Theoretical and Applied Economics
Volume XXX (2023), No. 3(636), Autumn, pp. 77-92

Analysing the interrelationship between Bitcoin price and it's energy consumption

Neha SETH
Symbiosis International (Deemed University), Pune, India
neha_seth01@yahoo.com
Kirti JAIN
Symbiosis International (Deemed University), Pune, India
kirtijain1057@gmail.com

Abstract. *An increasing trend in cryptocurrency prices shows the investors' attention towards digital currency, but the carbon emission effect due to cryptocurrency is also gaining importance. However, no study has investigated the relationship between these two variables. The study's objective is to investigate the relationship between Bitcoin energy consumption and the prices of Bitcoin. This paper uses Johansen's cointegration test, the Vector error correction model, Granger's causality, Impulsive response, and variance decomposition on daily frequency data. It indicates the existence of long-run cointegration between energy consumption and Bitcoin prices. On the other hand, VEC Granger causality indicates that one time series does not cause the other one and vice versa. Variance decomposition and impulsive response function also indicate that shocks in energy consumption insignificantly affect the Bitcoin prices and vice versa. Policymakers and regulators should pay attention to renewable energy resources in cryptocurrency mining.*

Keywords: cryptocurrency, Bitcoin, energy consumption, vector error correction model, integration.

JEL Classification: G11, G15, G18, G23, Q43, Q54.

1. Introduction

Researchers on climate change have agreed that carbon emission, a significant cause of global warming, is the result of fossil fuel energy consumption at a vast level. To achieve sustainable development goals to reduce global temperature growth below 2 percent, there is a need to reduce the consumption of fossil fuel energy. However, at the same time, cryptocurrency is also gaining popularity as a digital currency and increasing in value by passing the days. Many cryptocurrencies are based on the blockchain process to complete the validation process. To complete these algorithm processes, cryptocurrency miners require a large amount of energy. According to the sustainable think tank, i.e., Think Through Consulting, only Bitcoin consumed 131.80 TWh of power to complete the mining process in 2018, which was approximately equal to the power consumption of Argentina Country. Figure 1 also shows the recent upward trend of Bitcoin energy consumption.

Irrespective of all these carbon footprints of Bitcoin and other cryptocurrencies, the value of cryptocurrency is increasing in the financial market. The prices of Bitcoin have increased in the last few years, as shown in Figure 2. Graphical representation indicates that there are some relations between energy consumption and the prices of the Bitcoin. With the increasing demand for cryptocurrency, energy consumption has also increased. To some extent, some investors are now aware of the climate damage due to cryptocurrency demand, especially those using non-renewable resources for energy consumption, like Bitcoin.

In 2021, Elon Musk, the CEO of Tesla Motors, suspended the acceptance of Bitcoin in the selling process of vehicles because of fossil fuel energy used by Bitcoin in the mining process. The tweet reads, "Tesla has suspended vehicle purchases using Bitcoin. We are concerned about the rapidly increasing use of fossil fuels for Bitcoin mining and transactions, especially coal, which has the worst emissions of any fuel. Cryptocurrency is a good idea on many levels, and we believe it has a promising future, but this cannot come at a great cost to the environment. Tesla will not be selling any Bitcoin and we intend to use it for transactions as soon as mining transitions to more sustainable energy. We are also looking at other cryptocurrencies that use < 1 percent of Bitcoin energy/transaction."

At that time, the Bitcoin price faced a sudden decrease due to this tweet. That shows Bitcoin price also has been impacted by the market news, investors' sentiments, and climate-related news. Much literature shows the cryptocurrency's impact on carbon emission (Li et al., 2019; Stoll et al., 2019; Corbet and Yarovaya, 2020; Karmakar et al., 2021; Polemis and Tsionas, 2021) and carbon emission relationship with the stock market price (Chang et al., 2020; Garzón-Jiménez and Zorio-Grima, 2021; Sharma et al., 2021; Liu and Gong, 2022). However, studies have yet to investigate the interrelation between Bitcoin price and its energy consumption. To fill this research gap, our study examines the Bitcoin price relation with Bitcoin energy consumption which helps explain the investor's perspective on environmental damage. Econometrics tools such as the unit root test, Johansen's cointegration test, Vector error correction model (VECM), Impulsive response, and Variance decomposition have been applied to time series in the process of getting results. Classification of further sections of the article are these; Section 2 discusses the existing literature in this field to form a base for the empirical research. An explanation of variables and data sample is contained in section 3. Section 4 model used for empirical research can be found with an explanation of methods. Section 5 will help to understand the empirical research findings on the interrelationship between Bitcoin prices and energy consumption. A conclusion with policy implications can be found in section 6.

