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Network effects and store-of-value features in the cryptocurrency market

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ABSTRACT

It is important to determine the network effects and store-of-value feature of cryptocurrencies due to the argument that it could be considered as a new 'asset class'. Current studies on cryptocurrencies' network effects mainly focused on using Metcalfe's Law to evaluate the relationship between cryptocurrency prices and the squared number of active wallets addresses. In terms of cryptocurrencies' store-of-value features, previous studies primarily compared daily volatility of limited number of popular cryptocurrencies to Gold. Extant studies are also based on out-of-date data. This research extends the literature by using up-to-date daily data of a sample of the top 100 cryptocurrencies covering 2010–2023 to explore the network effects and the store of value characteristics of a wide range of cryptocurrencies. Firstly, we used nonlinear regression models to examine the relationship between cryptocurrency prices and active wallets addresses, the number of transactions and circulations. Secondly, to deepen our understanding of the store-of-value features of cryptocurrencies, we used a combination of GARCH models and time series analysis to explore the volatility in the daily returns of the sampled cryptocurrencies. Findings indicate that at least one of the network factors (i.e., active wallets addresses, the number of transactions, and number of circulation supply) have a significant effect on cryptocurrency prices. The study also finds that stable coins have comparable daily volatility as Gold, while only mature cryptocurrencies, such as PAXG, Bitcoin, Ethereum, BNB and LINK, demonstrate strong correlation with Gold. Bitcoin also showed a high positive time-series correlation with 24 of the 42 cryptocurrencies. Findings from this study provide important insights to investors, market analysts, regulators and other stakeholders on the marketisation and the store of value potentials of cryptocurrencies.

1. Introduction

In 2008, the pseudonymous Satoshi Nakamoto developed Bitcoin [1]. Since then, based on blockchain technology, an explosion of alternative cryptocurrencies have emerged. The cryptocurrency market capitalisation was estimated at 1.22 trillion USD on June 22, 2023 [2], which is quite desirable in the global assets market. This 'supposed' new assets class has drawn broad interests from investors, traders, market regulators and academic researchers. However, according to European Supervisory Authorities [3], cryptocurrencies, such as Bitcoin, are subject to extreme price volatility and have shown clear signs of a pricing bubble. ESMA warned that investors should be aware that there is a high risk of losing a large amount, or even all of the money invested in cryptocurrencies.

Blockchain enthusiasts, cryptocurrency investors regulators and finance researchers [4,5] have been investigating the driving factors of cryptocurrency prices. Various models have been developed to explore the network effects using squared number of active wallets addresses as independent variable, and to examine the store-of-value features of cryptocurrencies by comparing their volatility with other asset classes. Extant studies have focused on the limited number of the most popular cryptocurrencies, such as Bitcoin and Ethereum [6,7], and have often used out-of-date datasets (i.e., prior to 2019). Although some recent studies [8,9] have examined the economic behaviour of various altcoins, they have often neglected their network effects and store of value features. For example, Vidal-Tomás [8] examined the explosive dynamics in the metaverse niche using 196 available metaverse fungible tokens and all the non-fungible token transactions belonging to the metaverse marketplace. Demir et al. [9] examined the impact of investor mood changes and football match results on fan token prices of the clubs. They found that match results, especially losses, from UEFA Champions League significantly affected the fan token abnormal returns, while domestic matches and Europa League matches were not followed by similar reactions from the investors. Therefore, there is a lack of general

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and broad valuation of different cryptocurrencies. Meanwhile, the effects of the Covid pandemic, Ukraine conflicts and other recent current affairs cannot be accounted for if the data is as old as 2019. Therefore, the aim of this research is to evaluate the network effects and store-of-value capability of a large range of cryptocurrencies using the datasets as recent as 2023. The first part of this study used nonlinear regression models for each cryptocurrency to evaluate the comprehensive relationship between cryptocurrency prices and the number of active wallets addresses, the number of transactions and number of supply circulations. The second part of this study adopted daily volatility comparison, GARCH analysis and time-series correlation to examine the store-of-value feature of different cryptocurrencies. The rest of the paper is organized as follows: Section 2 presents the literature review; Section 3 details the research methodology; Section 4 presents the dataset and the empirical results while Section 5 concludes.

2. Literature review

2.1. Theoretical context – Metcalfe's law

Metcalfe's Law is a theoretical concept used to represent the value of a network. Metcalfe's law states that a network's true value is its squared number of nodes (i.e., users). The model uses a generalised sigmoid function called the netoid to show the growth of users. As users grow, the value of a network grows exponentially according to this law. For example, if a network had 10, then its intrinsic value is 100. If 2 new users were to join the network, the value would be 144, increasing by 44% despite only growing by two users. This framework was originally tested on Facebook and its user growth, finding a strong relationship between Metcalfe's law and the companies associated revenue [10]. Zhang et al. [11] validated the use of Metcalfe's Law as a valuation method by using the model on Tencent and Facebook, finding that Metcalfe's law fitted the data well. Hove's [12] study on Metcalfe's law extended Zhang et al. [11] findings by filtering out costs and revenues that were unrelated to social network services and found that Metcalfe's law could provide useful explanations for network value. Despite the validity of Metcalfe's law, Metcalfe [10] himself agrees with critics who argued that although the law is proven, it could be a gross overestimation of value. This study is underpinned by this theoretical framework.

2.2. Network valuation

Network factors were originally modelled in the context of competing technologies [13–15]. Dowd and Greenaway [16] were the first set of researchers who assumed that money also follows the network effect. The network effect means that the value granted to the owner of a currency is dependent on the number of other owners' participation in the transactions with that particular currency. In terms of the network effects of cryptocurrencies, previous studies have mainly focused on limited number of famous cryptocurrencies. For example, Alabi [17] analysed the blockchain networks of Bitcoin, Ethereum and Dash to test whether they satisfy Metcalfe's Law using the cryptocurrency data during the period between 2009 and 2017. The network value was modelled based on the price of the chosen cryptocurrency, while the number of users was represented by the number of unique addresses that engaged in transactions. The analysis showed that Bitcoin, Ethereum and Dash prices substantially reflected Metcalfe's Law. Peterson [18] validated the use of Metcalfe's Law as a valuation model for Bitcoin using one year's cryptocurrency data (i.e., 2013–2014). He used the number of active wallets addresses to represent the connected Bitcoin users, whist testing its relationship with cryptocurrency price. The results of the regression showed that Bitcoin price was significantly correlated to squared number of active wallets addresses with an R^2 value of 0.85. Vliet [19] made two changes to Peterson's model for valuing Bitcoin by using a bounded exponential function and modelling growth as a logistic function, which enabled forecasting of the number of Bitcoins and the logistic diffusion. The study covered January 2009 and November 2011, using regression analysis to test the Bitcoin's Metcalfe value against its market capitalisation. The results showed an R^2 value of 0.9977 thus demonstrating more significance than Peterson's [18] research. Wheatley [20] proposed a new method by combining a generalised Metcalfe's Law and the Log-Periodic Power Law Singularity (LPPLS) model to evaluate the herding and imitation of Bitcoin. The Bitcoin dataset covered the period 2010–2018. Shanaev et al. used Metcalfe's Law to test six proof-of-work cryptocurrencies (i.e., Bitcoin, Litecoin, Bitcoin Cash, Bitcoin SV, Dash and Dogecoin) using the dataset from 2014 to 2019. They found that there was no positive effect from hash rate and the number of transactions on cryptocurrency prices. Pele [21] investigated the statistical properties of Bitcoin using alpha-stable distributions, Metcalfe's Law and the bubble behaviour through the LPPLS modelling using the dataset from 2013 to 2018. They found that the validity of Metcalfe's Law for the evaluation of cryptocurrencies did exist in the medium to long term (i.e., longer than 250 days); however, its validity was questionable in short-term (i.e., 60–90 days) analysis. To validate previous literature and to assist in determining the best method of valuation for cryptocurrencies, we test the following hypothesis.

Hypothesis 1. There is a relationship between network factors (i.e., number of active wallet addresses, number of transactions, and number of circulation supply) and cryptocurrency prices.

