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Trade volume affects bitcoin energy consumption and carbon footprint

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A R T I C L E I N F O

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A B S T R A C T

The environmental sustainability of bitcoin is making waves in the empirical literature, yet, no study has thus far examined the financial determinants of bitcoin energy consumption and carbon footprint. Here, we use novel estimation methods comprising dynamic ARDL simulations and general-to-specific VAR to examine steady-state effects, cumulative impulse-response, and counterfactual shocks of bitcoin trade volume on bitcoin energy and carbon footprint to ensure genuine causal inferences. We observed an increase in bitcoin trade volume spur both carbon and energy footprint by 24% in the long-run, whereas a dynamic shock in trade volume escalates bitcoin energy and carbon footprint by 46.54%.

1. Introduction

Blockchain technology is widely believed to be the most attractive and promising technological breakthrough for various industries, namely logistic management, supply chain system, operational management, and internet of things (IoT) (Gallagher et al., 2019; Jiang et al., 2021). The increase in the adoption of bitcoin in finance, retail, and politics is gradually bridging the gap between bitcoin and traditional assets that have existed in the past. Institutional adoption of cryptocurrencies, particularly bitcoin, is growing, thus altering the factors that affect current bitcoin trading compared to historical trends. The stock market crash of 2020 triggered a massive bitcoin bull run that lasted over a year—as investors used it as a conduit for the store of value during high uncertainty, low confidence in the economy, and expectations of higher future inflation (BinanceAcademy, 2021). Indeed, inflation has risen in almost all developed countries to levels not experienced over the last four decades. Cryptocurrencies have by far outperformed all traditional asset classes despite the high risk and price volatility. On average, bitcoin observes ~200% yearly growth with a reported all-time-high price of about US$68,000 and market capitalization of approximately US$1.2 trillion as of November 2021 (BinanceAcademy, 2022; CMC, 2022). The greater demand for bitcoin coupled with bullish market trend leads to more miners using powerful computers to compete against others at a faster rate to enable transactions to go through. This computing process for bitcoin mining is energy-intensive and often relies heavily on cheap and pollution-intensive energy sources. Thus, carbon emissions from using the bitcoin proof-of-work consensus network have attracted significant criticism from proponents of environmental sustainability in recent years—as electricity for mining rigs and data centers are dependent on fossil fuels such as coal, oil, and gas.

Several studies have in recent years investigated the effect of bitcoin carbon emissions on climate change. For instance, a study that

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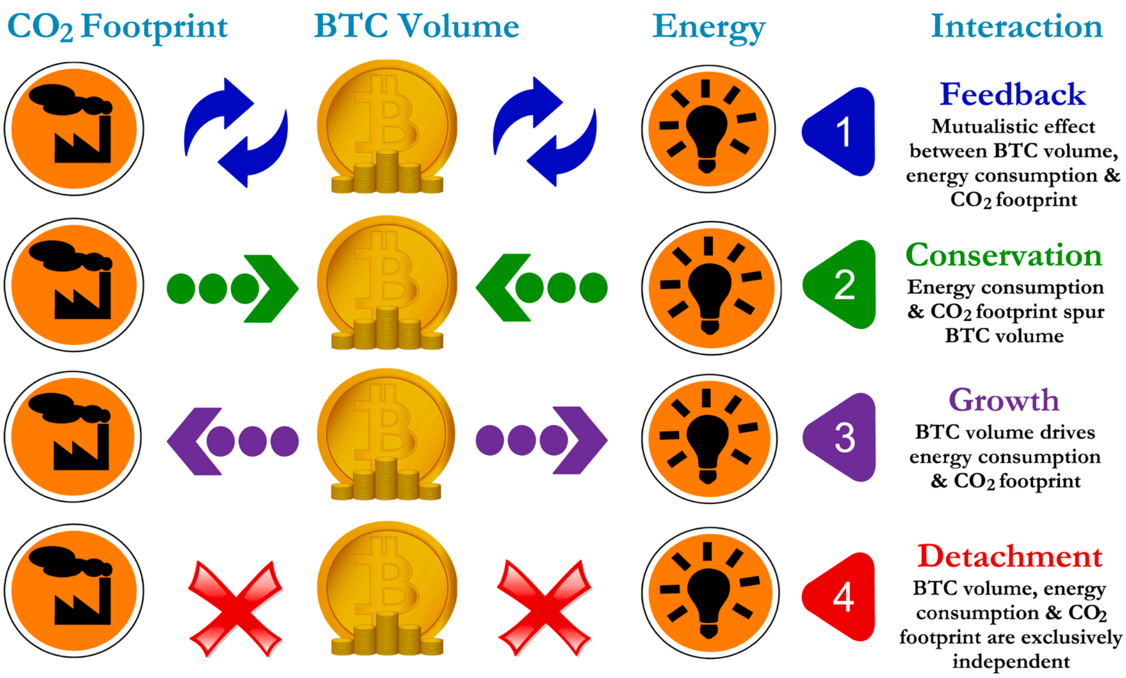

