, we anticipate that the dH time series becomes particularly relevant in the subsequent analysis, being spontaneously centred in zero and quantifying the rapidity of divergence and relaxation compared with the quasi-steady state. Accordingly, we now aim to infer a causal relationship between H and ATH, whose task constitutes a complex and old problem [34]. For this purpose, we consider approaches relying on statistics and dynamical systems theory. For the first case, i.e. approaches based on statistics, we perform the Granger causality test [35]. Given two variables, x and y, the Granger causality test compares the forecasting quality of future values of y, of a standard ARMA model (Null-hypothesis), with the same ARMA having additional information on previous values of the variable x. More in detail, x is said to be Grange-cause of y whether the quality of the forecasting using information over x is significantly higher (p-value <0.05) than the quality of the forecasting obtained without x. The plot (A) in figure 2 shows the result of this test, whose variables are H and ATH. In that figure, we report the p-value as a function of previous data points used in the fit of the ARMA model. Interestingly, the quality of the fit improves as the forecasting of ATH exploits more information on H, i.e. more historical data, suggesting a strong causal effect of H over ATH. The reverse is not the case since, according to the p-value, we have to accept the Null-Hypothesis, i.e. ATH has no Granger causality over H. For the sake of completeness, we also perform a cross convergent mapping (CCM) [36, 37] test, which relies on dynamical systems theory and is deeply related to the Takens theorem and embedding theory [38]. In this case, we look for a deterministic causality, which means that if two variables belong to the same dynamical system, one of them could be reconstructed by using the other (and vice versa) via a delayed embedding. Here, we consider the quality of the reconstruction of a variable y through a second variable x, which we refer to as $y|M_x$. If such a quality increases with the number of data samples (defined as library length) the variable x causally influences y. Moreover, the faster the convergence to an asymptotic value of the CCM test, the stronger the dependence between the considered variables. A critical point of the CCM test lies in the sample selection to compose the library. So, following [39], we perform the CCM test composing the library of samples by a random selection of contiguous segments and by a random selection of samples. Results are reported in the plot (B) of figure 2. Here, we observe that both sampling strategies suggest a causal relationship between the two variables, i.e. H and ATH, in both directions.

We deem that the difference between the results obtained by the CCM test and the Granger causality test, i.e. a bi-directional causal relationship and a one-directional causal relationship, respectively, might be motivated considering that the Granger causality test can only detect linear causal relationships.

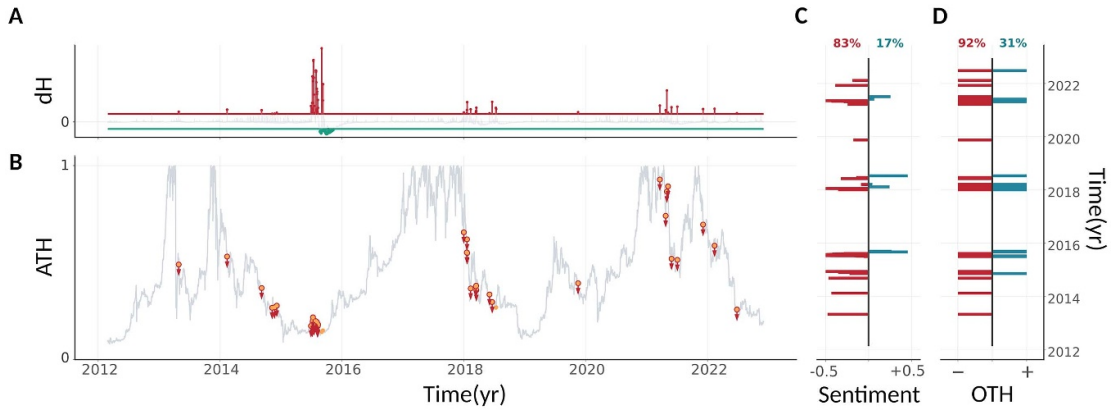

Figure 3. (A) The trend of the dH time series. Coloured lines indicate positive (red, above the 98.5 percentile) and negative (green, below the 1.5 percentile) fluctuations. (B)) Percentual drawdown from the All Time High in time. Coloured dots identify events of large fluctuations in dH. Red arrows highlight events followed by a decrease of at least 10% in the next 90 days. Rapid increases in the H time series can predict collapses in the *BTC* price, while fast relaxation may indicate a local market recovery. (C) Sentiment level after dH positive large fluctuation. In the 83% of cases, these events predate interval in which the *BTC* price remains below the initial price most of the time (taken a 90 day time window). (D) Boolean of the exceeding the minimum price change threshold ($\pm 10\%$, respectively $OTH = \pm$) after dH positive large fluctuation. 92% of these signals gets followed by a price reduction of at least -10% (in a 90 day time window), while only the 31% gets followed by a 10% price growth highlighting a clear downtrend.