2.3. Store of value analytics

Bitcoin is the only cryptocurrency that has previously been compared to Gold because it shares similar characteristics with Gold [22]. For example, they both have limited supply and are therefore scarce. Bitcoin is also costly to mine due to its proof-of-work consensus algorithm and large computational power required. It has also demonstrated great resilience during periods of turmoil, which highlights its potential hedging and safe haven abilities against global uncertainty [23]. Therefore, Bitcoin may be viewed as a store of value, in other words, an asset that maintains value without depreciating over time [24]. Yermack [25] explored this by testing Bitcoin based on the three functions of money: a measure of exchange, store of value, and unit of account, but found that Bitcoin did not meet any of these criteria. Yermack concluded that Bitcoin could not serve as a store of value due to its extreme level of volatility and lack of price stability. Kubat [26] built on this argument by suggesting that investing in Bitcoin is more of a risk than any other investment after comparing Bitcoin's volatility to other assets (i.e., Gold, Euro and Polish Zloty), therefore, suggesting that Bitcoin should be completely ruled out as a store of value. In contrast, Dyhrberg [22] compared Bitcoin to Gold, the US dollar and the FTSE index by using GARCH volatility models to test for correlations. The analysis used daily cryptocurrency and stock data between 2010 and 2015, finding that Bitcoin can be useful in hedging against the US dollar and the FTSE stock index in the short term, as on average they were uncorrelated. Therefore, he concluded that Bitcoin may have risk management capabilities through portfolio diversification. Baur et al. [27,28] replicated Dyhrberg's study using GARCH volatility models based on the same data and time period. However, Baur et al.'s findings and interpretations contradicted Dyhrberg's findings, as the coefficient estimation showed that Bitcoin was not related to contemporaneous changes of the US dollars, and it could not be used as a hedge. In addition, although Bitcoin was uncorrelated with all other assets including the return of Gold, which supported using Bitcoin for portfolio diversification, this did not imply that Bitcoin was similar to Gold [27]. Ugolini et al. [29] examined the return spillovers within and between different Decentralised Finance (DeFi), cryptocurrencies (i.e., Bitcoin, Ethereum, Tether, and BNB), stock and safe-haven assets. They found that DeFi assets and cryptocurrencies exhibit the highest spillovers while the safe-haven assets were those least connected with each other assets. Due to the dearth of studies on this issue and the value in exploring the potential for cryptocurrency to be a store of value, the current study predicts as below.

Hypothesis 2. Cryptocurrencies behave as a store-of-value assets.

2.4. Research gaps and innovation

Although various studies have evaluated the network effects of cryptocurrencies using Metcalfe's Law and its store-of-value capabilities by testing its volatility, significant research gaps are identified as follows. Firstly, only limited number of popular cryptocurrencies, such as Bitcoin, Ethereum, Dash Litecoin, Bitcoin Cash, Bitcoin SV, Dash, Dogecoin, Tether, and BNB, have been tested in previous studies. There is a lack of study exploring a wider range of new cryptocurrencies using Metcalfe's Law and assessing cryptocurrencies' store of value potentials. Secondly, existing studies have mostly used out of date data as most of the cryptocurrency data was collected before 2019. This only represents the early stage of cryptocurrencies. The global cryptocurrency market capitalisation has increased from 126 billion USD in early 2020 and reached a peak at 1.22 trillion USD on June 22, 2023 [2]. The network effects and store-of-value capability may have been changed due to the maturity of cryptocurrencies and other social events. These facts have not been considered in the extant literature.

Furthermore, only the number of active wallets addresses has been treated as network effect, and most of the studies investigated the relationship between squared number of active wallets addresses and cryptocurrency prices. Other factors such as the number of daily transactions and supply circulations have not been considered in the extant literature. Fourthly, in terms of cryptocurrencies' store of value capability, extant studies have mainly compared GARCH volatility of Bitcoin with US dollars and FTSE100. However, it is important to explore its comparison to other traditional asset class to deepen our understanding on its store-of-value potentials. Consequently, this study used GARCH model and time series analysis to compare cryptocurrencies volatility to a wide range of other traditional assets such as Gold, VDE Energy, Crude oil and S&P500.

3. Methodology

This section presents the data collection and analysis undertaken in the study. The nonlinear regression model is developed to evaluate the network effects of different cryptocurrencies. Meanwhile, daily, monthly and annual volatility; Pearson correlation; and GARCH volatility analysis are adopted to evaluate the store-of-value capability of different cryptocurrencies.

3.1. Data collection

We selected the top 100 cryptocurrencies based on market capitalisation (coinmarketcap.com) on June 1, 2023 as our initial sample [30]. However, lack of historical information and prices of some cryptocurrencies resulted in reduced sample size to 42 cryptocurrencies. The daily close prices, number of active wallets addresses, daily count of transactions, and circulation supply during the period between the birth of each cryptocurrency (i.e., as far back as July 2010) till May 31, 2023 of the selected 42 cryptocurrencies were collected through the database provided by Coinmarketcap. As demonstrated by Alexander [31] and Vidal-Tomas [32], Coinmarketcap is one of the most reliable sources of data on cryptocurrency. We also collected historical daily data on the close prices of Gold, Crude oil, Vanguard Energy ETF (VDE) Energy, S&P500, and FTSE100 within the range of July 19, 2010 and May 31, 2023 from yahoo stock (Yahoo! Finance [33]). We used July 19, 2010 as this is the earliest available daily closes price of Bitcoin, the oldest cryptocurrency.

3.2. Network effects analysis

Metcalfe's Law states that the value of a network is equal to the squared number of nodes [10]. Consistent with previous studies [17–19], we used the number of active wallets addresses to proxy for the number of nodes component in the formula for Metcalfe's Law. To test Hypothesis 1 and analyse whether cryptocurrency price is affected by its network effects, we used a nonlinear regression model to test the correlation between the number of active wallets addresses, number of transactions, number of circulation supply and cryptocurrency prices, as shown in Eq. (1).

$$Y_{i,t} = \alpha_{0,i} + \alpha_{1,i}X_{1,i,t}^{\beta_1} + \alpha_{2,i}X_{2,i,t}^{\beta_2} + \alpha_{3,i}X_{3,i,t}^{\beta_3} + \varepsilon_{i,t} \tag{1}$$

i: Different cryptocurrencies

T: Time frame.

Y: Cryptocurrency prices.

$X_{1,i,t}$: Number of active wallets addresses for cryptocurrency i at time step t.

$X_{2,i,t}$: Number of transactions for cryptocurrency i at time step t.

$X_{3,i,t}$: Number of circulation supply for cryptocurrency i at time step t.

$\alpha_{0,i}$: Intercept for cryptocurrency i.

$\alpha_{1,i}$, $\alpha_{2,i}$, $\alpha_{3,i}$: Linear coefficients of independent variables for cryptocurrency i.

$\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$: Power coefficients of independent variables for cryptocurrency i.

$\varepsilon_{i,t}$: Error term of the nonlinear regression model for cryptocurrency i at time step t.

The number of active wallets addresses, number of transactions and number of circulation supply are independent variable, while cryptocurrency price is the dependent variable. The number of active wallets addresses refers to total number of unique addresses that are active in the network at that time step. All parties in the ledger change action are counted while individual addresses are not double counted. One of the novelties of this paper is that the power coefficient of each independent variable is selected through a trial-and-error process within the range between 0 and 6 with an interval of 0.5. The optimal combination of three power coefficients is determined to achieve the smallest R^2 value of the non-linear correlation. Metcalfe's Law can only represent the linear correlation between the squared number of active wallet addresses and cryptocurrency prices, while this non-linear correlation can describe a more precise relationship among the number of active wallets addresses, the number of transactions, the number of circulation supply and cryptocurrency prices. Especially, a larger power coefficient indicates that the independent variable has a larger effect on the dependent variable.

3.3. Store of value analysis

The store of value describes an asset that maintains stability in value over a long period of time. Due to the prematurity of the cryptocurrency asset class, it is essential to examine the connectedness among different cryptocurrencies and traditional assets such as Gold, Crude oil, Vanguard Energy ETF (VDE), S&P500, and FTSE100 index to determine the extent to which they behave similarly. Since Gold has traditionally been the main store of value instrument against inflation and volatile assets, it has been selected to represent the precious metal markets [34]. Crude oil has been a vital element of the economy in different sectors such as transportation, agriculture, telecommunication and other industrial activities [35]. VDE is designed to provide broad exposure to the Energy Broad segment of the equity market [36]. The S&P500 index is the weighted market capitalisation index obtained from the 500 largest publicly traded companies in the US based on their market value, which is considered as the best indicator of the large-scale US stocks [37]. Meanwhile, FTSE100 index comprises the 100 most highly market capitalised blue-chip companies, representing about 81% of the UK market, and it is regarded as the best indicator of the large-scale UK stocks [38]. The daily volatility of each asset has been calculated from the standard deviation of daily return, as demonstrated in Eq. (2).

$$V_{d,i} = \sqrt{\frac{\sum_{t=1}^{t=N}\left(R_{i,t}-\mu_i\right)^2}{N_i}} \tag{2}$$

Where, $R_{i,t}$, calculated from Eq. (3), is the daily return of cryptocurrency or asset i on the tth day. μ_i is the average value from the population of the daily returns, and N is the total number of available days.