Fig. 1. Theoretical framework showing the relationship between bitcoin, carbon footprint, and energy consumption. Here, we use BTC volume in the scheme as a case study, yet, it can be replaced with either market price or market capitalization without losing the theoretical interpretations.

employed IPO filings of large hardware manufacturers, mining operations, and mining pools estimated the annual bitcoin power consumption and carbon footprint as 4.58 TWh and 22.9 $MtCO_2eq$ (i.e., est. November 2018) (Stoll et al., 2019). Another study argued that the rising level of annual bitcoin energy consumption is expected to peak at ~296.59 TWh with a corresponding 130.50 $MtCO_2eq$ in 2024 assuming no policy intervention in China's bitcoin operations (Jiang et al., 2021). The level of this energy consumption is comparable to the entire energy consumption of countries like Mexico and Italy and placing bitcoin consumption between the 10^{th} and 15^{th} largest consumer of all countries in the world. Similarly, other studies have assessed the determinants of bitcoin energy consumption and environmental degradation using regression models (Erdogan et al., 2022; Huynh et al., 2021). Evidence from asymmetric causality found a positive shock of bitcoin demand stimulates environmental degradation (Erdogan et al., 2022), whereas bidirectional causality is confirmed between bitcoin returns and energy consumption (Huynh et al., 2021). Moreover, Naeem and Karim (2021) analyze the tail dependence between bitcoin and green assets and find that due to the high energy consumption by bitcoin mining, clean energy is an effective hedge for bitcoin. However, there is limited research underpinning the role of financial determinants studied herein. As such, we provide novel insights into the linkage between bitcoin trade volume and bitcoin energy consumption and carbon footprint.

Yet, literature that examines the overarching effect of financial indicators on bitcoin energy consumption and carbon footprint is limited. Here, we investigate the complex nexus between bitcoin price, trade volume, market capitalization, bitcoin energy consumption, and carbon footprint using novel estimation methods [i.e., dynamic ARDL simulations, and general-to-specific vector autoregression (VAR) model] that control for counterfactual shocks, high-dimensional and threshold effects that cannot be captured by the standard VAR model.

2. Materials & method

2.1. Theoretical framework

The framework presented in Fig. 1 is inspired by the biological interaction between species where there is/no benefit for at least one species. This form of biological relationship highlights the importance of either symmetric or asymmetric interaction between sampled variables and their corresponding externalities (Von Jacobi, 2018). Mimicking the interaction where both species benefit, we hypothesize that bitcoin trade volume vs. carbon and energy footprint have mutualistic effects termed feedback interaction. In conservation interaction, energy and carbon footprint intensity are expected to increase bitcoin trade volume—of which any policy to reduce energy and carbon intensity will decrease bitcoin trade volume. Contrary, there is a possibility that increasing bitcoin trade volume will spur carbon and energy footprint termed as growth relationship. Finally, the detachment interaction suggests no relationship between bitcoin trade volume vs. carbon and energy footprint.

Table 1
Sampled variable description.

Abbrev	Variable Name	Variable – Description	Units
BTCP	Bitcoins Market Price	Average USD market price across major bitcoin exchanges.	US$
BTCVOL	USD Exchange Trade Volume of Bitcoins	The total USD value of trading volume on major bitcoin exchanges.	US$
BTCMCAP	Market Capitalization of Bitcoins	The total USD value of bitcoin supply in circulation, as calculated by the daily average market price across major exchanges.	US$
ESTENE	Estimated Consumption of Energy per Year	Estimated TWh per Year	TWh
BTCEMI	Estimated Carbon Emissions per Year	Estimated tCO_2 per Year	tCO_2

2.2. Data

This study constructed a bitcoin model based on daily frequency data spanning February 10, 2017-October 19, 2021. The sampled data series (Table 1) include bitcoins market price, USD exchange trade volume of bitcoins, and market capitalization of bitcoins collated from Blockchain (Blockchain, 2021), whereas estimated bitcoin energy consumption per year was collected from Digiconomist (Digiconomist, 2021). Data for estimated bitcoin carbon emissions per year were constructed following the empirical procedure presented in Sarkodie et al. (2022).

