NUMBER OF MINED UNITS TRADED ON THE CRYPTOCURRENCY NETWORK AND GLOBAL CARBON EMISSIONS: AN ARDL BOUNDARY TESTING APPROACH

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Received: 02/06 /2023/ Accepted: 19/09 /2024 / Published: 15/05 /2025
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ABSTRACT:

This paper investigates the relationship between the number of units extracted from cryptocurrency traded on their network and the increase in global carbon dioxide emissions. The analysis is based on monthly data for eight cryptocurrencies (independent variables) and carbon dioxide (CO2 dependent variable) extending from July 2015 to February 2023, the autoregressive distributed lag (ARDL) model was used.

The results extracted from the bounds test showed a long-term relationship between the variables, with Dash and Bitcoin having a greater impact than other cryptocurrencies. The results of the error correction model (ECM) estimation also demonstrated that the adjustment speed from the short term to the long term is 24.50% per year. Therefore, cryptocurrencies, especially the Dash and Bitcoin currencies, contribute to the increase in carbon dioxide emissions but with a negligible effect.

Keyword :Cryptocurrency; Bitcoin; Carbon dioxide (Co2); ARDL; Mining.

JEL classification : O320 ; C12 ; L720.

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عدد الوحدات الملغومة المتداولة على شبكة العملات المشفرة وانبعاثات الكربون العالمية: نهج اختبار حدود ARDL

الملخص:

تبحث هذه الورقة في وجود علاقة أو عدم وجود علاقة بين عدد الوحدات الملغومة من العملات المشفرة المتداولة على شبكتها وازدياد انبعاثات غاز الكربون العالمية؛ حيث تم الاعتماد على بيانات ذات تردد شهري لثماني عملات مشفرة (متغيرات مستقلة) وغاز الكربون (CO_2 متغير تابع) الممتدة من جويلية 2015 إلى فبراير 2023؛ تم استخدام نموذج الإنحدار الذاتي ذو الفجوات الزمنية المتباطئة (ARDL).

كشفت النتائج المستخرجة من اختبار Bounds على وجود علاقة طويلة الآجل بين المتغيرات حيث أظهرت عملة BitcoinوDash تأثير أكبر عن باقي العملات المشفرة الأخرى؛ كما بينت نتائج تقدير نموذج تصحيح الخطأ (ECM) أن سرعة تعديل الانحراف من الأجل القصير إلى الأجل الطويل 24.50 %في السنة. وعليه فإن العملات المشفرة وخاصة عملة BitcoinوDash تساهم في ازدياد انبعاث غاز الكربون ولكن بتأثير ضئيل.

الكلمات المفتاحية: عملة مشفرة؛ البيتكوين؛ ثاني أكسيد الكربون(CO_2) ؛ تعدين؛ ARDL.

تصنيف جال: O320; C12; L720.

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NOMBRE D'UNITÉS EXTRAITES ÉCHANGÉES SUR LE RÉSEAU DE CRYPTO-MONNAIE ET ÉMISSIONS MONDIALES DE CARBONE : UNE APPROCHE DE TEST DES LIMITES ARDL

RÉSUMÉ:

Cet article explore la relation entre le nombre d'unités extraites des cryptomonnaies échangées sur son réseau et l'augmentation des émissions mondiales de dioxyde de carbone, en s'appuyant sur des données mensuelles pour huit cryptomonnaies (variables indépendantes) et le dioxyde de carbone (variable dépendante CO2) s'étendant de juillet 2015 à février 2023. Le modèle de retard autorégressif à fenêtres glissantes (ARDL) a été utilisé.

Les résultats extraits du test de limites ont révélé une relation à long terme entre les variables, la cryptomonnaie Dash et Bitcoin présentant un impact plus important que les autres cryptomonnaies. Les résultats de l'estimation du modèle de correction d'erreur (ECM) ont également indiqué que la vitesse d'ajustement du court terme au long terme est de 24,50 % par an. Par conséquent, les cryptomonnaies, en particulier Dash et Bitcoin, contribuent à l'augmentation des émissions de dioxyde de carbone, mais avec un effet négligeable.

