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Crypto-currencies Trading and Energy Consumption

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ABSTRACT

This study empirically investigates the effects of crypto-currencies trading on the energy consumption as an important consequence of blockchain technology on climate change. In this article, we use the data of Bitcoin trading volume as well as all crypto-currencies trading volumes for the period going from 2014M1 to 2017M12 to investigate the effects on the primary energy consumption. Our empirical results show a positive correlation between crypto-currencies trading volumes and the energy consumption. Moreover, the crypto-currencies trading volume has a granger-causality to energy consumption in the period of study indicating that these two variables have a long-run co-integration. In other words, our findings show a significant positive (and increasing) influence of cryptocurrency activities on the energy consumption in both short-run and long-run. This study investigates one step further in examining the effects of residuals of the crypto-currencies trading volume on the residuals in energy consumption to confirm that a higher trading volume in cryptocurrencies might cause a higher energy consumption. Our findings show a negative influence of the trading of crypto-currencies - precisely, the higher the crypto-currency activities are, the higher the energy consumption is, affecting therefore the environment.

Keywords: Crypto-currencies, Environment, Energy consumption, Innovation
JEL Classifications: Q40, Q51, Q54, Q55, Q56

I. INTRODUCTION

Bitcoin and other cryptocurrencies got an increasing attention these recent years leading to an important media coverage (Polasik et al., 2015; Thies and Molnár, 2018). Furthermore, the technology behind these cryptocurrencies, a decentralized and open-source system named "blockchain" is often presented as one of the most innovative technology offering several many disruptive innovation in the next years (Casino et al., 2019; Macrinici et al., 2018; Underwood, 2016; Yli-Huumo et al., 2016).

Despite all potential innovations, blockchain might imply, this technology is paradoxically related to one of the most challenging collective problems around the world: the climate change (Harris, 2018). Change (2017) emphasized that Blockchain technology can play a major role in fighting climate change by (i) improving carbon emission trading, (ii) promoting clean energy trading, (iii) enhancing climate finance flows (Green, 2018). Sanderson (2018) mentioned that despite the growth of green bond markets in size and sophistication, the verification and reporting standards are lagged behind. In this context, blockchain technology could be a potential solution to encourage this market and establish its credibility so that it helps prove the effectiveness of the green bond market by reducing carbon emissions for both issuers and investors. As a final consequence, the blockchain could promote the higher development of this market and indirectly contribute to the strategy against climate change.

Duchenne (2018) added that smart contracts and blockchains are important in helping to remove significant friction in the attempts to tackle climate change. However, this author also emphasized that "this comes at a cost of understanding the real impacts of the disruption this new technology brings, both on the financing side of renewable energy projects, climate finance in general, and the various legislative scheme supporting same." Furthermore, Harris (2018) emphasized the importance of the potential solutions offered by blockchains to improve environmental issues in accordance with the objectives of the Paris climate agreement.

Blockchain technology is not all roses Schinckus (2020). It is worth mentioning that all transactions\records needs an algorithmic validation through the resolution of cryptographic problem. Such algorithmic consensus (namely proof-of-work for the vast majority of crypto-currencies) requires a particular level of energy to fuel the computers working on the cryptographic problem. There exist several algorithmic consensuses but the proof-of-work is the most commonly used for security reason. In this consensus, the cryptographic problem to solve is sent to all computer nodes in the network while only the node which solves the problem, will validate the new transaction\record and get the reward. This situation generates a context in which all other computer nodes simply consumed energy without any reason\reward (for an overview on the different algorithmic consensus, Dupont, 2019). The current situation actually calls for further investigations about the ecological aspects of blockchain technology.

In this context, this study investigates the influences of cryptocurrencies trading on the energy consumption. The relationship between all cryptocurrencies (including Bitcoin) trading volumes and the energy consumption is examined. Using a series of econometric techniques applied on monthly time series covering the period 2014M1-2017M12, we found that (i) the cryptocurrencies trading has a granger-causality to energy consumption; (ii) there is long-run co-integration between cryptocurrencies trading and energy consumption; (iii) the cryptocurrencies trading notably increases energy consumption in both short-run and long-run. The results have been supported by robustness checks as detailed in our methodology section.

The article is structured as follows. The next section will present an overview of the main studies dealing with blockchain and energy consumption while the third section will present our methodology and data. The fourth section will discuss our results before concluding this study with a fifth section.