Bitcoin prices exhibit high volatility, which varies substantially over time with sudden large movements (jumps) and is linked to the liquidity of the market as well as the liquidity of bitcoin itself [see, for example (Chaim et al. (2018), Leirvik (2021), Qian et al. (2022), and Zhang et al. (2022)]. One way to illustrate the intraday volatility is by the natural logarithm of the ratio of daily high and low prices:

$$\sigma_t = \ln \frac{P_{H,t}}{P_{L,t}}$$

Where $P_{H,t}$ $(P_{L,t})$ is the highest (lowest) price at day t. Fig. 2 illustrates the intraday volatility since 2017, which shows incidents of very high price movements in a day. The mean, maximum, and minimum intraday volatility for bitcoin is 0.05, 0.49, and 0.004. By comparison, the ETF SPY which tracks the US S&P500 index has a mean of 0.01, a maximum of 0.09, and a minimum of 0.001.

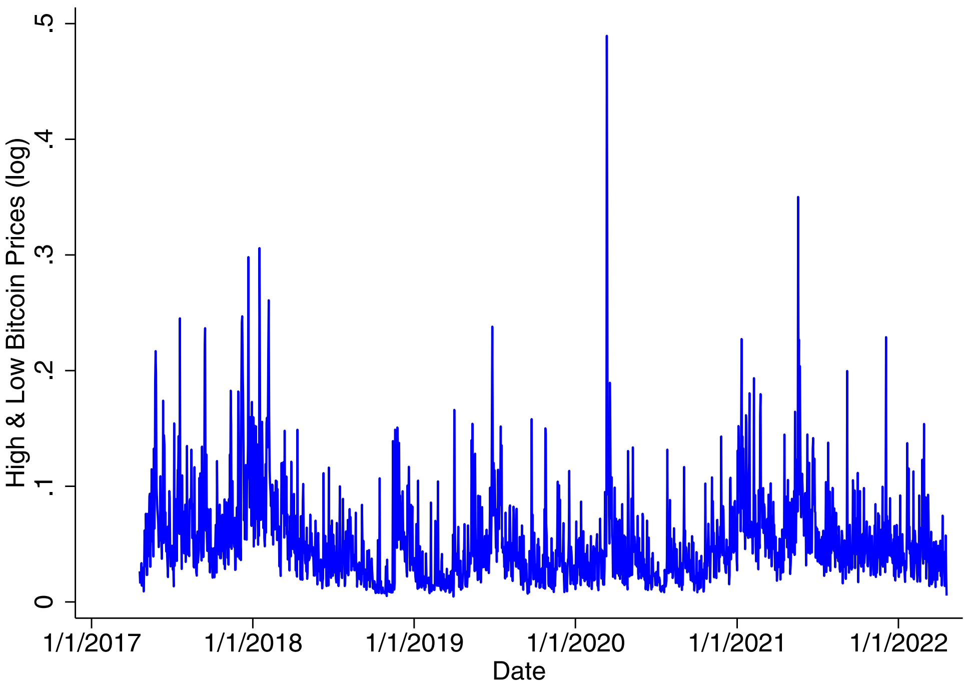

Fig. 2. Logarithm of daily high and low bitcoin prices.

Table 2
Descriptive statistical analysis.

Statistics	ESTENE	BTCVOL	BTCP	BTCMCAP	BTCEMI
Mean	65.536	3.92×10^8	14071.480	2.58×10^{11}	108.921
Maximum	177.429	5.35×10^9	63554.440	1.21×10^{12}	116.387
Minimum	9.291	1.48×10^7	941.920	1.52×10^{10}	294.886
Std. deviation	34.331	4.47×10^8	15087.540	2.86×10^{11}	15.441
Skewness	0.775	3.529	1.768	1.777	57.058
J-B test	289.597♣	34691.430♣	1144.118♣	1155.217♣	4.287♣
Observations	1712	1713	1713	1713	1712
Daily Δ (%)	0.002	0.151	0.003	0.003	0.002
Correlation					
ESTENE	1				
BTCVOL	0.022	1			
BTCP	0.740	0.282	1		
BTCMCAP	0.744	0.268	0.998	1	
BTCEMI	1.000	0.022	0.740	0.744	1
Unit root		L.PP	Δ.PP	L.ADF	Δ.ADF
lnESTENE		-2.106	-26.616***	-2.564	-26.075***
lnBTCVOL		-10.203***	NA	-11.724***	NA
lnBTCP		-1.861	-43.337***	-1.832	-43.386***
lnBTCMCAP		-1.883	-43.475***	-1.857	-43.533***
lnBTCEMI		-2.073	-26.638***	-2.514	-26.100***