$$R_{i,t} = \frac{P_{i,t}-P_{i,t-1}}{P_{i,t-1}} \tag{3}$$

Where, $P_{i,t}$ is the daily close price of cryptocurrency or asset i on the tth day. Monthly volatility $V_{m,cr,i}$ and annual volatility $V_{a,cr,i}$ of cryptocurrencies are calculated using Eqs. (4) and (5), respectively, while monthly volatility $V_{m,ta,i}$ and annual volatility $V_{a,ta,i}$ of traditional assets (i.e., Gold, Crude oil, VDE Energy, S&P500, and FTSE100) are estimated using Eqs. (6) and (7), respectively. The difference in the number of days is due to the fact that cryptocurrency can be traded every day, and not affected by the weekends and public holidays. We assume that there are 21 trading days per month and 252 trading days per year for the traditional assets [39].

$$V_{m,cr,i} = \sqrt{30}V_{d,i} \tag{4}$$

$$V_{a,cr,i} = \sqrt{365}V_{d,i} \tag{5}$$

$$V_{m,ta,i} = \sqrt{21}V_{d,i} \tag{6}$$

$$V_{a,ta,i} = \sqrt{252}V_{d,i} \tag{7}$$

We used Pearson correlation to evaluate the correlation among different cryptocurrencies and traditional assets, as shown in Eq. (8).

$$r = \frac{n\sum_{t=1}^{t=n}P_{i,t}P_{j,t} - \left(\sum_{t=1}^{t=n}P_{i,t}\right)\left(\sum_{t=1}^{t=n}P_{j,t}\right)}{\sqrt{n\sum_{t=1}^{t=n}{P_{i,t}}^2 - \left(\sum_{t=1}^{t=n}P_{i,t}\right)^2}\sqrt{n\sum_{t=1}^{t=n}{P_{j,t}}^2 - \left(\sum_{t=1}^{t=n}P_{j,t}\right)^2}} \tag{8}$$

Where, $P_{i,t}$ and $P_{j,t}$ are close prices of cryptocurrencies or assets i and j, n is the total number of available observations during the same time period. If two assets have different available observations during their time frame, the common available observations during the time frame will be selected.

The GARCH model was introduced by Bollerslev [40] as a generalization of ARCH model [41] and it is one of the most popular models for evaluating the volatility of time series data [42]. GARCH models with heteroscedastic errors are especially applicable to modelling financial market data which are highly volatile [43,44]. Therefore, we used GARCH model to evaluate the conditional variance as it allows the volatility at previous time step to be considered, as presented in Eq. (9).

$$\sigma_{i,t}^2 = \omega_i + \sum_{k=1}^{q}\alpha_{k,i}V_{t-k,i}^2 + \sum_{l=1}^{p}\beta_{l,i}\sigma_{t-l,i}^2 + \varepsilon_{i,t} \tag{9}$$

Where, ω_i is the weighted long-term variance, V_{t-k} is the immediate volatility during the previous period (t-k), and $V_{t,i} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, σ_{t-l} is the immediate variance during the previous period (t-l), ω_i, $\alpha_{k,i}$ and $\beta_{l,i}$ are fitting coefficients of the GARCH model for each cryptocurrency or asset. In this study, we set p = 1 and q = 1 to take only one time step lag as in most of previous GARCH stock market studies [22,27,28,45]. Therefore, Eq. (9) can be simplified as Eq. (10):

$$\sigma_{i,t}^2 = \omega_i + \alpha_{1,i}V_{t-1}^2 + \beta_{1,i}\sigma_{t-1}^2 + \varepsilon_{i,t} \tag{10}$$

4. Results and discussion

We present the results of our network analysis and store-of-value capability analysis in this section focusing on comparing the dynamics in prices of the cryptocurrency to other traditional asset classes.

4.1. Descriptive statistics

Tables 1 and 2 present the descriptive statistics of cryptocurrency compared to the traditional asset classes respectively. Bitcoin has the largest number of observations, as it is the oldest cryptocurrency. The observations of BNB, DOT, UNI, ICP, AAVE and 1INCH is smaller than 1000, because they are relatively new cryptocurrencies and were born after 2020. LEO has the smallest average number of active wallets addresses (i.e., 20) and transactions (i.e., 26) because it has few use cases outside Bitfinex [46,47]. WBTC has the largest average prices (i.e., 23, 203.26 USD), but the smallest number of circulation (i.e., 119,914). DOGE has the smallest average prices (i.e., 0.04 USD), TRX has the largest average number of active wallets addresses (i.e., 788,423), while XLM has the largest average number of circulation (i.e., 14 billion). In terms of traditional assets, the different number of observations are due to the different number of trading days. Crude oil has the smallest average price at 71.43 USD while FTSE100 index has the largest average price at 6632.41 USD.

4.2. Network analysis

The analysis in this study builds upon previous literature (i.e., as mentioned in Section 2) by expanding the scope of cryptocurrencies studied through Metcalfe's Law. Analysing 42 cryptocurrencies using a nonlinear regression with independent variables of number of active wallet addresses, number of daily transactions and number of circulations, it shows that most cryptocurrencies can be viewed as a network. As such, when the number of active wallet addresses, or the number of transactions or the number of circulations increases, the network gains value. To test Hypothesis 1, the statistical results of nonlinear regression model (Eq. (1)) are summarised in Table 3. The power coefficients of each independent variable are determined through a trial-and-error process and summarised in Columns 1–3. The linear coefficients are estimated from fitting the regression model and summarised in Columns 4–6. In our model, once β_1, β_2 and β_3 are set, $X_1^{\beta_1}$, $X_2^{\beta_2}$ and $X_3^{\beta_3}$ are regarded as independent variables. Therefore, Eq. (1) is converted to linear regression, while the standard error, t-value and p-value are determined for $X_1^{\beta_1}$, $X_2^{\beta_2}$ and $X_3^{\beta_3}$, respectively, and summarised in Columns 7–9, 10–12 and 13–15, respectively. The performance index of the regression model, such as coefficient of determination (R^2), F-statistic, p-value of F-statistic, loglikelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), are summarised in Columns 16–22. R^2 represents the proportion of the variance in the independent variables that can be explained by the dependent variable, where 0 indicates that the independent variables cannot be explained by the dependent variable while 1 indicates that the independent variables can be perfectly explained by the dependent variable. F-statistic tests the regression model as a whole and indicates whether the regression model provide a better fit to the data than a model that contains no independent variables. Probability is the p-value associated with the F-statistic. Log-likelihood value measures the goodness of fit of the regression model. AIC and BIC are common methods for scoring the regression model, while BIC penalizes the model more for its complexity [48].

Table 3 shows that the p-value of the F-statistics (Column 19) of almost all the cryptocurrencies are smaller than 0.01. This indicates that at least one of the independent variables, including the active wallet

Table 1
Descriptive variables of cryptocurrency data collection. (N.A. Not available due to lack of data collection).