2. LITERATURE REVIEW

The global development of cryptocurrencies generated a lot of debates and interests from scholars (Alvarez-Ramirez et al., 2018; Balcilar et al., 2017; Brandvold et al., 2015; Brauneis and Mestel, 2018; Jiang et al., 2018; Koutmos, 2018; Takaishi, 2018; Van Vliet, 2018). In this article, we mainly focus on the underlying technology used in the trading of cryptocurrencies: the blockchain technology whose Bitcoin is well-known to be the first application (Chen, 2018). Blockchain technology combines decentralized transactions and data management technology in a such way the security, anonymity and data integrity in transactions are out of controlling any third party organization (Yli-Huumo et al., 2016). This security and integrity are very important issues. Yli-Huumo et al. (2016) reviewed 41 primary papers and shown that <20% of studies focuses on Blockchain applications including e.g. smart contracts and licensing, while over 80% of studies paid more attention to the Bitcoin system revealing that most of the studies concentrated on improving Blockchain limitations from privacy and security perspectives. Underwood (2016) wrote that Blockchain technology has many potential applications for the digital economy. In their systematic review on the blockchain-based applications, Casino et al. (2019) concluded that there are various research gaps and future exploratory directions for academics and practitioners especially in supply chain, business, healthcare, IoT, privacy, and data management.

Because blockchain technology allow a decentralized network of economic agents to agree about the true state or the validation of shared data, it contributes to increase\improve competition, lowering entry barriers and privacy risk, while allowing participants to make join investments without assigning market power to a platform operator (Catalini and Gans (2016). Larios-Hernández (2017), for instance, explained that digital finance technologies using blockchain have empowered a new type of entrepreneurship seeking opportunities in relation to financially excluded individuals. The benefit of such applications for people who have limited or no access to formal financial services has been discussed in the literature (World Bank Report, 2017). Chen (2018) indicated that blockchain technology has given innovators the capability of creating digital tokens to represent scarce assets, potentially reshaping the landscape of entrepreneurship and innovation by giving innovators a new way to develop, deploy, and diffuse decentralized applications.

Several solutions have also been implemented in terms of energy. As mentioned in the speech of Alexandre Gellert Paris (Associate Programme Officer at the UNFCCC), blockchain technology is named as a potential solution for a better stakeholders' involvement, transparency and engagement of countries, regions and cities. Such context generates numerous business opportunities to bring more trust and further innovative solutions in the fight against climate change. Blockchain technology has been mentioned to develop peer-to-peer trade of clean energy, for certified and facilitated transactions among consumers by improving carbon emission trading, facilitating clean energy trading and enhancing climate finance flows. Sanderson (2018) wrote that blockchain technology could be a potential solution to encourage the growth of green bond markets in both size and sophistication with the credibility and then contribute to the climate change fighting. Woodhall (2018) explained that blockchain and smart contracts are important in helping to remove frictions in the attempts to tackle climate change. Hwang et al. (2017), for instance, introduced energy prosumer service model applying blockchain technology, big data and Internet of Things which allows various energy sources to be connected to various users and producers. These authors suggested that these technologies can improve the energy efficiency of renewable energy projects. In the same vein, Sikorski et al. (2017) analyzed the application of blockchain in facilitating machine-to-machine (M2M) interactions and improving the electricity use in the chemical industry. Brilliantova and Thurner (2018) wrote a literature review combined with expert interviews about the future energy landscape after the blockchain advent. Their study concluded that the widest impact of blockchain technology will have in the short-term is the electric vehicle integration while in the long-term blockchains are expected to enable peer-to-peer microgrids. Other articles\ studies (Green, 2018; Harnett, 2018) also discussed the important role of blockchain technology in climate change problem. Chen (2018) mentioned the necessity to mobilize economics and finance knowledge to generate a low-carbon transition and the necessity to work on this quickly enough to prevent dangerous anthropogenic interference with the climate system.