2. Review of literature

Many studies investigate the problem of carbon emission and environmental degradation, considering cryptocurrencies. Cryptocurrency's transaction validation process uses a proof-of-work mechanism, resulting in the annualized energy consumption of a cryptocurrency, i.e., Bitcoin equals a mid-size country's consumption. Stoll, Klaaßen and Gallersdörfer (2019) define the interrelationship among energy consumed by Bitcoin in the validation process and its carbon emission production level. The study found that energy consumption and carbon emissions produced in November 2018 equal the level of carbon emission produced by Kansas City. Corbet and Yarovaya (2020) also indicate that Cryptocurrency transactions as an ongoing carbon emission production process. The study examines the multiple Knock-on effects of increased energy consumption, like an increase in global temperature. Indirectly they also raise a question on investor perspective towards cryptocurrencies. Polemis and Tsionas (2021) to investigate the reasons behind the carbon footprint of Bitcoin uses the Beysian analysis and cointegrated vector autoregression (CQVAR) The research defines a strong and negative relationship between Bitcoin miners' income and carbon emission due to Bitcoin, indicating the energy consumption's impact on carbon emission. Karmakar, Demirer and Gupta (2021) investigate the impact of Bitcoin mining activities on volatility in the power market and indicates that an increase in trading activities of cryptocurrency results in volatility in power consumption and prices. This study shows the significant impact of the cryptocurrency sector on the power sector and, ultimately, on carbon emissions. Similarly, Corbet and Yarovaya (2020) investigate Bitcoin's price volatility impact on the energy sector and its companies. The study also strongly impacts and significantly indicates further research on carbon emissions. Following the same relationship but to get more generalized results, (Li et al., 2019) investigate the electricity consumption in the mining process of nine cryptocurrencies (other than the Bitcoin). As a case study, this paper also estimates that from April to December China will emit 19.12~19.42 carbon emissions, which again indicates the strong impact of energy consumption in cryptocurrency on carbon emission.

Erdogan, Ahmed and Sarkodie (2022) applies standard and asymmetric methods to get robust relationship results between cryptocurrency and environmental degradation. The Toda-Yamamoto and bootstrap-augmented Toda-Yamamoto test shows a causal relationship between Bitcoin and Ethereum regarding environmental degradation. The study also indicates that positive and negative demand shocks affect environmental degradation. By applying quantile methods, Chen and Xu (2022) explain the strong impact of cryptocurrencies on the price in the carbon market. The study also indicated that cryptocurrency is an efficient hedging tool in the carbon market. Krause and Tolaymat (2018) quantify the energy consumption used in earning one US$ worth of digital assets. The study found that cryptocurrency consumes a high amount of energy in comparison to the mineral mining process to generate the same market value of one US$. During the study period, four cryptocurrencies generated almost 3-15 tons of CO_2. It also shows the increasing trend of hash rate, which shows that energy consumption will also increase. All these studies investigate the nexus between energy consumption in cryptocurrency mining and carbon emissions. All studies provide empirical proof of the strong interrelationship among carbon emission and energy consumption in the mining process.

Much literature has investigated the interrelationship between carbon emissions and stock prices. Chang et al. (2020) investigated the cause-and-effect interrelationship among carbon emissions (due to energy resources) and the MSCI Index stock returns from 1971 to 2017. By applying the Granger causality test, the study shows that the stock market has a one-way causal effect towards carbon emissions. Alam et al. (2021) analyze the impact of R&D spending by taking into consideration panel data from 30 OECD nations from 1996 to 2013 and the stock market on carbon emission and renewable energy. The econometric panel model results indicate a positive impact of R&D spending and the financial market on Renewable energy, another side it hurts carbon emissions. The study suggests that stock market policymakers promote R&D and clean energy usage by companies registered in stock markets. (Sharma et al., 2021) propose a policy framework to help countries attain sustainable development goals. By using the Cross-Section Autoregressive Distributed Lag (CS – ARDL) approach on South Asian countries from 1990 to 2016, this study reveals that stock market development, per capita income, and increase in trade positively affect carbon emission. Liu and Gong (2022) explain the heterogeneous effect of financial development on carbon emission based on different indicators of financial development, years, and geographical areas. The geographically and temporally weighted regression (GTWR) method explains the heterogeneity in the results. Garzón-Jiménez and Zorio-Grima (2021) disclose some surprising results of the investigation of 929 firms. This study indicates that companies that generate high carbon emissions have a higher cost of equity in the market than companies that do environmental disclosure. It highlighted that companies are setting off the environmental cost by providing Montreal benefits. All these studies indicate that the stock market and financial development have a strong relationship/impact on carbon emissions.

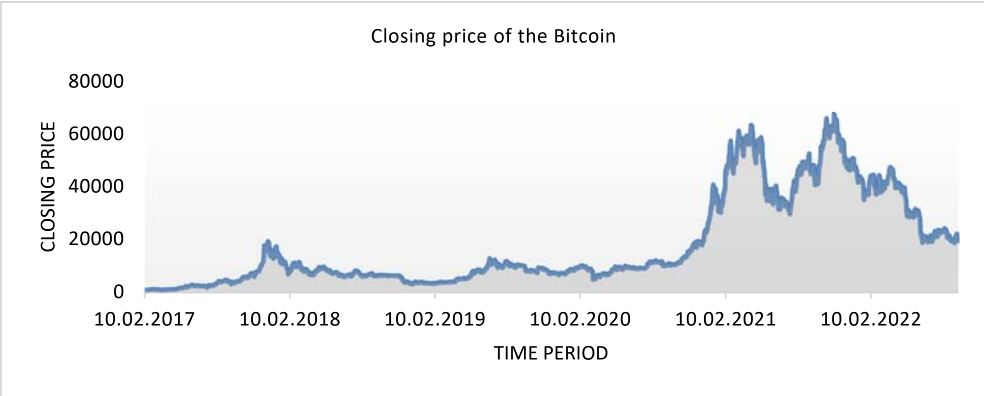
The above discussion of existing literature explains the proof-of-work process of cryptocurrency consuming a high amount of energy that affects carbon emissions. Many pieces of literature explore the relationship between the stock market and carbon emissions with different results. As cryptocurrency is also a part of the financial market, research work still needs to be done to explore the relationship between carbon emissions and cryptocurrency prices. This motivates me to conduct empirical research to explore the relationship between energy consumption in the cryptocurrency mining process and cryptocurrency prices.