Notes: J-B denotes Jarque-Bera test, ♣represents the violation of Jarque-Bera test based on H_0 of normal distribution at 1% significance level, *** denotes the rejection of H_0 (i.e., contains unit root) at 1% significance level, L.PP and L.ADF are Phillips-Perron and augmented Dickey-Fuller unit root test at level whereas Δ.PP and Δ.ADF are estimated in first-difference.

2.3. Model estimation

The traditional higher-order vector autoregression (VAR) models based on equation-by-equation OLS often suffer from over-parameterization with several variables, hence, producing weak statistical inferences. To solve this limitation, Campos et al. (2005) proposed the general-to-specific (GETS) technique based on a more efficient procedure, viz. seemingly unrelated regression (Zellner, 1962)—a system-estimation to improve statistical inferences after estimating VAR models. Subsequently, Asali (2020) developed the vgets algorithm that improves the general-to-specific VAR by adding long-run, cumulative impulse-response, and diagnostics to ensure genuine causal inferences. In this way, the parameters of the general-to-specific VAR can be used to validate the estimated VAR from traditional specifications. Using this novel estimation method, we investigate the following hypotheses—(1) bitcoin price, trade volume, and market capitalization have no effect on energy consumption and vice versa; and (2) bitcoin trade volume, price, and market capitalization have no effect on carbon footprint and vice versa. The empirical specification to examine the causal effects can be expressed as:

$$x_t = \sum_{i=1}^{2} \alpha_i x_{t-i} + \sum_{i=1}^{2} \beta_i y_{t-i} + z_t \delta_1 + \varepsilon_{x_t} \tag{1}$$

$$y_t = \sum_{i=1}^{2} \gamma_i x_{t-i} + \sum_{i=1}^{2} \varphi_i y_{t-i} + z_t \delta_2 + \varepsilon_{y_t} \tag{2}$$

where x_t and y_t denote a feedback causality between sampled variables in time t, x_t includes bitcoin price, bitcoin trade volume, and bitcoin market capitalization, y_t comprises bitcoin energy consumption, and bitcoin carbon footprint, z represents the exogeneous control variable (i.e., time trend), α, β, ϕ, γ, and δ are the parameter estimates, and ε represents the error term. The optimal lag order (i.e., 2) was selected using a combination of information criteria including AIC, SBIC, HQIC, and FPE. To assess causality from y to x and vice versa, we test the joint statistical significance of β parameters in Eq. (1), and γ parameters in Eq. (2). The short-run relationships across diverse variables are examined using $\sum_{i=1}^{2}\beta_i$ and $\sum_{i=1}^{2}\gamma_i$ in Eqs. (1) and (2), respectively.

The long-run effects are estimated using the empirical specifications expressed as:

$$L_{y\to x} = \frac{\sum_{i=1}^{2}\beta_i}{1 - \sum_{i=1}^{2}\alpha_i} \tag{3}$$

$$L_{x\to y} = \frac{\sum_{i=1}^{2}\gamma_i}{1 - \sum_{i=1}^{2}\varphi_i} \tag{4}$$

where $L_{x\to y}$ formulation is used to assess long-run effects of x on y whereas $L_{y\to x}$ specification is used to measure long-run effects of y on x.

The cumulative impulse-response *CIR* simultaneously examines the reactions and dynamics of sampled variables in the long-run