Gore (2018) promoted the first-ever, blockchain-based peer-to-peer energy transactions system implemented by a resident in Brooklyn (New York) who owns a roof-top solar panel and sells the world's first few kilowatt-hours of locally generated surplus solar energy to a neighbor through an Ethereum Blockchain smart contract (instead of selling this surplus of electricity to a traditional utility company). Gore (2018) explained that blockchain technology can also help consumers with a more streamlined and accurate billing or accounts experience on the demand side. A conclusion of this application is that the integration of blockchain in the energy sector implies a more accurate energy generation and a better consumption data tracking system. Such situation favors transparency and all stakeholders' benefit from fairer prices than they are under a classical centralized tariff system. Mengelkamp et al. (2018) evaluated the blockchain-based microgrid energy market in Brooklyn Microgrid project as a case study and they showed that blockchains are an appropriate technology to operate decentralized microgrid energy markets. Marke (2018) summarized that blockchain can contribute to smarter renewable energy deployment, smoother international climate finance transfers, fraud-free emissions management, and better green finance law enforcement. Truby (2018) indicated that blockchains could stimulate accountability and community-led reporting while promoting technology development, finance and cryptocurrency solutions for fighting climate change. Zhang et al. (2018) provided a list of examples from China and other countries about the contributions of blockchain technology to boost climate actions. One can observe an increasing number of applications using blockchains in improving the energy consumption (Andoni et al., 2019 for a review on this topic)[1].

However, the blockchain technology is not all roses. The environmental benefit related to blockchain-based applications is one part of the reality that must be nuanced simply because the use of blockchains also requires energy. The process of adding transaction records (block) to the past transactions (to constitute a blockchain) requires a specific computational power labeled as mining. Whatever the kind of algorithm that is used to validate cryptographically the transaction, blockchain-based currencies require a significant level of computational power that refers to the energy that computers need to solve the cryptographic problem associated with all new transaction in the network. In this context, Ongena et al. (2018) explained that there are several conditional challenges that still must be overcome to realize blockchain technology's full potential in terms of environment. Mora et al. (2018) or Morris (2018) warned about the negative externalities generated by the use of cryptocurrencies by explaining that the global temperature could increase of 2°C by 2034. Although they do not provide so apocalyptic numbers[2], several empirical studies suggest the same increasing trend in the Bitcoin's use of energy (Vranken, 2017; McCook, 2018; De Vries, 2018; Mora et al., 2018; Morris 2018; Stoll et al., 2019; Goodkind et al., 2020).

3. METHODOLOGY AND DATA

With the aim at examining the effect of cryptocurrency trading on the energy consumption, our study collected the monthly data of primary energy consumption from US Energy Information Administration and the trading volume of Bitcoin and all 1636 cryptocurrencies from 2014M1 to 2017M12. The details about our data are provided in the Table 1 presented below.

The Figure 1 exhibited in the following page shows the energy consumption and the cryptocurrencies trading volume during the period of study. It indicates an important rise in the cryptocurrencies trading volume at the end of 2017, which is in line with a gradual increase in the energy consumption. The nature of our monthly data related to energy requires a seasonal adjustment that we did by using a X-12-ARIMA seasonal adjustment program. The data are then presented in logarithms for the final econometric analysis. The data description is reported in the Table 2 on the following page.

The Table 3 presented in the following page shows the unconditional correlation matrix among variables.

It is interesting to notice that the Bitcoin trading volume and the energy consumption have a significant positive correlation (0.326)

1 Andoni et al. (2019) observed that the blockchain technology is an emerging technology, which has drawn considerable interest from energy supply firms, startups, technology developers, financial institutions, national governments and the academic community, promises transparent, tamper-proof and secure systems. They reviewed 140 blockchain research projects and startups to construct a map of the potential and relevance of blockchains for energy applications. They documented a range of blockchain application in energy from emerging peer-to-peer energy trading and Internet of Things (IoT) applications to decentralized marketplaces, electric vehicle charging and e-mobility.

2 Mora et al. (2018) study generated a lot of debates. Recent works (Houy, 2019; Dittmar and Praktiknjo (2019) questioned the Mora et al. (2018) methodology and provide less apocalyptic figures – but they do not deny the increasing trend in the Bicoin's electricity consumption.

Table 1: Primary data, sources, and description

Variable	Sources	Obs.	Mean	Std. Dev.	Min	Max
Total primary energy consumption (seasonal adjustment) (Quadrillion BTU)	U.S. Energy Information Administration (November 2018 Monthly Energy Review)	48	8.15	0.19	7.54	8.54
Total indigenous electricity production (seasonal adjustment domestic electricity production - TWH)*	U.S. Energy Information Administration (November 2018 Monthly Energy Review)	48	867773	12364.7	829437.3	893043.1
Trading volume of Bitcoin (USD)	www.coinmarketcap.com	48	5.8E+06	5.5E+06	7.3E+05	2.7E+07
Total trading volume on Cryptocurrency market (USD)	www.coinmarketcap.com	48	9.0E+11	1.9E+12	1.7E+11	1.3E+13

*The data is calculated basing on the data of 35 largest economies (Appendix for country list)