The primary objective of the study is to explore the interrelationship between the energy consumption of the cryptocurrency validation process and the cryptocurrency prices. To investigate this relationship, the existence of long-run integration, long-run causality and short-run run causality between the energy consumption of cryptocurrency and the prices of cryptocurrency has been tested in this research work.

3. Data description and source

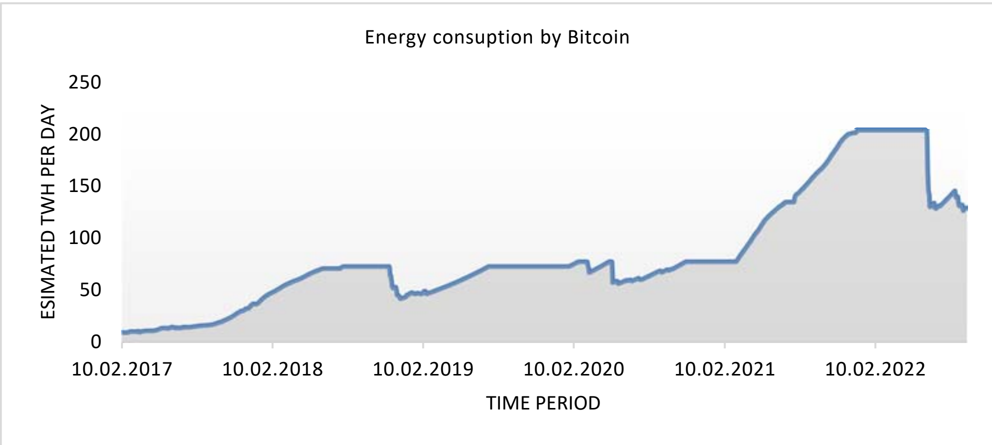
To investigate the relationship between the energy consumption the cryptocurrency during the validation process and the prices of cryptocurrency, Bitcoin (number one in energy consumption) has been considered as a proxy for Cryptocurrency. We plot the time series data of the Bitcoin energy consumption and Bitcoin closing prices in Figure 1 and Figure 2. It shows the upward trend in the series for the period of research. To get robust results, daily frequency secondary data has been used for a period from 02 February 2017 to 15 September 2022. The data period has been limited to the availability of energy consumption records. Table 1 represents the study's description and source of the variable used.

Figure 1. *Closing price of the Bitcoin*



Source: Data from Yahoo finance website.

Figure 2. *Energy consumption by Bitcoin in mining process*



Source: Data from Digiconomist website.

Table 1. *Data description and source*

Indicates	Variables	Source	Extension
Cryptocurrency Prices	Bitcoin Prices	Yahoo finance website	BTCP
Cryptocurrency energy consumption in proof-of-work process	Bitcoin energy consumption	Digiconomist website	BTEC

Source: Author's compilation.

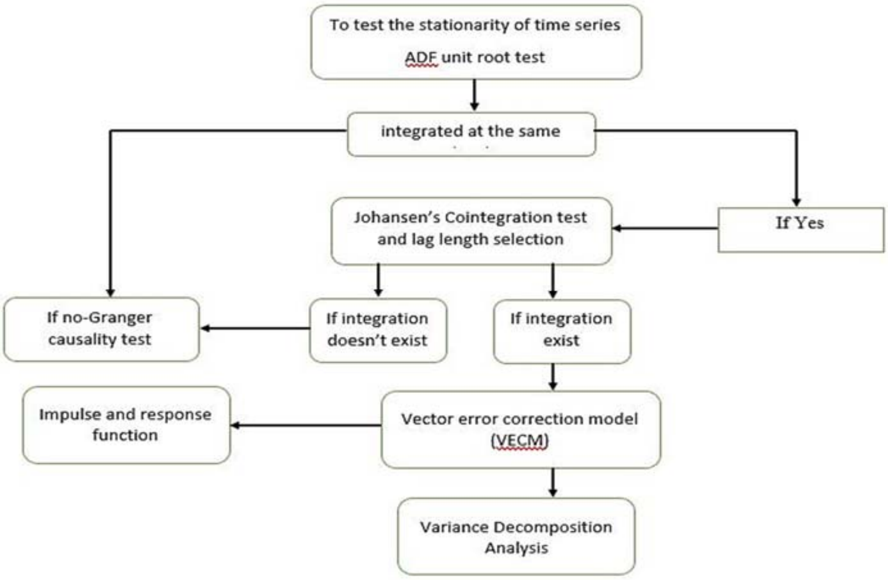
4. Research methodology

Cointegration of Bitcoin energy consumption and its prices has been focused on elaborating the level of long-run integration. Johansen's cointegration approach has been used to analyse the long-run equilibrium among variables. The rank of matrix is used under the context of Johansen's cointegration approach. If the cointegration vector r = 0, it means there will be no cointegration exist among the variables. On the other hand, if the cointegration vector $1 \leq r \geq k$, it means there is a long-run equilibrium that exists among the variables. Cointegration among variables then leads to perform Vector Error Correction Model (VECM) to examine the long run and short run adjustment of variables towards long run equilibrium. In situation of cointegration among Bitcoin energy consumption and Bitcoin closing prices, the VECM equation will be as follows:

$$\Delta BTEC_t = \varphi_1 + \sum_{i=1}^{n} \beta_1 \Delta BTEC_{t-1} + \sum_{j=1}^{n} \gamma_1 \Delta BTCP_{t-j} + E_1 ECT_{t-1} + \mu_{1t},$$