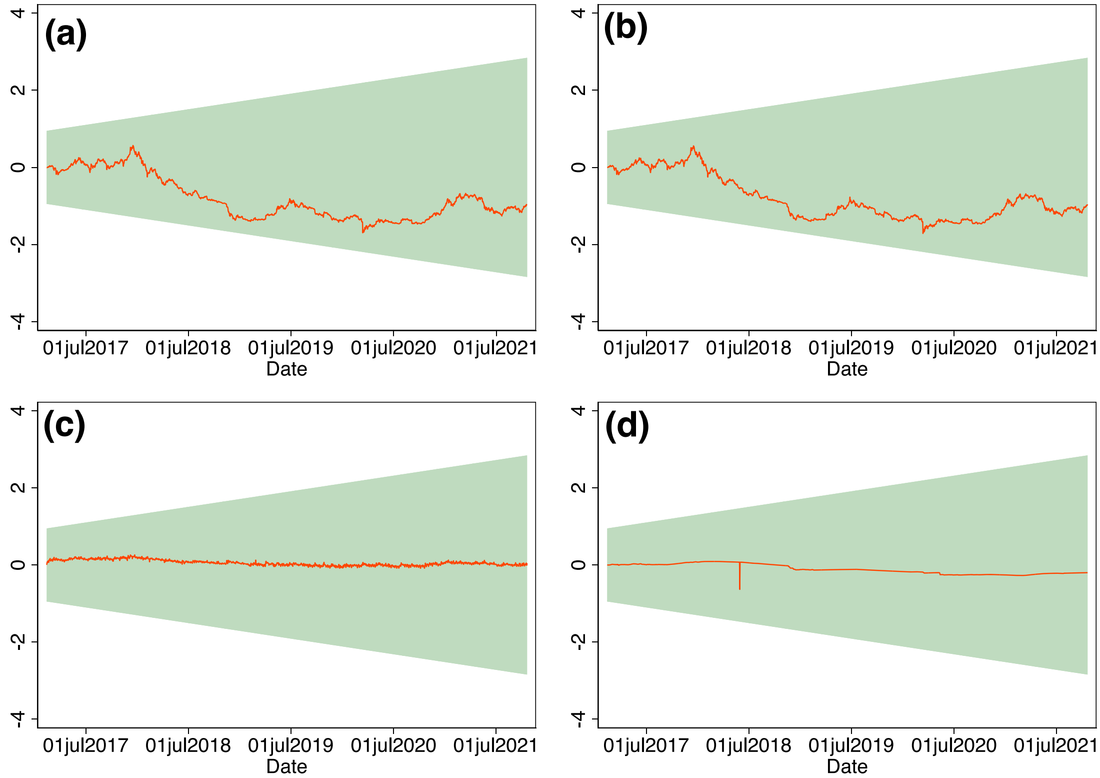

Fig. 3. CUSUM parameter stability test (a) BTC price (b) BTC market capitalization (c) BTC trade volume (d) BTC energy consumption.

using the expression:

$$CIR_{y\to x} = \frac{\sum_{i=1}^{2}\beta_i}{\left(1-\sum_{i=1}^{2}\alpha_i\right)\left(1-\sum_{i=1}^{2}\varphi_i\right) - \sum_{i=1}^{2}\beta_i \times \sum_{i=1}^{2}\gamma_i} \tag{5}$$

$$CIR_{x\to y} = \frac{\sum_{i=1}^{2}\gamma_i}{\left(1-\sum_{i=1}^{2}\alpha_i\right)\left(1-\sum_{i=1}^{2}\varphi_i\right) - \sum_{i=1}^{2}\beta_i \times \sum_{i=1}^{2}\gamma_i} \tag{6}$$

where $CIR_{y\to x}$ measures CIR effects of y on x while $CIR_{x\to y}$ formulation assesses CIR effects of x on y. Contrary to the traditional symmetric VAR, the general-to-specific VAR iteratively drops lagged-variables with estimated t-statistic less than 1 using cut-off based on Haitovsky rule (Asali et al., 2017). Thus, the general-to-specific VAR is estimated with the constrained parameters that pass the cut-off. The standard errors of nonlinear and cross-equation combination of parameters including long-run and cumulative impulse-response effects are estimated using the delta method (Asali et al., 2020).

3. Results & discussion

The daily summary of descriptive statistical analysis is presented in Table 2. The 5-year daily data shows an estimated average bitcoin energy consumption per year of 65.54 TWh and 108.92 tCO_2 average bitcoin carbon footprint per year. Both estimated bitcoin energy and carbon footprint correspond to an average daily market capitalization of US$ 2.58×10^{11} based on average market price of U$ 14071.48 and trade volume of US$ 3.92×10^{8}. Bitcoin energy and carbon footprint observed a 0.002% daily change whereas trade volume, price, and market capitalization observed a daily change of 0.151%, 0.003%, and 0.003%, respectively. The raw sampled data violate the normality assumption as depicted by the Jarque-Bera test—justifying logarithmic transformation of variables. The test for stationarity using Phillips-Perron (PP) and augmented Dickey-Fuller (ADF) unit root techniques confirms first-difference stationary variables excluding trade volume which exhibits level stationarity. The correlation test shows positive association among sampled variables, however, the underlying causal effect relationship useful for statistical inferences is examined hereafter.