Cryptos	Observation	Mean				Standard deviation				Minimum				Maximum			
		Address	Price (USD)	Circulation	Transaction	Address	Price (USD)	Circulation	Transaction	Address	Price (USD)	Circulation	Transaction	Address	Price (USD)	Circulation	Transaction
BTC	4702	500866	9132.94	12309200	179920	373327	14573.20	2749462	123860	408	0.05	3447800	94	1366494	67541.76	14647592	685711
ETH	2855	347296	853.99	99336690	695721	302246	1096.50	13276040	449982	1113	0.42	59596399	1329	7157228	4811.16	112764016	1932711
USDT	3161	3548	0.99	1012491808	6057	6674	0.02	861395639	11217	0	0.82	100	0	81005	1.11	2889039837	94558
BNB	647	919	8.85	71228993	1082	6072	5.42	27630857	5858	6	0.07	47512523	3	133792	24.93	112443301	126060
USDC	1708	19255	1.00	17033038128	32083	15348	0.00	18005986534	25474	2	0.97	3110439	1	119313	1.01	47191879206	201493
XRP	3213	22554	0.34	24552297917	855663	42054	0.35	11759714759	455660	573	0.00	6905340740	67075	883805	2.75	45610107489	4524200
ADA	2009	45102	0.49	28346618531	33808	54675	0.60	2141718915	43747	409	0.02	26100515958	164	485693	2.97	32610357053	495825
DOGE	3417	55756	0.04	105232626347	32833	31150	0.08	11111999503	104515	13362	0.00	34738545319	5875	752860	0.69	117235608827	2077710
MATIC	1497	2662	0.64	8645158991	3617	2693	0.67	656845623	3852	4	0.00	7254634993	13	16821	2.87	9768771477	26623
TRX	1803	788423	0.05	N.A.	3173792	780313	0.03	N.A.	2252056	545	0.01	N.A.	1397	4351099	0.17	N.A.	11109429
LTC	3714	112771	59.46	51010140	42891	126350	64.48	14137861	53630	7039	1.16	16260821	2148	830962	385.47	66435814	584861
DOT	653	19913	21.53	1075312355	134670	9435	12.60	55670844	186190	2243	2.87	968749906	16860	74205	54.01	1168358355	3791758
BUSD	1351	942	1.00	8652919076	1322	912	0.00	7793021413	1165	2	1.00	8092370	1	10868	1.00	23452767872	12482
DAI	1290	5304	1.00	4125448358	9601	2382	0.01	3149422957	5018	794	0.97	9067091	2299	14659	1.07	9944337457	39493
WBTC	1651	857	23203.26	119914	2200	728	16831.38	105036	1993	0	3185.07	0	0	3785	67541.76	285004	11192
LEO	1473	20	2.69	660000000	26	31	1.59	0	64	0	0.81	659999999	0	379	7.49	660000000	1060
LINK	2072	3161	8.69	410828394	4343	3770	9.96	51557860	5010	60	0.15	351409579	51	70468	51.75	510443718	71473
UNI	987	2438	12.95	180970841	3397	3687	9.72	33295541	5464	441	1.92	103306030	499	86131	43.54	240268311	128553
XMR	3300	N.A.	96.97	N.A.	9201	N.A.	94.56	N.A.	9363	N.A.	0.22	N.A.	0	N.A.	482.05	N.A.	61305
ETC	2503	60212	17.29	102734639	41592	210202	16.71	19197955	17129	1464	0.61	21699126	4409	5771390	133.65	123970614	199683
XLM	2802	69883	0.13	14390264886	1606419	147741	0.14	5994929330	2170938	0	0.00	20	0	1440327	0.88	22918099042	11062077
BCH	2131	58698	449.31	11245851	58503	35839	420.67	2343671	109836	8269	76.07	238336	4150	492819	3678.34	13428194	2168952
ICP	752	4566	25.27	195960441	8218	2636	35.68	54707521	4767	671	3.50	31058043	1622	16546	367.37	262515567	34148
TUSD	1792	558	1.00	N.A.	799	357	0.00	N.A.	600	57	0.98	N.A.	62	3106	1.01	N.A.	5552
CRO	1535	713	0.14	11156686810	1049	937	0.14	3053783442	1330	20	0.03	3278292006	15	10470	0.90	14582508821	14185
QNT	1539	603	72.10	12776097	814	615	78.50	948945	857	41	1.54	10535885	43	7364	393.92	24431259	9728
ALGO	1441	48416	0.61	3666413861	749594	122564	0.50	2791156837	698135	152	0.13	143836371	913	1773085	2.40	8762357143	9271981
EOS	1818	28969	3.38	N.A.	3028325	48621	1.96	N.A.	1964994	57	0.82	N.A.	8200	1217967	14.30	N.A.	10596145
AAVE	965	1094	182.20	13302716	1747	789	130.49	987706	1210	202	27.77	5202761	198	6237	627.18	14420147	11695
MANA	2107	836	0.52	2073409299	1129	992	0.84	355770273	1480	0	0.01	1719288037	0	12369	5.19	2805886393	22526
XTZ	1399	18456	2.56	607639144	87626	23959	1.65	146704359	115245	53	0.35	6790020	1031	107099	8.57	858359467	693276
NEO	2148	3616	25.92	56411675	101019	4265	26.03	4113869	93847	75	5.03	49990843	5535	47626	190.40	61715111	447382
CRV	1021	1103	1.87	716081087	1957	453	1.25	406732086	1103	329	0.34	2099213	320	5182	7.04	1477169203	14307
MKR	1984	405	1121.41	663572	734	382	941.40	110684	658	32	201.07	454620	29	4056	6066.12	840698	7704
BSV	1336	218068	147.44	9601291	696836	286116	66.34	2189526	1149793	2533	41.54	3778	1496	4920980	439.70	11886161	18763487
SNX	1149	876	6.35	188646819	1348	774	5.53	48345605	1114	119	0.63	99834477	106	5354	27.23	264407992	6797
GUSD	1720	171	1.00	158918268	289	147	0.02	182423030	279	6	0.94	139718	4	1180	1.82	858290836	2378
ZEC	2406	32702	124.83	7633137	4501	23345	121.85	4188909	2442	3583	24.35	326	1380	121221	2042.07	13166313	28641
PAXG	1203	252	1823.37	167096	314	162	102.07	119135	211	3	1473.33	2579	1	1679	2082.34	340090	2024
HT	1549	247	6.69	214887324	364	504	4.63	43936614	719	15	1.64	162888608	10	8844	36.08	302999999	12430
DASH	3401	44793	113.51	7924941	13516	32898	163.22	1881424	59245	581	0.12	3132601	313	267414	1447.47	10428976	3026767
1INCH	888	851	1.96	470453305	1317	1065	1.58	283862291	1824	177	0.37	71873544	174	13174	7.41	939336240	27081

Table 2
Descriptive variables of traditional asset prices.

Descriptive variable	Gold	VDE	Crude oil	GSPC	FTSE
Observation	3373	3375	3374	3374	3382
Mean (USD)	1464.26	95.92	71.43	2451.40	6632.41
Standard deviation (USD)	259.15	20.86	22.42	1014.22	724.92
Minimum (USD)	1050.80	31.29	−37.63	1022.58	4805.80
Maximum (USD)	2051.50	145.60	123.70	4796.56	8014.30

addresses, number of daily transactions, and number of circulation supply, have a significant effect on cryptocurrency prices. The R^2 values (Column 17) of ETH, XRP, LEO, XMR, ETC, XLM, BCH, ALGO, EOS, XTZ, BSV and DASH are smaller than 0.60, while their log-likelihood values (Column 20) are negative. For XMR and EOS, it might be due to a lack of data on its active wallet addresses and circulation supply. For ETH, XRP, LEO, ETC, XLM, BCH, ALGO, XTZ, BSV and DASH, this indicates that there are other significant factors affecting the prices of these cryptocurrencies. Inactive wallets could be one of these determinants of the price which creates value as long-term investors use the term "HODL" an abbreviation for "hold on to dear life" in relation to their cryptocurrency investments [47]. Therefore, they do not intend on selling which allows the price to rise. In addition, some cryptocurrencies (i.e., ETH, XRP, XLM, LEO, ETC, BCH and XTZ) have a predetermined deflation rate coded in the protocol, so that they can act as a deflationary supply mechanism and cause prices to rise if demand stays the same [49]. Despite the significance of this analysis agreeing with Alabi's [17] findings, the connotation made by Alabi [17] that "a rapid increase in price unaccompanied by the rapid increase in active wallets is a value bubble" may be invalid.

The number of active wallet addresses demonstrates a significant positive effect on most of the cryptocurrencies, with the p-value smaller than 0.05 and power coefficient higher than 1. TUSD has shown the strongest effect of the number of active wallet addresses, with a power coefficient of 5. Meanwhile, the power coefficient is higher than 2 for USDT, BNB, XRP, ADA, DOGE, MATIC, TUSD, and SNX, demonstrating a stronger effect than the Metcalfe's law (i.e., squared number of active wallet addresses). This might be because these 8 cryptocurrencies use proof-of-stake or other unique consensus mechanisms (i.e., BFT for BNB, PoR for USDT, and RPCA for XRP), which is said to be more energy-efficient than proof-of-work consensus mechanism. Also, XRP is planning to adopt smart contract on its blockchain, while the other 7 cryptocurrencies have already implemented smart contract.

On the contrary, BUSD, DAI, ETC, ALGO, EOS and BSV have demonstrated a negative linear coefficient of the number of active wallet addresses with p-values smaller than 0.05 and power coefficients higher than 2. This indicates that the number of active wallet addresses have a significant negative effect on prices of these cryptocurrencies. This might be owing to the unique features of these cryptocurrencies. For example, BUSD, DAI and EOS are backed as stablecoins and have unlimited supply, while ALGO, BSV and ETC are deflationary with limited supply. BSV is a hard fork from Bitcoin, while ETC is a hard fork from Ethereum. Although BSV has the advantages of larger block size and smaller transaction fees, BSV token is only available on a few exchange platforms. Another justification for this could be herd behaviour, as when price spikes without fundamental support, investors notice that the price is overvalued therefore initiate sell their cryptocurrency to boost profits. This in turn increases the number of active wallets addresses thus the number of active wallets addresses become a function of cryptocurrency price rather than cryptocurrency price being a function of the active wallets addresses. These results indicate that users may adopt different investment strategies and behave differently upon inflated prices according to the different features of cryptocurrencies. Hypothetically, a single active user with disproportionate wealth could stake his cryptocurrency and reduce supply significantly, which causes cryptocurrency prices to rise. This provides an alternative explanation for why prices rise with the decreased number of active wallets.

The effects from number of daily transactions are more varied, with only 25 of the 42 cryptocurrencies showing a positive effect. BTC has shown the strongest effect from the number of daily transactions, with a power coefficient of 5, followed by BCH, LTC and XPR, with power coefficients higher than 2. On the contrary, the number of daily transactions has shown significant negative effects on the other 15 cryptocurrencies. Especially, the number of daily transactions has shown strong negative effects on XRP, MATIC, WBTC and ETC, with power coefficients higher than 2. There is no relationship between cryptocurrency prices and number of transactions for LEO and XMR since the linear coefficients of number of transactions are 0.