Mots Clés : Crypto-monnaie; Bitcoin; Dioxyde de carbone (CO2); Minier **;** ARDL **.**

Cote jal : O320 ; C12 ; L720.

INTRODUCTION:

Cryptocurrencies are digital assets that use blockchain technology to facilitate secure transactions (Härdle & al, 2019). They are encoded data strings that can function as a unit of currency or its equivalent (Singh, 2022).These tokens are intended for use as a medium of exchange and are accounted for using a digital ledger, often maintained collectively and secured through cryptography (Pernice, & Scott, 2019). Bitcoin was the first cryptocurrency and the reason for the emergence of other digital currencies, such as Ethereum, Litecoin, Dogecoin ... etc. Today we find more than 22,932 cryptocurrencies with a total market capitalization of $1.1 trillion (Hicks, 2023) and global adoption of cryptocurrencies has risen to more than 880% (Scher, 2022).

As is well-known, cryptocurrency units are created through mining either by proof of work (PoW) as in Bitcoin, or by proof of stake (PoS) as in Ethereum. This mining process requires significant amounts of electricity and with the rapid development of the cryptocurrency market in recent years; the evolution of mining services has led to a discussion about cryptocurrencies and the significant energy requirements of mining operations; as well as the potential environmental impact resulting from them. According to figures from 2018 to 2022 the annual use of electricity for global crypto assets grew rapidly , with estimates of electricity usage quadrupling. As of August 2022, published estimates of total global electricity use of crypto assets range between 120 and 240 billion kilowatt-hours per year. This range exceeds the total annual electricity use of many individual countries such as Argentina or Australia, this is equivalent to 0.4% to 0.9% of the annual global use of electricity. This consumption is comparable to the annual use of electricity of all traditional data centers in the world (OSTP, 2022). The problem of energy use is exacerbated over time by incentives associated with mining for example every time a miner solves the complex hashing algorithm required to produce Bitcoin he receives a small amount of the same cryptocurrency (Scher, 2022). The amount of electricity consumption for mining a cryptocurrency varies from one crypto-currency to another. In some cases, the electricity consumption is equivalent to that of a country like Austria. This high level of consumption is due to the increase in the market value of the cryptocurrency and the increased difficulty of solving puzzles to create its units.

Our reliance on how this energy is produced may be a cause of the potential increase in the triad and pollution emissions (increased carbon emissions). In this context, this article aims to address the debate on how the production of new cryptocurrencies within the industry's network can contribute in some way to increasing global carbon emissions.

- Study Problematic:

Is there a statistically significant relationship between the number of mined cryptocurrency units circulating on their network and the increase in global carbon emissions?

To address the proposed problematic, we conduct a test:

- Hypothesis: the rise in the market value of the cryptocurrency leads to more mining activity on its network which leads to an increase in global carbon emissions.

The original contribution of this article is that the analysis is not limited to a single cryptocurrency such as Bitcoin, but rather includes the top eight virtual currencies to increase accuracy and transparency on the subject of cryptocurrency mining and increased carbon emissions.

1- LITERATURE REVIEW:

Cryptocurrencies have become popular in trading due to their unmatched features, offering lower transaction fees compared to traditional systems, particularly for international transactions. Additionally, blockchain technology provides transparency and security, making fraud and manipulation difficult. The decentralized nature of cryptocurrencies is the primary reason individuals are inclined to use them, as it eliminates the need for a third party in their transactions and allows them to maintain the confidentiality of their identities. Overall, the unique advantages and benefits of crypto-currencies make them an attractive trading alternative. However, as the popularity cryptocurrency trading increases, the volume of mining operations on their networks also increases, leading to a rise in electricity consumption derived primarily from fossil fuels. This results in the emission of greenhouse gases into the atmosphere raising concerns about the negative environmental impacts of cryptocurrency networks. Many studies have addressed this issue discussing various aspects of cryptocurrency mining with energy prices and energy production methods among others.