Where φ, γ, β denotes the coefficient of polynomials, n denotes the lag length and ECT denotes the error correction term. If this equation shows that null hypothesis ($\varphi = \beta = \gamma = 0$) is rejected, it means short term adjustment exist among the BTEC and the BTCP. ECT explains the long-term adjustment towards long run equilibrium, if null hypothesis ($E_1 = 0$) is rejected, it means long run causality is exist among BTEC and BTCP. The study also used the impulse response function and variance decomposition to analyze the impact of one tine and standard deviation shocks on change in another current and future value (Ur Rehman et al., 2021). The analysis has been performed according to model represent in following flow chart:

Figure 3. *Flow chart of model for analysis*



Source: Author's compilation.

4.1. Unit root test

Time series analysis is based on the specific assumption of stationarity. The existence of stationarity in data explains the relevance of the model. To extract effective results from the available data appropriate model plays a significant role. The null hypothesis i.e., no unit root exists in time series has been tested for individual series. The stationary of time series data is tested by the augmented Dickey-Fuller test. The following is the equation of the augmented Dicky-Fuller test:

$$Y_t = c + \beta_t + \alpha Y_{t-1} + \varphi \Delta Y_{t-1} + e_t$$

The Unit root test is based on the null hypothesis (H_0) = 0 i.e., no unit root in time series exists. The null hypothesis will be rejected if test statistics are less than the critical value of the time series.

4.2. Johansen's cointegration test

After satisfying the condition of non-stationarity at the level and stationarity at the first difference in the time series, Johansen's cointegration test has been applied to test the long-run equilibrium between the variables. This model frames the vector autoregression to compute linear relationships based on the maximum likelihood approach in the case of multiple time series. By considering the lags of the variable through the VAR model, the dependent variable becomes independent of itself. Two tests are used in Johansen's model, i.e., the trace test and the max eigenvalue test. Rizwanullah et al. (2020) mentioned these two equations for the trace and max eigenvalue tests.

Trace test: $\lambda_{max}(rr + 1) = -T \ln(1 - \lambda r + 1)$

Max eigenvalue test: $\lambda_{trace}(r) = -T\sum t = r + \ln(1 - \lambda r + 1)$

The trace test is based on the maximum likelihood trace in the matrix. The trace test checks whether adding more eigenvalue beyond the r^{th} eigenvalue increases the trace (Rizwanullah et al., 2020) The null hypothesis, i.e., no cointegration exists among variables, will be rejected if the p-value < 0.05 indicates that their long-run interdependence exists among variables.

4.3. Vector Error Correction Model (VECM)

The VECM model is a cointegration equation-based limited VAR model. VECM limits the variables' long-run behaviour in order to retain their long-run cointegration connection while allowing for short-run modifications (Zou, 2018). Because the deviation from the long run is gradually rectified by a succession of short-run adjustments, cointegration is used in the error correction term. This model is intended for non-stationary cointegrated series.

4.4. Impulse response function

The impulse response is a widely used method to examine the effect of one standard deviation shock in one variable on the innovation of another variable's current and future value (Ur Rehman et al., 2021) Researchers frequently use IRF since estimating the coefficient of the VAR model is always a complex undertaking (Damodar, 2004). When a one-unit shock is applied to one variable, IRF examines the time trajectories of the other variables' responses and vice versa. In another sense, it describes how time-series variables interact dynamically in the short run when a shock occurs (Kantaphayao and Sukcharoensin, 2021).

4.5. Variance decomposition

The study relies on variance decomposition to show the indication of the dynamic properties of the system. Variance decomposition determines the extent of interaction between the variables to examine the most and least influential variables (Roca, Wong and Tularam, 2010). The amplitude of the shocks in VEC is dispersed throughout time in respect of percentages that the variables impose on one another. The Variance decomposition determines each random innovation's relative importance in affecting the system's variables.

5. Empirical analysis

Table 2 contains the figures of descriptive statistics, which explain the value of the mean, median, maximum, minimum, skewness, standard deviation, and kurtosis of the Bitcoin price series (BTCP) and Bitcoin energy consumption series (BTEC). We can see a high difference between the maximum and minimum values in both time series. However, the mean is closer to the minimum value, showing the right-side skewness in the data. The coefficient of skewness is also positive, which shows the right-side skewness in data; the time series graphical plot also shows the same result. The Coefficient of Jarque-Beta test shows that no normality exists among the time series. A kurtosis value greater than 3 indicates that the distribution of the time series has peaked and has a thick tail.