The number of circulations also demonstrates statistically significant effects on most of the cryptocurrency prices. The effects from the number of circulations are not as strong as those from the number of active wallets addresses and the number of daily transactions, as the power coefficients of the number of circulations are not higher than 2. Distinctly, NEO shows a strong negative effect from the number of circulations, with the power coefficient being 2 and p-value of 0.00. XLM shows a weak negative effect from the number of circulations, with the power coefficient being 0.5 and p-value of 0.06.

Overall, at least one of the factors (i.e., the number of active wallets addresses, the number of daily transactions and number of circulations) have demonstrated strong significant effects on the cryptocurrency prices, except for XMR, XTZ and ZEC. Although initial coin offering was highly successful for XTZ, the power struggle between the Breitmans and Johann Gevers, along with corresponding lawsuit may have a stronger effect on XTZ than the network itself [50]. ZEC, initially called Zerocoin, is one of the top privacy coins from a privacy-focused extension to Bitcoin. Its unique zero-knowledge proof technology ensures that when transactions are executed by nodes on the network, thus they can be verified without revealing any sensitive information. This feature may have made ZEC prices more stable. As number of wallet address and circulation is not available for XMR, the nonlinear correlation may not be accurate.

4.3. *Store of value analysis*

Bitcoin have previously been compared to Gold, a store of value type asset. This is because Bitcoin shares fundamental characteristics with Gold like being scarce, costly to mine and can be used to diversify risk as it is uncorrelated to other traditional assets [51]. Therefore, it is interesting to see whether other cryptocurrencies could be used as a store of value by comparing them to Gold through daily volatility, GARCH models and correlation analytics.

The overall daily, monthly and yearly average volatility of each cryptocurrency and traditional asset have been calculated based on their daily prices using Eqs. (2)–(7) in Section 3.3, as summarised in the first 3 columns of Table 4. Gold, S&P500 and FTSE100 all have small volatility, with the value slightly larger than 1, while crude oil has relatively larger volatility value around 6. The volatility of USDC, BUSD, TUSD DAI, USDT and GUSD are 0.11, 0.06, 0.20, 0.33,1.30 and 1.66, respectively, which are smaller than Gold (i.e., 1.02). This is because these cryptocurrencies are created as stablecoins, with its value pegged to U.S. dollars [52]. Meanwhile, PAXG has a volatility of 1.08. It is because this crypto asset is backed by real Gold reserves held by Paxos, and is created to be redeemable for 1 troy fine ounce of Gold [53]. Cryptocurrencies such as ETH, BNB, ADA, CRO, QNT, ALGO, EOS, AAVE, XTZ, NEO, BCH, ICP and MKR have similar volatility as Crude oil, with the daily volatility in the range between 5.5 and 7.0. MANA has the largest daily volatility (i.e., 12.06), this might be due to the spikes in number of active wallet addresses, transactions and circulations, as its price is found to be significantly affected by these three factors. Other factors such as news in project and developments, public sentiment, the flow of assets on exchanges, and emerging trends in the wider cryptocurrency and global

Table 3
Summary of network regression analysis.

Cryptocurrency	Coefficients			Coefficients			Standard error			t-value			p-value			R^2	F-statistic	Prob.	L.L.	AIC	BIC
	β_1	β_2	β_3	α_1	α_2	α_3	α_1	α_2	α_3	α_1	α_2	α_3	α_1	α_2	α_3						
BTC	1.0	5.0	2.0	206183	726585	1106759	8800	7460	19988	23	97	55	0.00	0.00	0.00	0.94	23324	0.00	−60496	121000	121026
ETH	2.0	2.5	1.0	67375	−25358	853817	30476	34394	50452	2	−1	17	0.03	0.46	0.00	0.43	710	0.00	−39281	78570	78594
USDT	3.0	2.5	2.0	3357	7611	81308	598	180	677	6	42	120	0.00	0.00	0.00	0.91	10107	0.00	−28588	57184	57209
BNB	3.0	2.0	2.0	2157	227	142993	584	176	1907	4	1	75	0.00	0.20	0.00	0.90	1878	0.00	−5817	11642	11660
USDC	2.5	2.5	2.0	28471	12195	225667	5392	581	3917	5	21	58	0.00	0.00	0.00	0.80	2298	0.00	−17504	35016	35037
XRP	3.0	3.0	2.0	82646	76216	139717	11362	2038	10735	7	37	13	0.00	0.00	0.00	0.43	806	0.00	−37864	75736	75761
ADA	3.0	2.5	2.0	161111	74237	787776	4904	2186	18671	33	34	42	0.00	0.00	0.00	0.80	2741	0.00	−23130	46267	46290
DOGE	3.0	1.0	1.0	189687	−3712	63838	12444	3825	10177	15	−1	6	0.00	0.33	0.00	0.07	91	0.00	−40070	80149	80173
MATIC	3.0	3.0	2.0	5995	−1705	22216	350	114	505	17	−15	44	0.00	0.00	0.00	0.80	2051	0.00	−12725	25457	25479
TRX	1.0	1.0	N.A.	999716	2981309	N.A.	44919	41014	N.A.	22	73	N.A.	0.00	0.00	0.00	0.86	5351	0.00	−25273	50552	50568
LTC	1.5	3.0	1.0	202465	68751	916783	6481	2819	11000	31	24	83	0.00	0.00	0.00	0.90	10769	0.00	−44676	89360	89385
DOT	1.0	1.5	1.0	17042	18266	20147	838	663	4116	20	28	5	0.00	0.00	0.00	0.74	606	0.00	−6466	12941	12959
BUSD	3.0	2.5	2.0	−485	1221	12589	195	46	222	−2	27	57	0.01	0.00	0.00	0.80	1808	0.00	−10033	20074	20095
DAI	4.0	2.5	2.0	−2041	−359	21089	1038	160	465	−2	−2	45	0.05	0.02	0.00	0.64	756	0.00	−11205	22418	22439
WBTC	2.0	3.0	1.0	745	−268	3617	27	19	33	28	−14	110	0.00	0.00	0.00	0.92	6092	0.00	−11164	22336	22358
LEO	2.0	0	1.0	−5	0	478	2	0	4	−3	0	111	0.00	0.00	0.00	0.90	6288	0.00	−5477	10960	10976
LINK	1.5	2.0	2.0	9629	394	92262	232	109	1180	41	4	78	0.00	0.00	0.00	0.84	3502	0.00	−18132	36272	36295
UNI	4.0	1.0	2.0	3471	−4588	89019	437	222	1563	8	−21	57	0.00	0.00	0.00	0.81	1428	0.00	−8677	17363	17382
XMR	N.A.	0.5	N.A.	N.A.	401	N.A.	7	0	0	61	0	0	0.00	0.00	0.00	0.53	3677	0.00	−18459	36921	36933
ETC	3.0	4.0	2.0	−194996	−36919	301919	100917	14352	117298	−2	−3	3	0.05	0.01	0.01	0.00	4	0.01	−34221	68451	68474
XLM	0.5	0.5	0.5	54306	189776	−40620	17258	27636	18127	3	7	−2	0.00	0.00	0.03	0.06	59	0.00	−37242	74492	74516
BCH	2.0	4.0	0.5	296900	41658	137743	8887	2040	6601	33	20	21	0.00	0.00	0.00	0.48	657	0.00	−24672	49352	49374
ICP	2.0	1.5	1.0	−2032	275	16874	578	134	223	−4	2	76	0.00	0.04	0.00	0.89	1936	0.00	−6174	12356	12374
TUSD	5.0	1.0	N.A.	−229	3142	N.A.	47	21	N.A.	−5	146	N.A.	0.00	0.00	0.00	0.92	10704	0.00	−10781	21568	21585
CRO	2.0	2.0	1.0	424	−69	9269	101	24	112	4	−3	82	0.00	0.00	0.00	0.91	5348	0.00	−10808	21624	21645
QNT	1.0	1.0	1.0	65	790	6312	28	79	53	2	10	118	0.02	0.00	0.00	0.94	8439	0.00	−9864	19736	19757
ALGO	1.0	1.0	1.0	−62569	−73031	1229517	14060	9436	46815	−4	−8	26	0.00	0.00	0.00	0.39	313	0.00	−18566	37139	37160
EOS	2.0	1.5	N.A.	−24474	117683	0	12112	6844	0	−2	17	0	0.04	0.00	0.00	0.14	148	0.00	−22061	44129	44145
AAVE	2.0	2.0	1.0	721	−128	6182	74	64	116	10	−2	53	0.00	0.05	0.00	0.88	2247	0.00	−6802	13612	13631
MANA	1.0	1.0	1.0	631	−157	13360	37	15	89	17	−11	150	0.00	0.00	0.00	0.96	17308	0.00	−14106	28220	28243
XTZ	0.5	0.5	0.5	28645	40202	43444	3158	6574	4061	9	6	11	0.00	0.00	0.00	0.42	333	0.00	−15715	31437	31458
NEO	1.0	1.0	2.0	20894	−4983	−3993	342	165	390	61	−30	−10	0.00	0.00	0.00	0.79	2771	0.00	−19299	38606	38629
CRV	1.0	1.0	1.0	270	51	5002	36	24	85	8	2	59	0.00	0.03	0.00	0.82	1516	0.00	−6825	13658	13678
MKR	1.0	1.0	1.0	94	108	3825	32	17	49	3	6	78	0.00	0.00	0.00	0.77	2222	0.00	−13149	26306	26328
BSV	1.0	1.0	1.0	−467285	799736	1075013	38529	36773	107208	−12	22	10	0.00	0.00	0.00	0.41	311	0.00	−18326	36661	36681
SNX	3.0	2.0	1.5	1619	−94	4390	61	19	55	26	−5	80	0.00	0.00	0.00	0.93	4962	0.00	−7756	15520	15541
GUSD	1.0	1.0	2.0	−140	56	2144	71	9	35	−2	6	62	0.05	0.00	0.00	0.70	1320	0.00	−9992	19992	20014
ZEC	0.2	0.5	0.5	122712	−13287	57792	3284	1309	3126	37	−10	18	0.00	0.00	0.00	0.62	1281	0.00	−26464	52936	52959
PAXG	2.0	1.0	1.0	62	50	1356	8	5	17	8	10	82	0.00	0.00	0.00	0.89	3371	0.00	−6473	12955	12975
HT	2.0	2.0	1.0	443	−79	8223	55	17	86	8	−5	95	0.00	0.00	0.00	0.89	4024	0.00	−10150	20309	20330
DASH	1.0	1.0	1.0	28448	89369	221647	3357	1480	18966	8	60	12	0.00	0.00	0.00	0.57	1531	0.00	−38745	77498	77523
1INCH	2.0	0.5	2.0	1989	−490	17273	157	90	434	13	−5	40	0.00	0.00	0.00	0.74	843	0.00	−6850	13707	13726