In their study of four cryptocurrencies, authors (Krause & Tolaymat, 2018) found that they were responsible for between 3 and 15 million tons of carbon dioxide emissions. They indicated that cryptocurrency mining consumed an average of (Bitcoin 17, Ethereum 7, Litecoin 7, and Monero 14) megajoules to generate one US dollar during the period from 10/01/2016 to 30/06/2018 only. Authors (Mora & al, 2018) & (Dittmar & Praktiknjo , 2019) hypothesize that bitcoin mining could emit emissions that could drive global warming above 2°C. In their research the authors (Köhler & Pizzol, 2019) also found that in 2018 Bitcoin network consumed 31.29 TW/H with a carbon footprint of 17.29 million tons of carbon dioxide equivalent; they noted that the service life and production end-of-life of the equipment contribute slightly to the overall impact. While some authors found these estimates to be greatly exaggerated, (Masanet & al, 2019). They argued in their study that unreasonable assumptions are made in some literature overestimating short-term CO2 emissions for Bitcoin. (Houy,

2019) agreed with them on the exaggeration, as he criticized the inclusion of unprofitable mining platforms in the emissions calculation analysis, which leads to a significant overestimation of emissions. This is despite his findings. (Cano, 2019) argued that every Bitcoin mined, is responsible for 13,000 kg of carbon dioxide and 40,000 kg of carbon dioxide per hour. (Zade & al, 2019) studied the environmental impact of Bitcoin, Ethereum and the underlying blockchain industry. They concluded that increasing the efficiency of mining devices has only a limited effect on the total energy demand of blockchain networks. The current energy demand of the Ethereum network is similar to that of Bitcoin ranging from 0.6 to 3 GW in a scenario with linear growth in block difficulty and a relative increase in device efficiency until 2025. Under this scenario, the energy demand for Bitcoin blockchain mining would be around 8 GW. The authors also demonstrated that it is possible to build energy demand scenarios for other cryptocurrencies based on their model and study scenarios. (Goodkind & al, 2019) shed light on the United States and China; they found that in 2018 every $1 worth of Bitcoin created was responsible for $0.49 of climate and health damage in the United States and $0.37 in China. (Martynov, 2020) also highlighted that every $1 USD worth of crypto- currency value created was responsible for $0.66 USD in health and climate damage. (Schinckus & al, 2020) generally indicated in their study that as cryptocurrency trading activities increase energy consumption also increases; which consequently affects the environment.

2- DATA AND METHODOLOGY:

2.1- Data:

To study the number of circulating mined units on the cryptocurrency network and its relationship to global carbon emissions; monthly data from the period M07/2015 to M03/2023 was used. Eight cryptocurrencies[1] were employed as independent variables and CO_2 as the dependent variable (table 1).

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[1] *Due to the daily frequency of cryptocurrency data, an aggregation process was performed using the arithmetic mean to align it with the monthly frequency of carbon dioxide emission data.*

Table 1. Variables representation

Variables	Acronyms	Source	Online link
Bitcoin	BTC	Blockchair	Ultimate Cryptocurrency Dataset by Blockchair — Blockchair
Bitcoin Cash	BCH	Blockchair	
Litecoin	LTC	Blockchair	
Ethereum	ETH	Blockchair	
Dogecoin	DOGE	Blockchair	
eCash	XEC	Blockchair	
DASH	Dash	Blockchair	
Groestlcoin	GRS	Blockchair	
Carbon dioxide	Co_2	Global Monitoring Laboratory	https://bit.ly/4cHEsC3

Source : Made by the researchers

2.2- Methodology:

The study employs the autoregressive distributed lag (ARDL) bounds testing approach proposed by Pesaran et al 2001.This method is used to test for cointegration in econometric models (Nasrullah & al, 2021). It involves three steps. First, it assesses whether there is a long-term relationship between the variables in the model. The presence of both a long-term and a short-term relationship between the variables is then tested. The "ARDL" bounds test can be applied regardless of whether the variables are suitable in the model which is I (0)/ I (1) or mutually cointegrated, but it fails in the presence I (2).