Note that the correlation between ESTENE and BTCEMI is 1. BTC energy (ESTENE) is correlated with BTC carbon footprint (BTCEMI) because BTC footprint is constructed using IEA emission factors (i.e., emission factors are single values), hence, the supposed linearity only stems from the multiplication with the emission factor [*see* Sarkodie et al. (2022) for detailed calculations, and Owusu et al. (2022) for the constructed dataset]. Nevertheless, both variables are used exclusively as dependent variables in separate models.

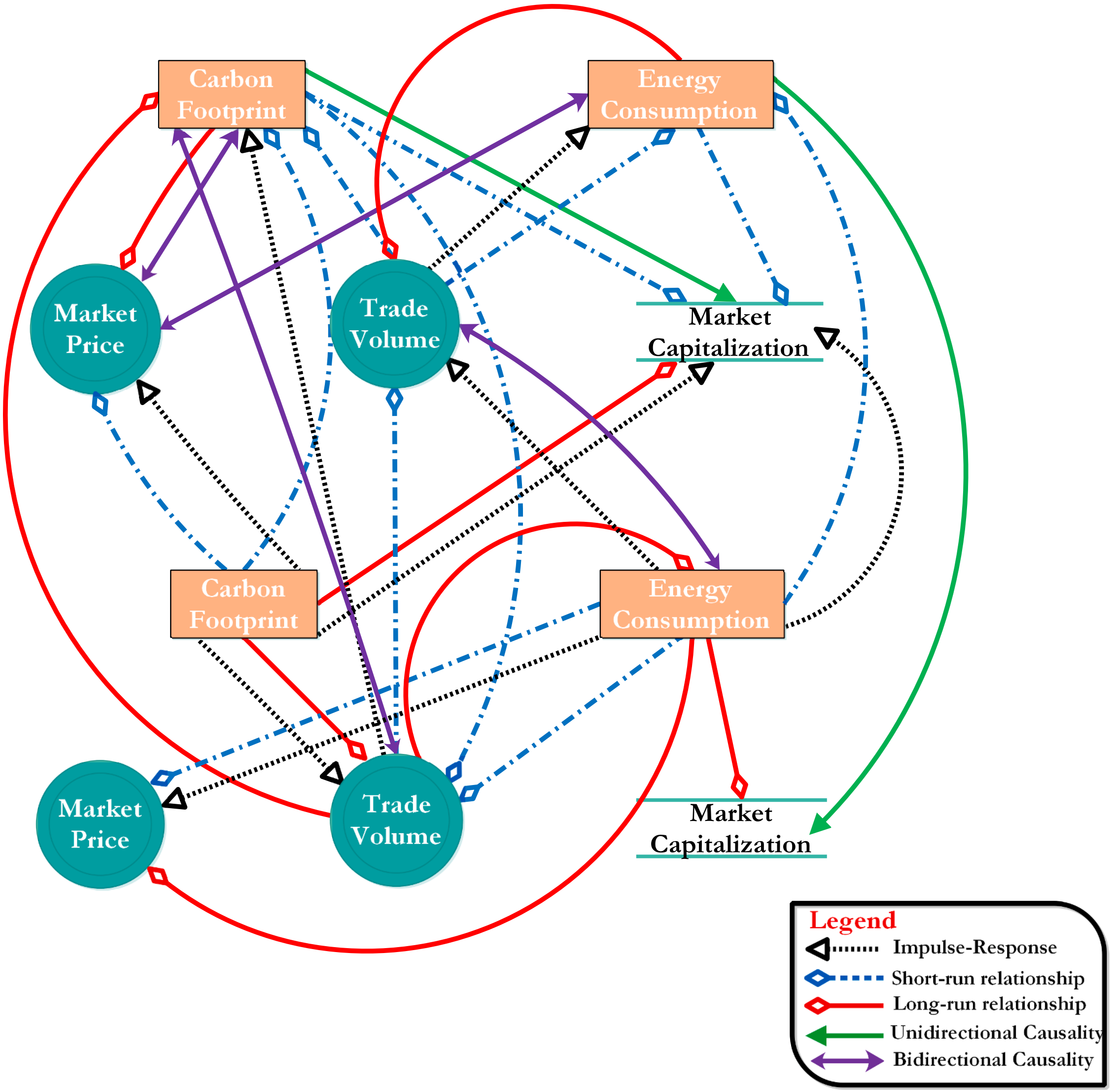

Fig. 4. Summary relationships of price, trade volume, and market capitalization in carbon and energy functions.