Figure 1: Cryptocurrency market and energy consumption

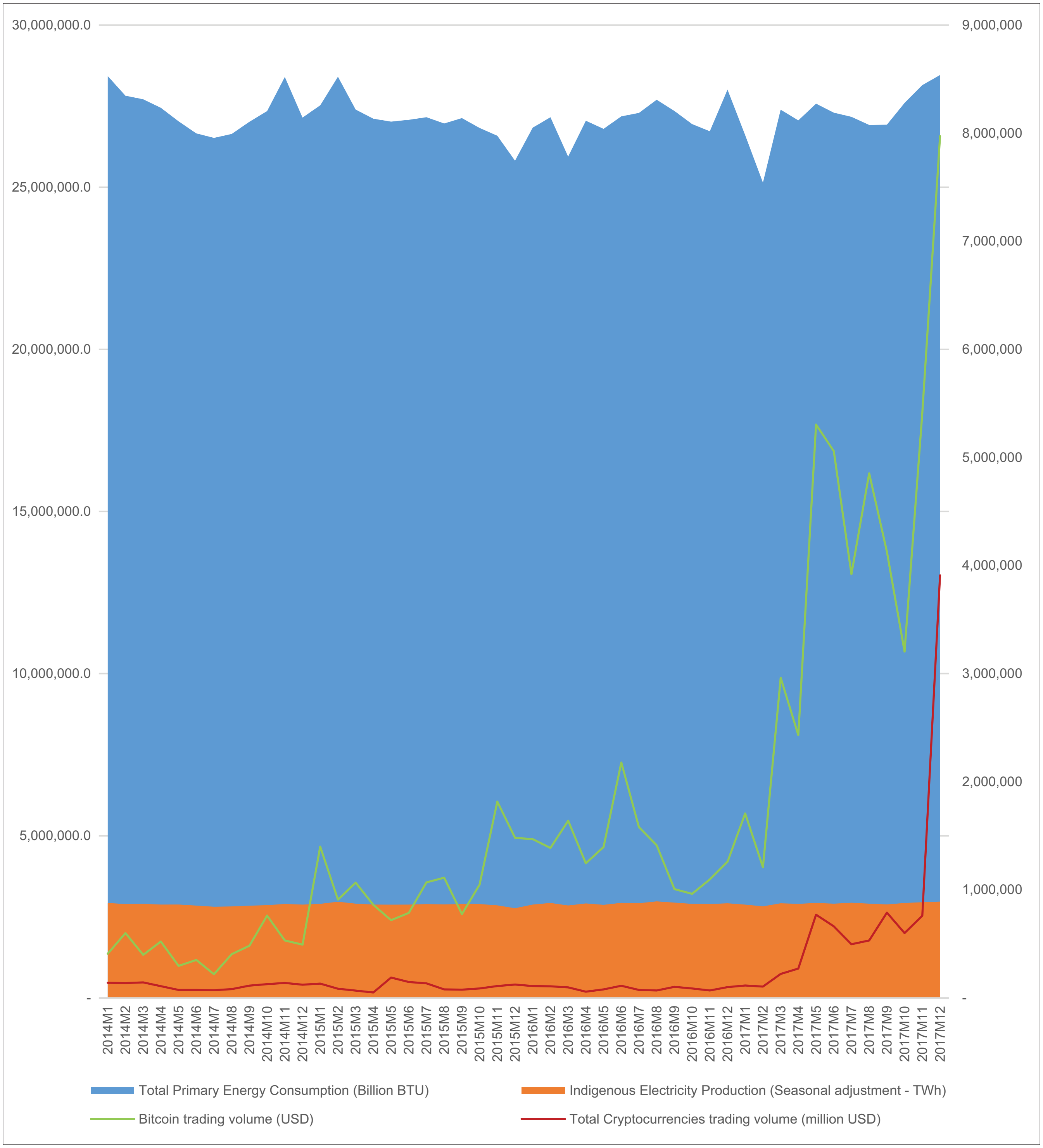

Table 2: Data calculations and description

Variable	Calculations	Obs.	Mean	Std. Dev.	Min	Max
Energy	Log of total primary energy consumption (seasonal adjustment)	48	2.098	0.024	2.021	2.145
Elecpro	Log of total indigenous electricity production	48	13.67	0.014	13.62	13.70
VoBit	Log of trading volume of Bitcoin	48	6.512	0.984	5.454	9.635
VoCry	Log of total trading volume on cryptocurrency market	48	15.216	0.836	13.499	17.096

while all cryptocurrencies trading volume has an insignificant but positive correlation with energy consumption (0.094). This suggests a positive relationship between cryptocurrency trading volume and energy consumption. The Table 3 also reports the results of unit root test (Dickey and Fuller, 1979) for levels and 1st difference of variables. The results show that the energy consumption is stationary at the level, while the trading volume of Bitcoin and all cryptocurrencies are stationary at the 1st difference. Based on this first results, we use the granger-causality test (Granger, 1969) and Johansen cointegration test (Johansen, 1991) for trading volume of Bitcoin/All cryptocurrencies with the energy consumption. These tests are presented in the Table 4 presented below.