In any variables (PESARAN & al, 2001). It is particularly useful when dealing with small sample sizes and mixed order of integration among the variables (PESARAN & al, 2001) (Yılmaz , 2021) (Nasrullah & al, 2021).

To investigate the relationship between the dependent variable and the independent variables; following model was constructed:

$$\mathbf{Co_{2t} = f\,(BIT_{t},\ BCH_{t},\ LTC_{t},\ ETH_{t},\ DOGE_{t},\ XEC_{t},\ Dash_{t},\ GRS_{t})\ ....(1)}$$

Prior to conducting estimation and diagnostic tests, the independent variables will be subjected to the stepwise regression approach " It is a data mining tool that utilizes statistical significance to identify the important variables to be used in the multiple regression model (Smith, 2018, p. 1)". The aim of this procedure is to identify the independent variables that have the greatest impact on the dependent variable in order to build a better and more accurate predictive model (Li & al, 2019, p. 4). There are three progressive regression strategies: a forward-selection, a backward-elimination, and a bi-directional stepwise. We adopted the forward stepwise regression approach; where we enter the first selected variable with the highest correlation with the dependent variable (Figures 01-08 Correlation analysis outcomes) into the built model. Once the variable is selected, it is evaluated based on certain criteria the most common of which are Mallows' cp or Akaike's information criterion (AIC). If the first selected variable meets the inclusion criterion, the forward selection will continue, i.e., the statistics of the variables not included in the equation are used to determine the next variable. The procedure stops when there are no other variables that meet the inclusion criterion (Walczak & Massart, 2000, p. 324). Therefore, all the variables in the model become significant and all the variables outside the model become insignificant. As for the criteria for evaluating the variables for inclusion in our model, we relied on the probability value "P" thre shold threshold, it must be less than 0.15 for the feature to enter the model and greater than 0.15 for it to leave the model (Kuhn & Johnson, 2019). We then followed this by evaluating the Akaike information criterion (AIC) to achieve a balance between model performance and complexity and the R-squared coefficient as an indicator of the model's fit to the data (Narisetty, 2020, pp. 210-211).

After testing, it was found that the optimal combination achieving the significance of the independent variables in the model that includes the variables (Dash, Grs, Ltc). However, the model showed a problem of spurious regression, as the Durbin-Watson value appeared to be very low. To address this problem, we re-estimated the stepwise regression model with the same evaluation criteria and included two lags of the dependent variable (table2). The new model now includes two variables (Dash and BIT) and the dependent variable.

Table 2. Re Stepwise Forwards

Stopping criterion: p-value forwards/backwards = 0.05/0.5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
C	91.85051	12.34718	7.438985	0.0000
CO2(-1)	1.521435	0.064041	23.75714	0.0000
CO2(-2)	-0.766461	0.063192	-12.12905	0.0000
DASH	6.84E-20	1.48E-20	4.625608	0.0000
BIT	2.19E-20	1.01E-20	2.176865	0.0323

R-squared	0.981964	Mean dependent var	411.2004
Adjusted R-squared	0.981116	S.D. dependent var	5.755438
S.E. of regression	0.790916	Akaike info criterion	2.422702
Sum squared resid	53.17154	Schwarz criterion	2.561580
Log likelihood	-104.0216	Hannan-Quinn criter.	2.478706
F-statistic	1156.970	Durbin-Watson stat	2.202909
Prob(F-statistic)	0.000000		

Source: Eviews13 outputs

3- EMPIRICAL RESULTS& DISCUSSION:

3.1- Unit root test:

Before verifying the possibility of a cointegration relationship between the variables, the time series under study must be stationary. Therefore, we conduct unit root tests on the variables included in the study model. To perform this step, we used the "Phillips-Perron" test. The null hypothesis of the "PP" test is that a time series contains a unit root. The PP test results (table 3) indicate that the study variables have a unit root, CO2 emissions, BIT, and Dash are not stationary at level I(0) at a 5% significance level, hence the null hypothesis is accepted. However, after taking the first differences, these variables become first-order stationary I (1) at a 5% significance level. Therefore, the ARDL bounds test can be applied.