In light of the above result, we study whether the H time series contains information to forecast Bitcoin trends in the crypto market. Remarkably, rapid variations of H predate large fluctuations of *ATH*. Therefore, the dH time series becomes particularly relevant for quantifying such phenomenon (figure 3). More in detail, we observe that rapid increases in the H time series (i.e. large positive fluctuations of dH) can predict collapses in the *BTC* value. In particular seems to well define the beginning of bear market periods, i.e. long periods of supply predominance—see plot (B) in figure 3. The 83% of positive large fluctuations of dH are followed by time interval in which the *BTC* price remains below the initial price most of the time (taken a 90 day time window) and the 92% precede a reduction of the *BTC* value of at least -10% (see plots (C) and (D) in figure 3).

In addition, Fast relaxations may indicate a local market recovery. Up to now such events are solely localized to the post Flood Attack months but mark the beginning of the subsequent bull market, i.e. a long period of demand predominance.

These results reinforce the idea that the structure of the blocks reflects the sentiment of agents operating in the market and that proximity to a course change can be extracted from them.

4. Conclusion

In summary, this work unveils relevant relationships between the dynamics of the Blockchain and the crypto market, focusing on the Bitcoin price. The investigation, motivated by observing that human behaviour affects both the dynamics of the Blockchain and those of the crypto market, exploits tools from statistical physics (see also [40]). More specifically, we generated time series describing the evolution of the Blockchain via a spin-lattice model. Such time series allowed us to obtain the following results. Firstly, we detected a causal relationship between the Blockchain and the crypto market, and then we found Blockchain contains information to forecast some trends in Bitcoin price. Remarkably, disordered patterns in the Blockchain, identified via the spin model, predate the phenomenon of Bitcoin panic selling, suggesting a fascinating connection between disorder and panic. To the best of our knowledge, the Forex market is not directly affected by the transactions individuals perform with a fiat currency like the Euro, e.g. buying a coffee, shopping, and making other daily payments. On the other hand, we found that the way simple transactions get performed on the Blockchain can potentially drive trends in the crypto market. Therefore, albeit the management of a fiat currency is drastically different from cryptocurrencies, we deem the above observation on the Forex market can further clarify the relevance of our findings. In addition, we recall that the reported analyses have a tight focus on single crypto, i.e. BTC. The latter is particularly representative in this domain, being the first created crypto and still the most capitalised in the market. Despite that, further investigations on a richer set of crypto assets are essential for corroborating our results. Before concluding, let us report a few observations about some previous investigations. In [10], authors highlight the potential role of Bitcoin transactions in driving the Bitcoin trading volume and price. That is confirmed by our results, as we show

that the number of Bitcoin transactions plays a role in forecasting the Bitcoin market trends. In addition, some ideas and outcomes of our investigation remind works [41, 42], which aimed at forecasting financial market trends by looking at Wikipedia and Google Trends analytics, respectively. Likewise, here we aim to foresee relevant phenomena in the crypto market, e.g. panic selling, by exploiting analytics data related to an external system, i.e. the Blockchain. Finally, we deem the proposed model sheds light on relevant aspects of Bitcoin dynamics. Therefore, future works based on this investigation could address the behaviour of other cryptocurrencies and assess whether related results can support the design of trading strategies for the crypto market.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://www.blockchain.com/.

Acknowledgments

M A J wishes to thank Marco Corradino, Mario Bortoli, and Cristiano Esclapon for stimulating discussions and helpful suggestions. M A J is supported by the PNRR NQST (Code: PE23).