These results indicate that there is a granger-causality between the trading volume of all cryptocurrencies and the energy consumption, while there is a statistical evidence on the Granger-causality from Bitcoin trading volume on energy consumption and the Granger-causality from energy consumption to Bitcoin/All cryptocurrencies trading volume. This result provides evidence on the influence of cryptocurrencies trading on the energy consumption. Interestingly, the results of Johansen co-integration test show that there is a long-run relationship between Bitcoin/all cryptocurrencies trading volume and the energy consumption. With the primary observation, the co-integration, Granger-causality, and the stationary of variables in different levels, the influences of cryptocurrency trading on the energy consumption will be examined through an autoregressive distributed lag (ARDL) model (Hassler and Wolters, 2006; Pesaran and Shin, 1998; Pesaran et al., 2001) as detailed in the following equation:

$$Energy_t = \beta_0 + \beta_1 Energy_{t-1} + \ldots + \beta_p Energy_{t-p}$$
$$+\alpha_1 VoCry_t + \ldots + \alpha_k VoCry_{t-k} + \varepsilon_t \quad (1)$$

where t refers to time (monthly data); *Energy* is the primary energy consumption (in log form); *VoCry* is the total cryptocurrency trading volume (in log form), which is also replaced by Bitcoin trading volume (*VoBit*) for robustness check; β and α are estimated coefficients; ε is the classical residual term. We apply the bound test of Pesaran et al. (2001) to find the optimal lags for the equation (2). Furthermore, the long-run and short-run effects are estimated with the ARDL model.

It is worth mentioning that the revolution of energy consumption in equation might be due to many exogenous factors (Ekholm et al., 2010; O'neill and Chen, 2002; Schipper, 1995) so that we implement a second step by estimating the following equations to extract the residuals of each variable:

$$Energy_t = \partial_0 + \partial_1 Energy_{t-1} + \partial_2 T_t + \vartheta_t \quad (2)$$

$$VoCry_t = \gamma_0 + \gamma_1 VoCry_{t-1} + \gamma_2 T_t + \mu_t \quad (3)$$

$$VoBit_t = \theta_0 + \theta_1 VoBit_{t-1} + \theta_2 T_t + \rho_t \quad (4)$$

In which: T proxies the monthly data (to catch the time effect). These estimations help to extract the residuals describing the unexplained part of 3 particular dynamics: the energy consumption, the trading of all crypto-currencies and the trading of bitcoin, respectively. The results of equation (2), (3), and (4) are reported in Table 5 shown in the following page.

Table 3: Correlation matrix and unit root tests

Correlation	Energy	Elecpro	VoBit	VoCry
Energy	**1.000**			
Elecpro	**0.756*****	**1.000**		
	0.000			
VoBit	**0.326****	**0.444*****	**1.000**	
P-value	0.024	0.001		
VoCry	**0.094**	**0.356****	**0.735*****	**1.000**
P-value	0.525	0.012	0.000	

Variable	Dickey-Fuller test for level		Dickey-Fuller test for 1st difference	
	Z (t)	P-value	Z (t)	P-value
Energy	−4.659***	0.0001	−9.193***	0.0000
Elecpro	−3.932***	0.001	−9.040***	0.0000
VoBit	−1.002	0.7524	−9.865***	0.0000
VoCry	0.574	0.9869	−3.575***	0.0063