Table 3. Unit root test pp

Variables	Level			First difference		
	Trend + con	Con	Without con	Trend + con	Con	Without con
Co2	-1.5575	-3.9656	1.0124	-4.4230	-4.3994	-4.5637
Prob	0.5001	0.0132	0.9171	0.005	0.0036	0.0000
Dash	-0.8535	-10.0230	2.1248	-33.1207	-33.1292	-16.7964

Prob	0.7985	0.0000	0.9918	0.0001	0.0001	0.0000
BIT	-4.1507	-10.6379	0.6823	-27.3792	-27.2999	-24.8691
Prob	0.0013	0.0000	0.8614	0.0001	0.0001	0.0000

Source: Eviews13 outputs

3.2- ARDL Bounds Test for Co-Integration:

Before applying the ARDL test to investigate the cointegration between the variables, it is necessary to determine an appropriate lag order for the variables. In this study, the optimal lag length "2" was determined based on the Akaike information criterion (AIC). Therefore, the ARDL (2,0,0) model was selected as the best model (table 4).

Table 4. Results of ARDL model

Equation case02: Restricted Constant and No Trend				
Variables	**Coefficient**	**Std. Error**	**t-Statistics**	**Prob**
Co2(-1)	1.521435	0.064041	23.75714	0.0000
Co2(-2)	-0.766461	0.063192	-12.12905	0.0000
DASH	6.84E-20	1.48E-20	4.625608	0.0000
BIT	2.19E-20	1.01E-20	2.176865	0.0323
C	91.85051	12.34718	7.438985	0.0000

Source: Eviews13 outputs

Table 4 also contains the following information:

• Student's t-test:

All variables are significant at the 5% level, with p-values less than 0.05. This confirms the partial significance of the model.

• Fisher's F-test:

The model is significant at the 5% level, with a p-value less than 0.05. This confirms the overall significance of the model and its reliability in analyzing the relationship between the variables.

Regarding the explanatory power of the model, it demonstrates a strong explanatory power, as 98% of the information about the dependent variable (CO2) is explained by the independent variables in the model (Bitcoin and Dash). The remaining 2% is attributed to other factors or variables.

For the study variables, we employed the bounds testing approach to cointegration based on the autoregressive distributed lag (ARDL) model. The F-statistics test is used for the following hypothesis:

$H_0 = \Theta_1 = \Theta_2 = \Theta_3 = 0$

$H_1 = \Theta_1 \neq \Theta_2 \neq \Theta_3 \neq 0$

The results of the cointegration test (table 05) show that the calculated fisher test value F-statistic = 15.034 is greater than the upper bound critical value of the I(1) test at all levels 1%, 5%, and 10%. Therefore, the alternative hypothesis that there is a long-run equilibrium relationship between the independent variables and the dependent variable is accepted.

Table 5. ARDL Bounds Test Result

I(0) Bound	I(1) Bound	Significant Level	F Statistics
4.35	5.39	1%	15.0343
3.23	4.05	5%	
2.71	3.45	10%	

Source: Eviews13 outputs

$$\Delta CO2_t = c + \sum_{i=1}^{p} \beta_{1i} \Delta CO2_{t-i} + \sum_{i=1}^{q_1} \beta_{2i} \Delta DASH_{t-i} + \sum_{i=1}^{q_2} \beta_{3i} \Delta BIT_{t-i} + \alpha_1 CO2_{t-1} + \alpha_2 DASH_{t-1} + \alpha_3 BIT_{t-1} + \varepsilon_t$$

So, the ARDL model equation for our study becomes as follows:

where:

- Δ: The first difference.
- β1, β2, β3: Long term dynamics.
- α1, α2, α3: Short term dynamics.
- ε: the white noise.

- P, q: The maximum number of lags for each variable in the study.
- t, i: The time period of the study.
- c: Constant.