Table 2. *Descriptive statistics of Bitcoin price and Bitcoin energy consumption*

	CLOSING_PRICE	ESTIMATED_TWH_PER_YEAR
Mean	17906.75	84.44162
Median	9477.660	73.12146
Maximum	67566.83	204.4955
Minimum	937.5200	9.290790
Std. Dev.	17168.19	54.71366
Skewness	1.167377	0.960570
Kurtosis	3.017702	3.074433
Jarque-Bera	463.8225 (0.00000)	314.4949 (0.00000)

Source: Author's compilation.

5.1. Unit root test

First, we apply the unit root test to check the stationarity characteristics in the time series of the variables. Augmented dicky fuller test based on selected automatically, using Schwarz criteria. The null hypothesis that the variable has a unit root has been used in the test.

Table 3. *Analysis of unit root test*

Test statistics	Variable	At level	First Difference
ADF	BTCP	-1.454102 (0.5569)	-46.28465 (0.0001)
	BTEC	-1.185283 (0.6830)	-14.39789 (0.000001)

Source: Author's compilation.

Table 3 represents the results of the unit root test of both variables. The null hypothesis that the variable has a unit root failed to be rejected because the p-value was insignificant at a level for both variables. It means BTCP and BTEC have characteristics of unit root at the level. To check their stationarity, both the variables have been tested at first difference. At the first difference level as shown in the table, p value was significant, so the null hypothesis that the variable has characteristics of the unit root was rejected for both the variables. It means BTCP and BTEC have characteristics of stationarity at first difference. This indicates that BTCP and BTEC have integration at the same level I(1), so our time series fulfil the condition for applying Johansen's integration test.

5.2. VAR lag selection

The lag selection is essential to test Johansen's cointegration, VECM, and granger causality test. VAR order lag selection criteria have been used to select lag for further calculation. Table 4 reports the results of the lag length of different selection criteria of endogenous variables. According to the table, all the selection criteria sequential modified LR test statistic, Final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion indicate 6 lag length as optimal at a 5 percent significance level. So for further analysis, lag length 6 has been considered optimal lag.

Table 4. *Lag intervals with lag length criteria*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-19594.93	NA	808614.4	19.27883	19.28436	19.28086
1	-19124.67	939.1314	511133.6	18.82014	18.83672	18.82622
2	-19106.09	37.06672	503855.0	18.80580	18.83343	18.81593
3	-19091.47	29.14935	498615.9	18.79535	18.83403	18.80954
4	-19087.92	7.063575	498838.0	18.79579	18.84553	18.81404
5	-19059.09	57.35650	486798.5	18.77136	18.83215	18.79366
6	-19035.98	45.92141*	477733.0*	18.75256*	18.82440*	18.77892*
7	-19032.59	6.733466	478019.1	18.75316	18.83605	18.78357
8	-19030.90	3.338034	479110.0	18.75544	18.84938	18.78990

*Indicate lag order selection by criterion.
Source: Author's compilation.

5.3. Johansen's cointegration test

Table 5 represents Johansen's cointegration test results to check the long-run integration among BTCP and BTEC. Trace statistics show that a 0.05 critical value is less than the trace statistics, and the p-value is also significant at a 5 percent significance level. This result shows that one cointegration equation exists among BTCP and BTEC. The same results have been shown by the Max-Eigen test, which shows the significance of the cointegration equation existence. It means that in the long run, BTCP and BTEC are co-integrated with each other, so further VECM model can be applied to check the long-run and short-run error correction terms.

Table 5. *Analysis of Johansen's cointegration test*

Hypothesis of cointegration	Trace statistic	0.05 critical value	Prob.**
None*	25.05914	15.49471	0.0014
At most 1	3.349952	3.841466	0.0672
Hypothesis of cointegration	Max-Eigen Statistics	0.05 critical value	Prob.**
None*	21.70919	14.26460	0.0028
At most 1	3.349952	3.841466	0.0672

*Trace test and max – eigenvalue indicates 1 cointegration eqn(s) at 5 percent significant level.
*Denotes rejection of the hypothesis at the 0.05 level.
**MacKinnon-Haug-Michelis (1999) p-values.
Source: *Author's compilation.*

5.4 Vector Error Correction Model

The cointegration equation explains the long-run equilibrium relationship between BTCP and BTEC. However, whether short-term error correction terms to maintain long-run equilibrium exist can be checked by the Vector error correction model. According to VAR lag selection criteria, 6 optimum lag has been used to conduct VECM in the statistical software package. According to Table 6, Johansen's equation was developed from the VECM model.

Table 6. *Results of cointegration equation*

Cointegration Eq:	CointEq 1
BTCP (-1)	1.000000
BTEC (-1)	-287.9043 (40.9102) [-7.03747]
C	6412.534

Source: Author's compilation.

The negative and significant equation coefficient explains the positive relationship between BTCP and BTEC. According to the equation, if other things remain constant, 1 percent change in BTEC will lead to a positive 289.479 percent change in BTCP. It indicates the ability among variables to reach again at an equilibrium point.

Table 7 represents the error correction terms of the VECM. The Bitcoin price index shows a positive and insignificant error correction coefficient, which means no correction exists to reach an equilibrium level in case of any disequilibrium. Bitcoin energy consumption also shows a positive but significant error correction term. It is also evident that the speed of adjustment towards long-run equilibrium with short-run adjustment is not happening between variables.