N.A. Not available due to lack of certain variables from data collection.
L.L. Log-likelihood.
Prob. Probability of F-statistic.

Table 4
Volatility analytics of traditional assets and cryptocurrencies.

Assets	Average volatility			GARCH volatility												GARCH model				
				ω				α				β								
	Daily	Monthly	Yearly	Coef	std err	t- value	p- value	Coef	std err	t- value	p- value	Coef	std err	t- value	p- value	R^2	R^2-adj	Loglikelihood	AIC	BIC
Gold	1.02	5.58	19.46	0.02	0.01	1.3	0.18	0.04	0.02	2.3	0.02	0.94	0.03	34.8	0.00	0.00	0.00	−4677	9362	9387
Crude oil	6.29	34.46	120.19	0.05	0.18	0.3	0.77	0.09	0.02	6.2	0.00	0.91	0.07	12.7	0.00	0.00	0.00	−7908	15823	15848
Energy	1.81	9.89	34.50	0.03	0.01	2.9	0.00	0.09	0.02	5.7	0.00	0.90	0.01	60.8	0.00	0.00	0.00	−6147	12302	12327
S&P500	1.12	6.12	21.34	0.04	0.01	4.8	0.00	0.18	0.02	7.8	0.00	0.80	0.02	37.3	0.00	0.00	0.00	−4375	8758	8782
FTSE100	1.02	5.60	19.53	0.05	0.01	4.4	0.00	0.15	0.02	6.4	0.00	0.80	0.03	28.2	0.00	0.00	0.00	−4393	8794	8819
BTC	5.07	27.75	96.78	0.83	0.29	2.9	0.00	0.17	0.04	4.3	0.00	0.81	0.04	21.2	0.00	0.00	0.00	−13244	26497	26523
ETH	5.96	32.66	113.91	1.76	0.59	3.0	0.00	0.15	0.03	4.5	0.00	0.80	0.04	19.3	0.00	0.00	0.00	−8788	17584	17608
USDT	1.30	7.11	24.79	0.00	0.00	1.9	0.06	0.16	0.02	8.7	0.00	0.84	0.02	43.1	0.00	0.00	0.00	−1	10	35
BNB	6.87	37.63	131.26	0.62	0.36	1.7	0.08	0.16	0.05	3.4	0.00	0.84	0.04	18.7	0.00	0.00	0.00	−6522	13051	13074
USDC	0.11	0.61	2.11	0.00	0.00	0.3	0.74	0.20	0.13	1.6	0.11	0.78	0.21	3.7	0.00	0.00	0.00	2523	−5038	−5016
XRP	7.45	40.82	142.39	4.22	1.42	3.0	0.00	0.43	0.11	4.1	0.00	0.57	0.08	7.0	0.00	0.00	0.00	−10013	20034	20058
ADA	6.46	35.39	123.44	0.87	0.48	1.8	0.07	0.07	0.03	2.3	0.02	0.90	0.04	22.6	0.00	0.00	0.00	−6282	12571	12594
DOGE	8.99	49.22	171.70	0.31	0.35	0.9	0.38	0.07	0.01	7.4	0.00	0.93	0.02	38.5	0.00	0.00	0.00	−11238	22484	22508
MATIC	8.33	45.64	159.20	2.54	1.60	1.6	0.11	0.23	0.08	2.9	0.00	0.76	0.08	9.5	0.00	0.00	0.00	−5010	10028	10050
TRX	5.13	28.08	97.95	0.43	0.34	1.3	0.20	0.14	0.04	3.3	0.00	0.86	0.05	18.7	0.00	0.00	0.00	−5280	10568	10590
LTC	7.79	42.67	148.82	1.13	0.52	2.2	0.03	0.08	0.01	5.6	0.00	0.90	0.01	67.2	0.00	0.00	0.00	−11737	23483	23508
DOT	6.23	34.13	119.04	0.77	0.40	1.9	0.05	0.10	0.02	4.4	0.00	0.88	0.02	40.2	0.00	0.00	0.00	−3158	6325	6344
BUSD	0.06	0.33	1.16	0.00	0.00	1.4	0.18	0.23	0.09	2.7	0.01	0.75	0.11	7.1	0.00	0.00	0.00	2408	−4808	−4787
DAI	0.33	1.81	6.30	0.00	0.01	0.5	0.62	0.66	0.89	0.7	0.46	0.34	0.11	2.9	0.00	0.00	0.00	576	−1145	−1124
WBTC	3.70	20.29	70.76	1.24	0.50	2.5	0.01	0.08	0.03	2.5	0.01	0.83	0.05	17.5	0.00	0.00	0.00	−4448	8905	8926
LEO	3.59	19.66	68.58	0.36	0.29	1.2	0.22	0.18	0.06	3.2	0.00	0.82	0.07	11.0	0.00	0.00	0.00	−3577	7161	7183
LINK	7.02	38.45	134.10	0.61	0.25	2.4	0.02	0.10	0.02	6.2	0.00	0.90	0.01	66.1	0.00	0.00	0.00	−6737	13481	13504
UNI	6.48	35.50	123.81	0.16	0.38	0.4	0.68	0.08	0.04	2.0	0.05	0.92	0.04	22.2	0.00	0.00	0.00	−3149	6306	6326
XMR	6.50	35.61	124.22	0.86	0.40	2.2	0.03	0.13	0.03	4.4	0.00	0.87	0.03	29.9	0.00	0.00	0.00	−10391	20789	20814
ETC	9.19	50.32	175.51	4.89	1.58	3.1	0.00	0.23	0.05	4.2	0.00	0.68	0.07	10.1	0.00	0.00	0.00	−8008	16024	16047
XLM	7.56	41.40	144.42	2.38	1.64	1.5	0.15	0.24	0.07	3.5	0.00	0.76	0.08	9.9	0.00	0.00	0.00	−9015	18037	18061
BCH	6.65	36.44	127.12	0.78	0.50	1.6	0.12	0.07	0.03	2.4	0.02	0.91	0.03	26.1	0.00	0.00	0.00	−6760	13527	13550
ICP	6.55	35.86	125.09	0.58	0.54	1.1	0.29	0.07	0.06	1.1	0.27	0.92	0.06	14.5	0.00	0.00	0.00	−2402	4812	4830
TUSD	0.20	1.08	3.76	0.00	0.00	2.9	0.00	0.20	0.03	6.1	0.00	0.78	0.03	24.6	0.00	0.00	0.00	1623	−3237	−3216
CRO	5.58	30.54	106.52	1.58	0.45	3.5	0.00	0.21	0.04	4.8	0.00	0.76	0.03	28.0	0.00	0.00	0.00	−4610	9228	9250
QNT	6.88	37.66	131.36	0.24	1.32	0.2	0.86	0.06	0.10	0.6	0.56	0.94	0.11	8.4	0.00	0.00	0.00	−5057	10122	10143
ALGO	6.42	35.15	122.60	1.20	0.89	1.4	0.17	0.14	0.06	2.3	0.02	0.84	0.07	12.4	0.00	0.00	0.00	−4609	9225	9246
EOS	5.67	31.08	108.41	0.92	0.50	1.9	0.06	0.07	0.02	3.9	0.00	0.90	0.03	32.0	0.00	0.00	0.00	−5596	11200	11222
AAVE	6.68	36.60	127.66	0.70	0.45	1.5	0.13	0.10	0.03	3.5	0.00	0.89	0.03	27.1	0.00	0.00	0.00	−3102	6213	6232
MANA	12.06	66.08	230.48	0.75	1.18	0.6	0.53	0.09	0.10	0.8	0.40	0.91	0.10	9.3	0.00	0.00	0.00	−7361	14730	14752
XTZ	6.05	33.14	115.59	1.73	0.72	2.4	0.02	0.13	0.03	4.0	0.00	0.83	0.04	20.4	0.00	0.00	0.00	−5645	11299	11320
NEO	6.59	36.11	125.95	1.63	1.06	1.5	0.12	0.11	0.05	2.0	0.04	0.86	0.07	12.7	0.00	0.00	0.00	−6899	13805	13828
CRV	8.58	47.01	163.98	1.68	1.51	1.1	0.26	0.14	0.07	2.0	0.04	0.85	0.07	12.1	0.00	0.00	0.00	−3543	7093	7113
MKR	6.64	36.37	126.87	2.70	0.99	2.7	0.01	0.14	0.04	3.3	0.00	0.80	0.04	19.3	0.00	0.00	0.00	−6310	12628	12651
BSV	7.33	40.15	140.06	3.56	1.13	3.2	0.00	0.30	0.10	3.2	0.00	0.70	0.04	16.4	0.00	0.00	0.00	−5263	10534	10556
SNX	7.30	40.01	139.54	2.72	2.66	1.0	0.31	0.10	0.05	2.1	0.04	0.85	0.09	9.4	0.00	0.00	0.00	−3865	7739	7759
GUSD	1.66	9.07	31.65	0.05	0.04	1.1	0.25	0.34	0.06	6.1	0.00	0.66	0.09	7.3	0.00	0.00	0.00	−1987	3983	4004
ZEC	7.54	41.29	144.03	2.36	1.11	2.1	0.03	0.14	0.06	2.4	0.01	0.81	0.07	12.3	0.00	0.00	0.00	−7707	15423	15446
PAXG	1.08	5.92	20.63	0.03	0.01	2.7	0.01	0.06	0.02	2.4	0.02	0.90	0.03	29.2	0.00	0.00	0.00	−1566	3139	3160
HT	5.06	27.71	96.64	2.08	2.06	1.0	0.31	0.21	0.17	1.2	0.22	0.74	0.21	3.6	0.00	0.00	0.00	−4482	8973	8994
DASH	8.38	45.90	160.11	2.44	0.70	3.5	0.00	0.25	0.05	4.8	0.00	0.73	0.05	15.9	0.00	0.00	0.00	−10818	21645	21669
1INCH	6.59	36.10	125.92	0.23	0.17	1.3	0.18	0.05	0.02	2.3	0.02	0.94	0.02	50.8	0.00	0.00	0.00	−2796	5599	5618