This implies BTC carbon footprint and BTC energy will produce nearly similar results but differences in magnitude. This idea in accordance with IEA is to depict how either energy consumption or carbon footprint is crucial in the proof-of-work ecosystem of BTC and the dynamics of Bitcoin trading. From a modeling perspective, both scenarios represent the robustness of the estimated models.

Existing studies show the effect of mining on bitcoin energy consumption and subsequent emissions (Stoll et al., 2019). Contrary, we assessed the financial-related impacts of bitcoin transactions on energy and carbon footprint. Using novel estimation techniques, we assessed steady-state effects, Granger causality, and cumulative impulse-response relationships. To verify the estimated models, we employed post-estimation diagnostic tests to examine the stability and robustness of the general-to-specific VAR to make genuine-causal inferences. The diagnostic tests (see Appendix A-F) reveal the estimated GETS specification has no serial correlation—rendering the optimal lagged-variables weakly exogeneous, hence, validating the robustness of the parameters to provide true causal effects and statistical interpretations.

Moreover, we examined the time series regression for residual structural breaks using cumulative sum (CUSUM) test presented in Fig. 3. The structural evidence of the depicted results confirms parameter stability of sampled variables over time. This implies the selected variables can genuinely be used to examine causal-effect relationships and counterfactual shocks without estimation bias.

Fig. 4 presents the summary relationships of price, trade volume, and market capitalization in carbon, and, energy functions while accounting for relationships contrariwise. We observe unidirectional granger causality from either carbon footprint or energy consumption to market capitalization—which validates the existence of conservation interaction. This infers a reduction in bitcoin energy consumption and subsequent carbon footprint has potential of declining BTC market capitalization. In contrast, a bidirectional granger

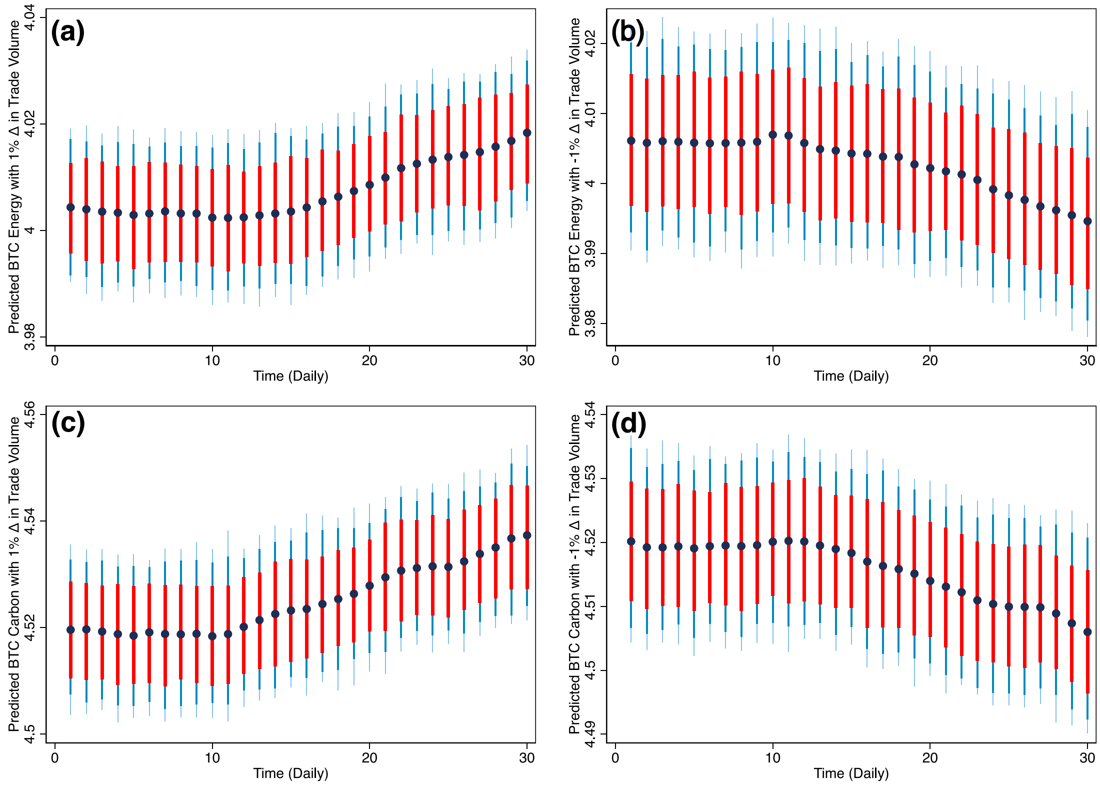

Fig. 5. Predicted BTC energy consumption with (a) 1% change in trade volume (b) -1% change in trade volume. Predicted BTC carbon footprint with (c) 1% change in trade volume (d) -1% change in trade volume. Legend: blue dots (•) denote the predicted value whereas the red to light blue vertical bands represents the 95% confidence interval.