3.3- Estimating the error correction model:

An error correction model (ECM) can be derived from the ARDL bounds test. This model captures the short-term dynamics (table 6) shows the error correction model, which represents the short-term relationship between the variables included in the model. The results indicated that the coefficient of the error correction term (cointeq) is statistically significant and negative (student t-test probability less than 0.05). This demonstrates the validity of the model and confirms the existence of a cointegration relationship between the study variables. This coefficient can be interpreted as the speed of error correction. If there is a short-term deviation of the $CO2$ variable from the long-term equilibrium relationship, this deviation will be corrected by 24.50% per year.

Table 6. Error correction model estimates

Equation case02: Restricted Constant and No Trend				
Variables	**Coefficient**	**Std. Error**	**t-Statistics**	**Prob**
COINTEQ	-0.245026	0.031053	-7.890475	0.0000
D(CO2(-1))	0.766461	0.061078	12.54885	0.0000

Source: Eviews13 output

3.4- Long-Run Estimates:

This stage involves obtaining the long-term parameter estimates, according to the ARDL model the estimated parameter values that express the long-term parameters of the model were obtained (table 7).

Table 7. Long-Run Estimates

Cointegrating Coefficient:				
Variables	**Coefficient**	**Std. Error**	**T-statistics**	**Prob**
DASH	2.79E-19	4.20E-20	6.649454	0.0000
BIT	8.94E-20	4.13E-20	2.164774	0.0331
C	374.8601	4.354867	86.07843	0.0000

Source: Eviews13 outputs

The long-term relationship can be expressed according to the following formula:

$$\mathbf{CE} = \mathbf{CO2}\ (-\mathbf{1}) - (\mathbf{0.00000} * \mathbf{DASH} + \mathbf{0.00000} * \mathbf{BIT} + \mathbf{374.860116})$$

3.5- Robustness Checks (Diagnostic Tests):

To ensure the quality of the model used in the analysis and its freedom from statistical problems, several tests were conducted as follows:

3.5.1. Normality Test of Residuals:

In this test, the Jarque Bera test was used to assess the normality of the residuals. The results of the residuals distribution test show that the p-value of the Jarque-Bera test (0.063..) is greater than the 5% significance level, leading to accepting the hypothesis of the normal distribution of the data(table 8).

Table 8. Results of the Normality Test of Residuals

Test:		**prob**
Skewness	0.5894…	/
Kurtosis	3.2826…	/
Jarque-Bera	5.509…	0.0636…

Source: Eviews13 outputs

3.5.2. Residuals Tests:

Additional tests were conducted to verify the validity of the model (table 9)

The Breusch--Pagan-Godfrey test was used to test the homoscedasticity of the errors. The fisher test p-value (0.14) was greater than 0.05, leading to accepting the hypothesis of homoscedasticity of the random errors.

The Breusch-Godfrey test was used to test the autocorrelation of the residuals. The fisher test p-value (0.23) was greater than 0.05, leading to accepting the hypothesis of no autocorrelation between the random errors.

Table 9. Results of the Model Residuals Tests

Tests	**F-statistic**	**prob**
Breusch-Pagan-Godfrey: heteroskedasticity test	1.742…	0.148..
Breusch-Godfrey serial correlation lm test:	1.459….	0.230..

Source: based on the Eviews13

3.5.3. The Stability Tests (CUSUM & CUSUMSQ):

After estimating the error correction form of the ARDL model, the step is to test the structural stability of the short-run and long-run coefficients. To achieve this, two tests will be used: the cumulative sum of recursive residuals (cusum) test and the cumulative sum of squared recursive residuals (cusumsq) test. These tests will be used to ensure that the data employed in this study is free of any structural changes.

As it can be seen from figures (9) and (10), there is no structural change and the model is stable overall. The cusum and cusumsq statistics lie within the critical bounds (upper and lower bounds) at a 5% significance level. Therefore, the estimated coefficients of the model are structurally stable over the study period, indicating that there is consistency and stability between the long-run and short-run results of the estimated model.