economies may also have significant effects on MANA prices [54].

The GARCH results of traditional assets and cryptocurrencies are also summarised in Table 4, from the 4th column to the last column. As discussed in Section 3, ω, α and β reflects the effects of long-term variance, immediate volatility during the previous time step and immediate variance during the previous time step, respectively. The p-value being lower than 0.10 for ω (Column 7) would demonstrate significant effects from long-term variance. Only 3 (i.e., VDE Energy, S&P500, and FTSE100 index) out of the 5 traditional assets have demonstrated significant effects from long-term variance, along with 21 out of the 42 cryptocurrencies. Cryptocurrencies such as ETH, XRP, LTC, WBTC, ETC, XLM, CRO, XTZ, MKR, BSV, ZEC and DASH, have demonstrated a strong effect from long-term variance, with coefficient of ω higher than 1. The p-value being lower than 0.10 for α (Column 11) would demonstrate significant effects from the immediate volatility. All the traditional assets and most of the cryptocurrencies have demonstrated significant effects from the immediate volatility, except USDC, DAI, ICP, QNT, MANA and HT. The p-value being lower than 0.01 for β (Column 14) would demonstrate significant effects from the immediate variance. Therefore, all the traditional assets and cryptocurrencies have demonstrated significant effects from the immediate variance, with the p-value being approximately 0.00. Moreover, the effects from immediate variance are generally stronger than those from immediate volatility, as the value of β coefficient is generally higher than that of α coefficient. For most of the cryptocurrencies, the total value of α coefficient and β coefficient is very slightly close to 1 (i.e., larger or equal to 0.91), which shows that when a variation in price takes place at a specific time, it will be transmitted at a certain future time. If the total value of α coefficient

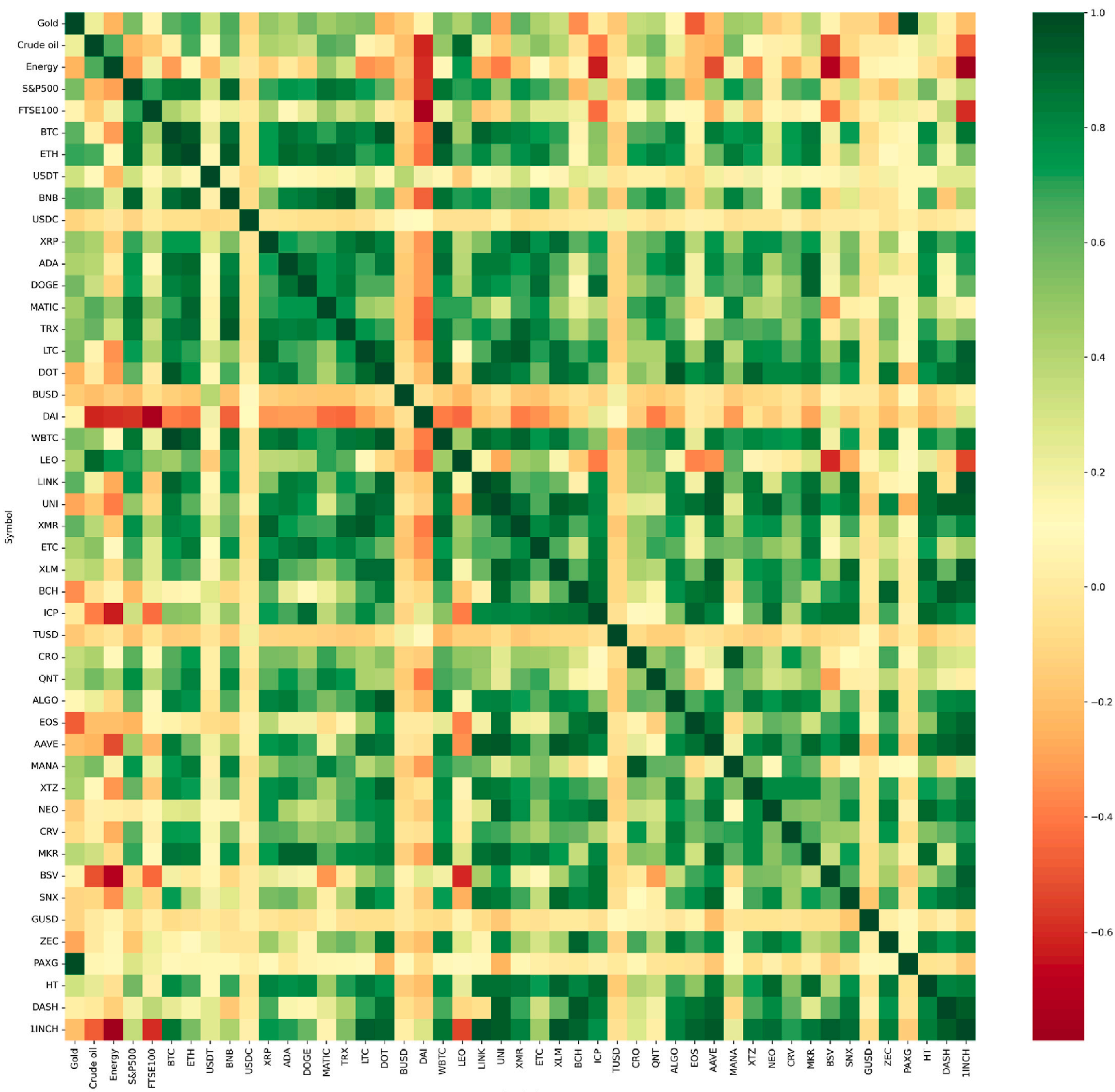

Fig. 1. Heatmap of correlation coefficients.

and β coefficient is smaller than 1, it indicates that the unconditional variance of the error term $\varepsilon_{i,t}$ is stationary.