causality is observed between—market price and carbon footprint/energy footprint (Appendix A and D), and trade volume and energy consumption/carbon footprint (Appendix B and E). These mutualistic effects confirm the feedback interaction, implying the potential impact of market price and trade volume on either bitcoin energy consumption or carbon footprint and vice versa.

Next, we examined the direction of these causal effects in both short- and long-run while accounting for cumulative impulse-responses. Historical bitcoin energy consumption, carbon footprint, and trade volume have short-term inertia effects that determine future consumption, emissions, and trade patterns (see Appendix A-F). The long-run effect shows 10% growth in energy consumption and carbon footprint increases bitcoin market price by 0.25% whereas trade volume grows by 0.01%. However, 1% increase in bitcoin trade volume spurs both carbon and energy footprint by ∼24% in the long-run. The cumulative impulse-response function validates the estimated long-run effects showing significantly higher impacts (see Appendix A-F). For example, 1% shock in bitcoin trade volume increases energy and carbon footprint by 46.54%. This implies among all financial indicators, increasing bitcoin trade volume has significant effect on bitcoin transactions, which has direct impact on network hashrate, electricity used for mining, and carbon footprint.

After identifying trade volume as the main energy and carbon footprint driver, we exclusively test the causal-effect relationship and counterfactual shocks between trade volume vs. energy consumption and carbon footprint, respectively, using both standard ARDL and dynamic ARDL simulation techniques. The ARDL technique applies to I(0), I(1), or a mixture of both excluding I(2) variables. In contrast, aside from all-inclusive conditions of the standard ARDL technique, the dynamic ARDL simulations further require strict I(1) dependent variable and residual independence (i.e., parameter stability and robustness). Both standard ARDL and dynamic ARDL simulations show trade volume spur BTC energy consumption in the long-run, yet has mitigation effect in the short-run (Appendix G). We further examine the effect of counterfactual shock in trade volume on BTC energy consumption and carbon footprint, respectively in Fig. 5. Forecasting the effect in 30 days, a positive change (1%) in trade volume escalates BTC energy consumption and carbon footprint whereas a negative shock (-1%) in trade volume declines long-term BTC carbon footprint and energy consumption (Fig. 5).

Fig. 5 shows a 1% shock in trade volume slightly increases predicted BTC energy in the short-run but increases at a higher rate in the long-run. However, a -1% shock in trade volume stimulates fluctuation at a lower rate in predicted BTC energy in the short-run but decreases at a higher rate in the long-run. The stochastic simulation of 1% shock in trade volume triggers a stabilized trend in predicted BTC carbon footprint but eventually decreases at a higher rate in the long-run. On the contrary, -1% shock produces a stable effect in the short-run but drifts downwards in the long-run. These findings are consistent with the notion that BTC consumes a lot of electricity per transaction and electricity sources used for BTC mining rigs are mostly dependent on fossil fuels (Küfeoğlu & Özkuran, 2019). This may provide information for investors and policymakers to enact policies driving the use of renewable energy in mining rigs while increasing the technological development of energy-efficient mining components.

4. Conclusion

This study examines the effect of financial indicators on bitcoin energy and carbon footprint using several empirical techniques. The additional diagnostic tests that assess residual independence validate the robustness of the estimated models to facilitate genuine causal inferences. The adoption of environmental, social, and governance (ESG) criteria is becoming widespread in many companies' standard operations. Hence, environmentally conscious investors who employ these ESG criteria may fail to adopt bitcoin as a prospective investment option, due to its energy and carbon-intensive proof-of-work consensus algorithm. This explains the significant nexus between financial indicators (i.e., market capitalization, market price, and trade volume) bitcoin energy, and carbon footprint.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Maruf Yakubu Ahmed:** Writing – original draft. **Thomas Leirvik:** Supervision, Writing – review & editing.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.102977.

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