Table 7. *VECM estimation and calculation*

Error Correction:	D(BTCP)	D(BTEC)
CointEq1	0.000626 (0.00206) [0.30394]	7.11E-06 (1.5E-06) [4.64723]
D(BTCP (-1))	-0.032265 (0.02249) [-1.43434]	1.03E-05 (1.7E-05) [0.61746]
D(BTCP(-2))	0.002369 (0.02248) [0.10541]	2.60E-05 (1.7E-05) [1.55442]
D(BTCP(-3))	0.015341 (0.02250) [0.68168]	-2.04E-06 (1.7E-05) [-0.12186]
D(BTCP(-4))	0.034343 (0.02251) [1.52585]	1.22E-05 (1.7E-05) [0.73173]
D(BTCP(-5))	0.009340 (0.02252) [0.41472]	4.21E-06 (1.7E-05) [0.25155]
D(BTCP(-6))	0.029555 (0.02247) [1.31559]	-2.33E-05 (1.7E-05) [-1.39763]
D(BTEC(-1))	53.59577 (29.7626) [1.80078]	0.699734 (0.02212) [31.6309]
D(BTEC(-2))	-45.17665 (35.5619) [-1.27037]	-0.229688 (0.02643) [-8.68969]
D(BTEC(-3))	15.50773 (36.0952) [0.42963]	0.129804 (0.02683) [4.83825]
D(BTEC(-4))	27.31014 (36.0888) [0.75675]	-0.099276 (0.02682) [-3.70101]

Error Correction:	D(BTCP)	D(BTEC)
D(BTEC(-5))	-22.19002 (35.5883) [-0.62352]	0.253086 (0.02645) [9.56777]
D(BTEC(-6))	-35.60361 (29.6000) [-1.20283]	-0.148822 (0.02200) [-6.76434]
C	8.904616 (21.4296) [0.41553]	0.023297 (0.01593) [1.46264]

Source: Author's compilation.

5.5. VEC Granger Causality test

A cointegration relationship between Bitcoin price and Bitcoin energy consumption leads to investigating the causality among variables. There a cointegration equation exists, so granger causality has been tested in the VEC model. Table 8 shows that the p-value is insignificant, meaning there is no causality running from Bitcoin price towards Bitcoin Energy consumption and vice versa. It is evident Bitcoin energy consumption will not affect due to a change in Bitcoin price. In the same way, the Bitcoin price will not significantly affect due to changes in Bitcoin energy consumption.

Table 8. *VEC Granger causality test results*

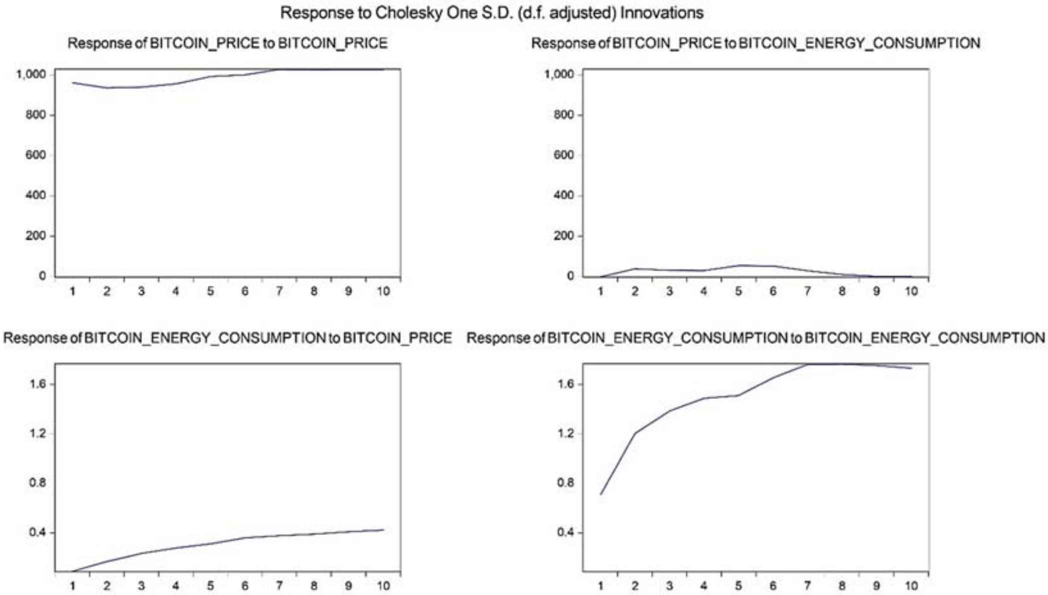
Dependent	Independent	
	Wald $\varkappa^2$ Test	
	ΔBTCP	ΔBTEC
ΔBTCP	-	1.483396 (0.2232)
ΔBTEC	1.552244 (0,2128)	-

Source: Author's compilation.