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References

[1] Nakamoto S 2008 Bitcoin: a peer-to-peer electronic cash system (available at: https://bitcoin.org/bitcoin.pdf)
[2] Antonopoulos A M 2014 *Mastering Bitcoin: Unlocking Digital Cryptocurrencies* (O'Reilly Media, Inc.)
[3] Javarone M A and Wright C S 2018 Modeling a double-spending detection system for the bitcoin network (arXiv:1809.07678)
[4] ElBahrawy A, Alessandretti L, Kandler A, Pastor-Satorras R and Baronchelli A 2017 Evolutionary dynamics of the cryptocurrency market *R. Soc. Open Sci.* **4** 170623
[5] de Marzo G, Pandolfelli F and Servedio V D 2022 Modeling innovation in the cryptocurrency ecosystem *Sci. Rep.* **12** 1–12
[6] Tasca P and Tessone C J 2019 Taxonomy of blockchain technologies. Principles of identification and classification *Ledger* **4** 1–39
[7] Spychiger F, Tasca P and Tessone C J 2021 Unveiling the importance and evolution of design components through the "tree of blockchain" *Front. Blockchain* **3** 613476
[8] Kristoufek L 2015 What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis *PLoS One* **10** e0123923
[9] Blau B M 2017 Price dynamics and speculative trading in bitcoin *Res. Int. Bus. Finance* **41** 493–9
[10] Aalborg H A, Molnár P and de Vries J E 2019 What can explain the price, volatility and trading volume of Bitcoin? *Finance Res. Lett.* **29** 255–65
[11] Amjad M and Shah D 2017 Trading bitcoin and online time series prediction *NIPS 2016 Time Series Workshop (PMLR)* pp 1–15
[12] Javarone M A and Wright C S 2018 From Bitcoin to Bitcoin Cash: a network analysis *Proc. 1st Workshop on Cryptocurrencies and Blockchains for Distributed Systems—ACM* pp 77–81
[13] Vallarano N, Tessone C J and Squartini T 2020 Bitcoin transaction networks: an overview of recent results *Front. Phys.* **8** 286
[14] Lin J H, Primicerio K, Squartini T, Decker C and Tessone C J 2020 Lightning network: a second path towards centralisation of the Bitcoin economy *New J. Phys.* **22** 083022
[15] Campajola C, Cristodaro R, De Collibus F M, Yan T, Vallarano N and Tessone C J 2022 The evolution of centralisation on cryptocurrency platforms (arXiv:2206.05081)
[16] De Collibus F M, Partida A, Piškorec M and Tessone C J 2021 Heterogeneous preferential attachment in key ethereum-based cryptoassets *Front. Phys.* **568**
[17] De Collibus F M, Piškorec M, Partida A and Tessone C J 2022 The structural role of smart contracts and exchanges in the centralisation of ethereum-based cryptoassets *Entropy* **24** 1048
[18] Lin J H, Marchese E, Tessone C J and Squartini T 2022 The weighted Bitcoin lightning network *Chaos Solitons Fractals* **164** 112620
[19] Bartolucci S, Caccioli F and Vivo P 2020 A percolation model for the emergence of the Bitcoin Lightning Network *Sci. Rep.* **10** 4488
[20] Yu M 2019 Forecasting bitcoin volatility: the role of leverage effect and uncertainty *Physica* A **533** 120707
[21] Ortu M, Uras N, Conversano C, Bartolucci S and Destefanis G 2022 On technical trading and social media indicators for cryptocurrency price classification through deep learning *Expert Syst. Appl.* **198** 116804
[22] Garcia D, Tessone C J, Mavrodiev P and Perony N 2014 The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy *J. R. Soc. Interface* **11** 20140623
[23] Garcia D and Schweitzer F 2015 Social signals and algorithmic trading of Bitcoin *R. Soc. Open Sci.* **2** 150288
[24] Matta M, Lunesu I and Marchesi M 2015 Bitcoin spread prediction using social and web search media *UMAP Workshops* pp 1–10
[25] Cocco L, Concas G and Marchesi M 2017 Using an artificial financial market for studying a cryptocurrency market *J. Econ. Interact. Coord.* **12** 345–65
[26] Alessandretti L, ElBahrawy A, Aiello L M and Baronchelli A 2018 Anticipating cryptocurrency prices using machine learning *Complexity* **2018** 1–16
[27] Kondor D, Csabai I, Szüle J, Pósfai M and Vattay G 2014 Inferring the interplay between network structure and market effects in bitcoin *New J. Phys.* **16** 125003
[28] Blockchain.com 2022 (available at: www.blockchain.com/) (Accessed 20 September 2022)
[29] Glassnode Studio 2022 (available at: https://studio.glassnode.com/metrics?a = BTC&m = addresses.ActiveCount) (Accessed 20 September 2022)

[30] Dai D, Bao F S, Zhou J and Chen Y 2016 Block2vec: a deep learning strategy on mining block correlations in storage systems *45th Int. Conf. on Parallel Processing Workshops (ICPPW)* (IEEE) pp 230–9
[31] Stanley H E 1968 Dependence of critical properties on dimensionality of spins *Phys. Rev. Lett.* **20** 589
[32] Welsh D J and Merino C 2000 The Potts model and the Tutte polynomial *J. Math. Phys.* **41** 1127–52
[33] 2017 July 2015 flood attack (available at: https://en.bitcoin.it/wiki/July_2015_flood_attack) (Accessed 20 September 2022)
[34] Cecconi F, Cencini M, Falcioni M and Vulpiani A 2012 Predicting the future from the past: an old problem from a modern perspective *Am. J. Phys.* **80** 1001–8
[35] Granger C W J 1969 Investigating causal relations by econometric models and cross-spectral methods *Econometrica* **1969** 424–38
[36] Sugihara G, May R, Ye H, Hsieh C H, Deyle E, Fogarty M and Munch S 2012 Detecting causality in complex ecosystems *Science* **338** 496–500
[37] Vinci G V and Benzi R 2018 Economic complexity: correlations between gross domestic product and fitness *Entropy* **20** 766
[38] Kantz H and Schreiber T 2004 *Nonlinear Time Series Analysis* (Cambridge University Press)
[39] Luo M, Kantz H, Lau N-C, Huang W and Zhou Y 2015 Questionable dynamical evidence for causality between galactic cosmic rays and interannual variation in global temperature *Proc. Natl Acad. Sci.* **112** E4638–9
[40] Galam S 2016 The invisible hand and the rational agent are behind bubbles and crashes *Chaos Solitons Fractals* **88** 209–17
[41] Moat H S, Curme C, Avakian A, Kenett D Y, Stanley H E and Preis T 2013 Quantifying Wikipedia usage patterns before stock market moves *Sci. Rep.* **3** 1–5
[42] Preis T, Moat H S and Stanley H E 2013 Quantifying trading behavior in financial markets using Google Trends *Sci. Rep.* **3** 1–6