Figure 9. CUSUM Test

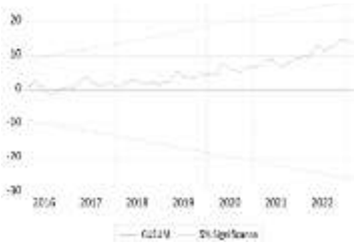
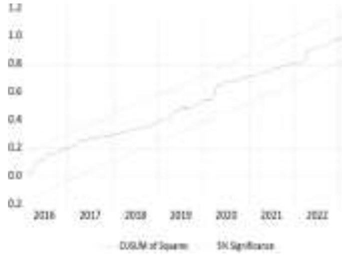


Figure 10. CUSUM-SQ Test

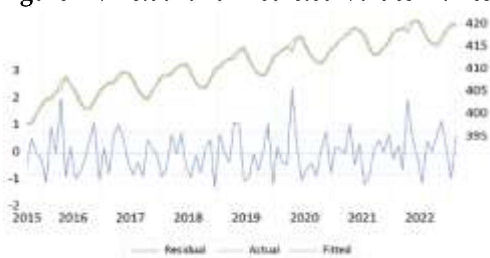


Source: Eviews13 Output

3.5.4. Actual and Predicted Values Fit Test:

The correspondence between the actual and predicted values of the dependent variable is crucial to ensuring the accuracy and reliability of the model. Figure (11) shows that the test results demonstrate a near-perfect correspondence between the actual values of the dependent variable (CO_2) and the predicted values generated by the model, confirming a high level of accuracy.

Figure 11. Actual and Predicted Values Fit Results



Source: Eviews13 outputs

CONCLUSION:

The mining of cryptocurrencies, such as Bitcoin, Ethereum, Dogecoin, and many others, is essential for producing currency units on the network for trading. However, this process has been associated with numerous issues, such as high energy consumption, electronic waste, and increased carbon emissions. Therefore, our study investigates whether there is a statistical correlation between the number of cryptocurrencies mined on a network and increased carbon emissions.

Our study used eight cryptocurrencies, but through the forward stepwise regression test, we separated the significant variables from the insignificant ones. Accordingly, Dash and Bitcoin were employed in the model for the study. Overall, the results were statistically and theoretically acceptable using the ARDL methodology for cointegration.

Among the most important findings of our study are the following:

- The time series under study are integrated of order one (I(1)) using the Phillips-Perron test.
- The bounds test indicated the presence of a long-run cointegration relationship between CO_2 and Dash and Bitcoin at a 5% significance level.
- There was a positive and significant impact of Dash and Bitcoin on CO_2, meaning that:

- Mining 1% of Dash contributes to a 6.84% increase in carbon emissions.
- Mining 1% of Bitcoin contributes to a 2.19% increase in carbon emissions.

- The speed of error correction in the CO_2 variable was found to be 24.50% in the error correction bounds test.
- The cusum and cusumsq tests showed the structural stability of the model in the short and long run.

Recommendations:

The results of our study suggest that there is a need for policymakers to take steps to reduce the environmental impact of cryptocurrency mining.

We recommend that policymakers transition to clean and renewable energy in cryptocurrency mining, impose strict regulations and policies on cryptocurrency mining and trading, and launch awareness campaigns about the risks and damage that cryptocurrency mining causes to the planet.

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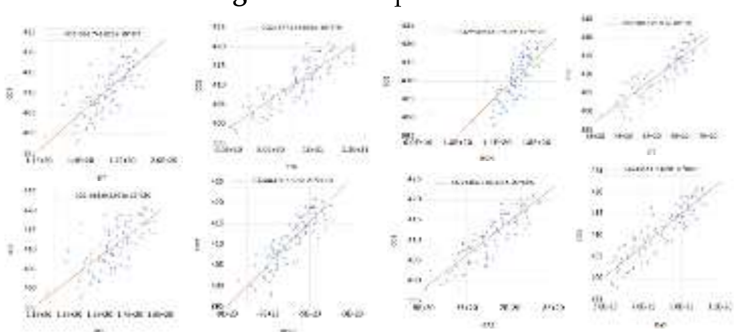
Appendix:

Finger 01-08. Scope of diffusion



Source: Eviews13 Output