5.6. Impulse response function

Impulse response function shows the dynamic response by a variable due to one standard deviation shock to another variable. The methodology is widely used to interpret the dynamic interaction among variables and disturbances in VAR. The exogeneity criteria was first used to sequence the variables, then the VECM was applied at optimal lag of six. The impulse response analysis was conducted to examine the impact of innovation on Bitcoin price and Bitcoin energy consumption. Fig. 4 shows the results with horizontal axis representing the periods and vertical showing the response intensity. The second graph shows that there is a very minimal positive response of Bitcoin price to shock stemming from the Bitcoin energy consumption which starts to fall after period five. Thus, there is almost negligible effect of shock in Bitcoin energy consumption in predicting the price of Bitcoin. Further, the third graph shows that with the one standard shock given to Bitcoin price, the response of Bitcoin energy consumption started with a gradual increase till sixth period and after that remains to be constant. Thus, there is a positive response in Bitcoin energy consumption to the standard shocks in Bitcoin price with an increasing trend. Further the results also shows that both the variables are positively influenced by the shock given by their own lagged values, implying that the past information and innovations significantly impacts the current movement of the variables.

Figure 4. *Impulse response function*



Source: Author's compilation.

5.7. Variance decomposition

Table 9 interprets the VDC findings for the periods ranging from one to ten days. The results show that the price of Bitcoin is explained by its variance accounting for 100 per cent on day one, which stays higher for all ensuing periods, indicating that Bitcoin price is only affected by its own lagged values. Thus, the variation in the Bitcoin price is explained by its own variance. Further, the result shows that the variation in the Bitcoin energy consumption is minimally explained by price of Bitcoin as only 1.568 percent variation is explained by Bitcoin price in period 1 and goes highest to 4.94 percent in period 10. The result shows that the Bitcoin price is the least influenced and the energy consumption of Bitcoin does not explain the Bitcoin price.

Table 9. *Variance decomposition analysis*

Variance Decomposition of BITCOIN_PRICE			
Period	S.E.	BITCOIN_PRICE	BITCOIN_ENERGY_CONSUMPTION
1	962.2481	100	0
2	1343.336	99.92039	0.079612
3	1640.11	99.91095	0.089049
4	1899.083	99.90958	0.090417
5	2143.53	99.8651	0.134899
6	2366.441	99.84212	0.157881
7	2580.579	99.85511	0.144886
8	2776.743	99.87328	0.126725
9	2960.175	99.88848	0.111521
10	3133.432	99.90045	0.099554

Variance Decomposition of BITCOIN_ENERGY_CONSUMPTION			
Period	S.E.	BITCOIN_PRICE	BITCOIN_ENERGY_CONSUMPTION
1	0.715216	1.567616	98.43238
2	1.411108	1.833745	98.16626
3	1.992011	2.308777	97.69122
4	2.503123	2.694851	97.30515
5	2.94084	3.083082	96.91692
6	3.393819	3.449314	96.55069
7	3.843088	3.658479	96.34152
8	4.247463	3.845292	96.15471
9	4.613834	4.043788	95.95621
10	4.946492	4.25141	95.74859
Cholesky Ordering: BITCOIN_PRICE BITCOIN_ENERGY_ CONSUMPTION			

Source: Author's compilation.

6. Discussion and conclusion

This paper explores the relationship between Bitcoin price and energy consumption in the last five years. The main objective was to identify the effect of Cryptocurrency energy consumption on cryptocurrency prices and vice versa. With the application of econometrics tools, this study indicates that H01 is rejected on the significant evidence that shows that long-run cointegration exists between Bitcoin prices and the energy consumption of Bitcoin. However, H02 and H03 failed to be rejected due to insufficient significant evidence. Without a causal relationship between Bitcoin prices and energy consumption, this paper cannot explain any long-run and short-run causal relationship between them. Variance decomposition and Impulsive response also indicate that minimal variation can be seen in one time series due to any shock in another. It means Bitcoin prices and energy consumption move together in the long run but don't affect each other to maintain equilibrium.

Based on this, it can be concluded that energy consumption is also increasing as much as the Bitcoin price is increasing. Energy consumption by Bitcoin affect the carbon emissions in the economies (Corbet and Yarovaya, 2020; Polemis and Tsionas, 2021; Erdogan et al., 2022) and Cryptocurrency energy consumption and carbon emission in a year approximately equals the carbon emission by a small or middle-sized companies (Stoll et al., 2019). Li et al. (2019) also estimated an increasing trend in the Cryptocurrency's hash rate, which denotes the higher demand for Cryptocurrency as a result of higher demand for energy consumption and carbon emission. However, investors pay no attention to the increasing environmental degradation. Investors only concentrate on their investments' financial and economic benefits irrespective of environmental harm. During the COVID-19 pandemic, the investor's attention to the digital currency ultimately resulted in tons of carbon emissions in the economies. Karmakar, Demirer and Gupta (2021) is proof of investors' negligence towards the environment.

In the 2015 Paris Agreement, all United Nations member states agreed on 17 sustainable goals. According to this paper's result, Cryptocurrency contradicts Sustainable development goal 13 concentrates on "Take urgent action to combat climate change and its impacts," and sustainable development goal 17, which concentrates on "promotion and development of environmentally sound technology." According to the previous discussion, one side, Cryptocurrency, cause carbon emission due to the consumption of non-renewable energy, and another, according to the central bank digital currency tracker, 105 countries represent 95 percent of the total world GDP exploring the Central bank digital currency.

Bitcoin is a disaster for the climate; as the value of Bitcoin increases, the climate will suffer. However, now many cryptocurrencies conduct their mining work with renewable energy consumption, such as Acciona Energy & Iberdrola – Spain, The Brooklyn Microgrid, United States, and The Sun Exchange, South Africa. The policy implication of this paper suggests that different nations build policy work and regulations for issuing central bank-based Cryptocurrency with consideration of renewable energy. The study also suggests a need to change investor behaviour towards environmental upgradation.