The time-series correlation between each traditional asset and cryptocurrency is illustrated in Fig. 1 below. PAXG has the highest correlation (i.e., 0.99) with Gold, because it was created to be a stablecoin backed up by Gold. BTC, ETH, BNB and LINK also demonstrated strong correlation with Gold, with correlation coefficients higher than 0.60. It might be because these cryptocurrencies have become more mature with the blockchain technology development. On the contrary, USDC, BUSD, DAI, TUSD, ALGO, NEO, CRV, SNX, GUSD, DASH and 1INCH have demonstrated weak correlation with Gold. It might be because USDC, BUSD, DAI, TUSD, and GUSD are designed as stablecoins backed up by U.S. Dollars. The inflation in U.S. Dollars might make its price to trend far away from Gold. NEO was the first public blockchain in China, and one of its unique selling points is its continuous development, this might make its price trend less relevant to Gold [55]. Sasmaz and Tek [56] also demonstrated that NEO prices are more correlated with Twitter sentiment. CRV uses an automated market maker to manage liquidity, which may make its price trend different from Gold. SNX was originally designed to expose users to the underlying assets through synths, and users do not need to hold the underlying asset. SNX tokens are used as collateral for the synthetic assets that are minted [57]. This special feature may make the trend of SNX price to vary from Gold. DASH devotes 10% of the block rewards to the development of the DASH project in a competitive and decentralised way. It also shows an equal effect from active wallet addresses, number of transactions and circulation with 56% correlation. These indicate that the prices of DASH may also be affected by market sentiments and other factors, so the price trend has a large volatility (8.38) and behaves quite differently from Gold [58]. 1INCH network provides a decentralised exchange aggregator solution that searches deals across multiple liquid sources and offers users better rates than individual exchanges [59]. Therefore, the daily volatility of 1INCH is relatively large (6.59) and is quite different from that of Gold.

However, LEO has a high positive correlation with Crude oil and VDE Energy, with the correlation coefficient at 0.90 and 0.75, respectively. There was no relationship between transaction volume and LEO price. This might be because there is a LEO token burn to deflate the supply overtime [60]. Meanwhile, most of the other cryptocurrencies demonstrated a weak correlation with Crude oil. BTC, ETH, BNB, ADA, DOGE, MATIC, TRX, LTC, WBTC, LEO, LINK, XMR, QNT and MANA have all shown high positive correlation with S&P500 as the correlation coefficients are higher than 0.70, while none of the cryptocurrencies demonstrates a high negative correlation with S&P500. DAI shows a high negative correlation with FTSE100 with its coefficient at −0.75, while none of the cryptocurrencies demonstrates a significant positive correlation with FTSE100. Bitcoin also witnesses a high positive correlation with most of the cryptocurrencies, including ETH, BNB, XRP, ADA, DOGE, MATIC, TRX, LTC, DOT, WBTC, LINK, UNI, XMR, ETC, XLM, ALGO, AAVE, MANA, XTZ, CRV, MKR, SNX, HT and 1INCH.

5. Conclusion and practical implication

The current study explores the network effects and the store of value features of cryptocurrencies using the most up to date data compared to previous studies. We used the latest data, from the birth of each cryptocurrency till 2023. Our empirical analysis relied on nonlinear regression models and time series analysis to explore the volatility of cryptocurrencies compared to other traditional asset classes. While previous studies mainly used Metcalfe's Law to evaluate the relationship between cryptocurrency prices and squared number of active wallets addresses of Bitcoin and Ethereum, our study is distinctive because we used a nonlinear regression model and used an extensive number of cryptocurrencies to evaluate the comprehensive relationship between cryptocurrency prices and active wallet addresses, number of transactions and circulations of 42 cryptocurrencies. The different power coefficients and linear coefficients are fitted for different cryptocurrencies, which gives a more general and broad view of the network effects on cryptocurrencies. We found that at least one of the independent variables (i.e., active wallet addresses, number of transactions, and number of circulation supply) have a significant effect on cryptocurrency prices. The number of active wallet addresses has a significant positive effect on most of the cryptocurrencies except BUSD, DAI, ETC, ALGO, EOS and BSV. Twenty-five of the 42 cryptocurrencies also show a positive relationship between cryptocurrency prices and number of transactions. The number of transactions has a strong positive effect on Bitcoin, with its power coefficient at 5. The number of circulations also demonstrates strong effect on most of the cryptocurrencies, although the power coefficients are not higher than 2. Thus, when selecting cryptocurrency for investment, it could be naive to simply rely on its active wallet addresses only. Our evidence shows that other factors (i.e., number of transactions and supply circulation) also matter in determining the price of the cryptocurrency.

Furthermore, to deepen our understanding of the store of value features of cryptocurrencies, we compared the volatility of a vast number of cryptocurrencies to those of established store of value asset classes such as Gold and stock market index. We evaluated the store-of-value capability of cryptocurrencies through daily volatility, GARCH analysis and time-series correlation. We found that stable coins such as USDC, BUSD, TUSD DAI, USDT, GUSD and PAXG have small daily volatility, with the value ranging between 0.06 and 1.66. ETH, BNB, ADA, CRO, QNT, ALGO, EOS, AAVE, XTZ, NEO, BCH, ICP and MKR have similar volatility as Crude oil, with the daily volatility in the range between 5.5 and 7.0. MANA has the largest daily volatility at 12.06. Only half of the cryptocurrencies have demonstrated a significant effect from long-term variance. The immediate volatility demonstrates a strong and significant effect on traditional assets and most of the cryptocurrencies, except USDC, DAI, ICP, QNT, MANA and HT, while all the traditional assets and cryptocurrencies have demonstrated a significant effect of the immediate variance. Mature cryptocurrencies, such as PAXG, BTC, ETH, BNB and LINK, demonstrated strong correlation with Gold, while most of other cryptocurrencies did not. Bitcoin also showed a high positive correlation with 24 of the 42 cryptocurrencies. Therefore, the unique features of different cryptocurrencies may play an important role in determining its volatility and store-of-value features. Due to the maturity in blockchain and cryptocurrency development, some cryptocurrencies have shown similar time-series correlations as Gold. However, it is impossible to generalise on the store of value potential of all cryptocurrencies because they have varying features which may affect their network and store of value features.

Future studies could aim at integrating inactive and staked users into a new network valuation model as this would be more representative of cryptocurrencies' true value. This is because there are many mechanisms within the cryptocurrency ecosystem that add value without requiring users to be classified as active. It is also important to explore the other factors that might have a significant effect on cryptocurrency prices to develop a comprehensive and accurate model for cryptocurrency price prediction, especially for those cryptocurrencies (i.e., ETH, XRP, LEO, XMR, ETC, XLM, BCH, ALGO, EOS, XTZ, BSV and DASH) whose R^2 value of network nonlinear model are lower than 0.60. These factors could include outstanding supply, new and total insurance, active supply, miner supply, hash rate, Twitter sentiments and Reddit subscribers.

We established that there is statistically significant difference in the price volatility between most cryptocurrencies and the traditional asset classes. Although some matured cryptocurrencies showed similar volatility with traditional asset classes, evidence from our study suggest we cannot generalise on the volatility behaviour of cryptocurrencies and that the store of value evaluation would have to be on a case-by-case basis. This study supports investor anxiety in relation to the volatility of cryptocurrency which is visually apparent from the GARCH models and justifies cryptocurrencies being labelled as a risk on the asset class.

As indicated by Watorek [61], cryptocurrency market has gradually been pursuing its way to maturity. Another direction for future study might be to examine the moving-window correlation and multiscale characteristics of various cryptocurrencies and stock markets in different countries to investigate the hedging and spill over effects of cryptocurrencies during various economic periods. Based on these results, investors can potentially use various cryptocurrencies as part of their investment portfolio optimisation.

Credit author statement

Tiam Bakhtiar: Conceptualisation, data curation, formal analysis, methodology, validation, writing -original draft, Xiaojun Luo: Supervision, writing-review & editing, revision, validation, Ismail Adelopo: data curation, formal analysis, writing-review & editing, revision.

Data availability

Data will be made available on request.

Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DeFi	Decentralised Finance
ESMA	European Supervisory Authorities
GARCH	Generalised AutoRegressive Conditional Heteroskedasticity
HODL	Hold on to dear life
LPPLS	Log-Periodic Power Law Singularity
VDE	Vanguard Energy ETF

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