Although this study has explored the relationship between energy consumption and the price of Cryptocurrency, this type of study is dynamic; with changing patterns of technology and the mining process, the impact of energy consumption on the environment may be changed. So further studies can consider different energy sources and their impact on price by using mediating factors like investor attention, carbon emission, and renewable energy to add more literature in this field.

References

Alam, M.S., Apergis, N., Paramati, S.R. and Fang, J., 2021. The impacts of R&D investment and stock markets on clean-energy consumption and CO_2 emissions in OECD economies. *International Journal of Finance and Economics*, *26*(4), 4979-4992. <https://doi.org/10.1002/ijfe.2049>

Chang, C.L., Ilomäki, J., Laurila, H. and McAleer, M., 2020. Causality between CO_2 emissions and stock markets. *Energies*, *13*(11). <https://doi.org/10.3390/en13112893>

Chen, H. and Xu, C., 2022. The impact of cryptocurrencies on China's carbon price variation during COVID-19: A quantile perspective. *Technological Forecasting and Social Change*, *183*. <https://doi.org/10.1016/j.techfore.2022.121933>

Corbet, S. and Yarovaya, L., 2020. The environmental effects of cryptocurrencies. In: *Batten-Corbet-Lucey Handbooks in Alternative Investments*. Walter de Gruyter GmbH. 149-184. <https://doi.org/10.1515/9783110660807-009>

Damodar, N., 2004. Basic Econometrics-McGraw-Hill. [online] Available at: <http://196.188.170.250:8080/jspui/bitstream/123456789/656/1/Basic%20Econometrics-McGraw-Hill%20%282004%29%20Damodar%20N.%20Gujarati%20%20-.pdf> [Accessed 20 September 2022].

Erdogan, S., Ahmed, M.Y. and Sarkodie, S.A., 2022. Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability. *Environmental Science and Pollution Research*, *29*(21), 31723-31733. <https://doi.org/10.1007/s11356-021-17998-y>

Garzón-Jiménez, R. and Zorio-Grima, A., 2021. Effects of carbon emissions, environmental disclosures and CSR assurance on cost of equity in emerging markets. *Sustainability*, *13*(2), 1-11. <https://doi.org/10.3390/su13020696>

Kantaphayao, W. and Sukcharoensin, S., 2021. Cointegration and Dynamic Spillovers between Cryptocurrencies and Other Financial Assets. *Southeast Asian Journal of Economics*, [online] *9*(3), 43-73. Available at: <https://so05.tci-thaijo.org/index.php/saje/article/view/255869> [Accessed 20 September 2022].

Karmakar, S., Demirer, R. and Gupta, R., 2021. Bitcoin mining activity and volatility dynamics in the power market. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3934561>

Krause, M.J. and Tolaymat, T., 2018. Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability*, *1*(11), 711-718. <https://doi.org/10.1038/s41893-018-0152-7>

Li, J., Li, N., Peng, J., Cui, H. and Wu, Z., 2019. Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies. *Energy, 168,* 160-168. <https://doi.org/10.1016/j.energy.2018.11.046>

Liu, H. and Gong, G., 2022. Heterogeneous impacts of financial development on carbon emissions: evidence from China's provincial data. *Environmental Science and Pollution Research*, *29*(25), 37565-37581. <https://doi.org/10.1007/s11356-021-18209-4>

Polemis, M.L. and Tsionas, M.G., 2021. The environmental consequences of blockchain technology: A Bayesian quantile cointegration analysis for Bitcoin. *International Journal of Finance and Economics*. <https://doi.org/10.1002/ijfe.2496>

Rizwanullah, M., Liang, L., Yu, X., Zhou, J., Nasrullah, M. and Ali, M.U., 2020. Exploring the Cointegration Relation among Top Eight Asian Stock Markets. *Open Journal of Business and Management*, *08*(03), 1076-1088. <https://doi.org/10.4236/ojbm.2020.83068>

Roca, E., Wong, V.S.H. and Tularam, G.A., 2010. Are socially responsible investment markets worldwide integrated? *Accounting Research Journal, 23*(3), 281-301. <https://doi.org/10.1108/10309611011092600/FULL/HTML>

Sharma, R., Shahbaz, M., Sinha, A. and Vo, X.V., 2021. Examining the temporal impact of stock market development on carbon intensity: Evidence from South Asian countries. *Journal of Environmental Management, 297.* <https://doi.org/10.1016/j.jenvman.2021.113248>

Stoll, C., Klaaßen, L. and Gallersdörfer, U., 2019. The Carbon Footprint of Bitcoin. *Joule*, *3*(7), 1647-1661. <https://doi.org/10.1016/j.joule.2019.05.012>

Ur Rehman, R., Zain Ul Abidin, M., Ali, R., Nor, S.M., Naseem, M.A., Hasan, M. and Ahmad, M.I., 2021. The integration of conventional equity indices with environmental, social, and governance indices: evidence from emerging economies. *mdpi.com*. [online] <https://doi.org/10.3390/su13020676>

Zou, X., 2018. VECM Model Analysis of Carbon Emissions, GDP, and International Crude Oil Prices. *Discrete Dynamics in Nature and Society*, <https://doi.org/10.1155/2018/5350308>