, * are significant levels at 5% and 1%, respectively

Table 4: Granger-causality tests and cointegration tests

Variable: X		X does not granger-cause energy		Energy does not granger-cause X	
		Z-bar	P-value	Z-bar	P-value
VoBit		0.674	0.411	0.723	0.395
VoCry		2.991*	0.084	0.139	0.709
Variable: X	**Maximum rank**	**Cointergation test of energy with X**			
		Trace statistics	**5% critical value**	**Max statistic**	**5% critical value**
VoBit	0	20.58**	15.41	19.21**	14.07
	1	1.373	3.76	1.373	3.76
VoCry	0	21.93**	15.41	21.64**	14.07
	1	0.293	3.76	0.293	3.76
Variable: X		**X does not granger-cause Elecpro**		**Elecpro does not Granger-cause X**	
		Z-bar	**P-value**	**Z-bar**	**P-value**
VoBit		7.343***	0.007	0.082	0.774
VoCry		4.135**	0.042	0.024	0.875
Variable: X	**Maximum rank**	**Cointergation test of Elecpro with X**			
		Trace statistics	**5% critical value**	**Max statistic**	**5% critical value**
VoBit	0	22.15**	15.41	21.04**	14.07
	1	1.112	3.76	1.112	3.76
VoCry	0	18.38**	15.41	18.02**	14.07
	1	0.364	3.76	0.364	3.76

*, **, *** are significant levels at 10%, 5%, and 1%, respectively

The Table 6 below describes the correlations and the unit root test for residuals of energy consumption, all cryptocurrencies trading volume, and Bitcoin trading volume. It shows that the unexplained evolution of all crypto-currencies trading volume have a significant positive correlation with the unexplained evolution of the energy consumption while the unexplained evolutions in Bitcoin trading volume have an insignificant positive correlation. Such results confirm the positive correlation between cryptocurrencies trading volume with energy consumption not only in levels but also in terms of unexplained evolutions. The Figure 2 below shows the unexplained evolutions in energy consumption, all crypto-currencies trading volume, and bitcoin trading volume.

It is worth noticing that the fluctuations in unexplained evolution of the energy consumption around 2015M1 and 2017M1 are in line with high fluctuations in cryptocurrencies trading volume. We then examine possible structural break for each residual using the Wald test as suggested by Donald (1993) and Patrick (1992). The LM ARCH test of Engle (1982) is then used to examine the ARCH disturbance for each variable. The Table 7 below shows the results of structural tests and ARCH disturbance test showing no evidence of structural break and no ARCH disturbance.

Therefore, we can finally estimate the effect of the unexplained evolution of cryptocurrencies trading volume on the unexplained evolution of the energy consumption through the following equation:

$$EnergyR_t = \sigma_0 + \sigma_1 VoCryR_t + \tau_t \quad (5)$$

Table 5: Estimations for each variable to extract the residuals (the unexplained evolutions)

Model: OLS estimation	(1)	(2)	(3)	(4)
Dep. Var:	Energy	Elecpro	VoCry	VoBit
L.Energy	**0.355****			
	[0.143]			
L.Elecpro		**0.348****		
		[0.139]		
L.VoCry			**0.933*****	
			[0.101]	
L.VoBit				**0.506*****
				[0.136]
T (monthly)	0.0001	0.0003**	0.011**	0.028***
	[0.0002]	[0.0001]	[0.005]	[0.008]
Constant	1.290***	8.686***	−5.597*	−11.082***
	[0.362]	[1.878]	[3.106]	[3.591]
N	47	47	47	47
R-squared	0.123	0.286	0.786	0.844

*, **, *** are significant levels at 10%, 5%, and 1%, respectively

Table 6: Data description, correlation matrix, and unit root tests for unexplained evolutions

Residuals	Obs	Mean	Std. Dev.	Min	Max
EnergyR	47	−8.6E-11	0.0217	−0.0707	0.0439
ElecproR	47	−1.2e-12	0.0121	−0.0399	0.0277
VoCryR	47	−2.7E-09	0.4116	−0.6608	1.4268
VoBitR	47	2.3E-09	0.3270	−0.6313	0.8865
Correlation		**EnergyR**	**ElecproR**	**VoBitR**	**VoCryR**
EnergyR		**1.000**			
ElecproR		**0.838*****	**1.000**		
		0.000			
VoBitR		**0.236**	**0.168**	**1.000**	
P-value		0.111	0.257		
VoCryR		**0.263***	**0.034**	**0.379*****	**1.000**
P-value		0.074	0.816	0.009	
Variable		**Dickey-Fuller test for level**			
		Z (t)		**P-value**	
EnergyR		−6.597***		0.0000	
ElecproR		−6.576***		0.0000	
VoBitR		−7.331***		0.0000	
VoCryR		−6.108***		0.0000	

*, **, *** are significant levels at 10%, 5%, and 1%, respectively. The residuals are predicted from the estimations in Table 6

Figure 2: Cryptocurrency market and Energy consumption: the residuals in the two

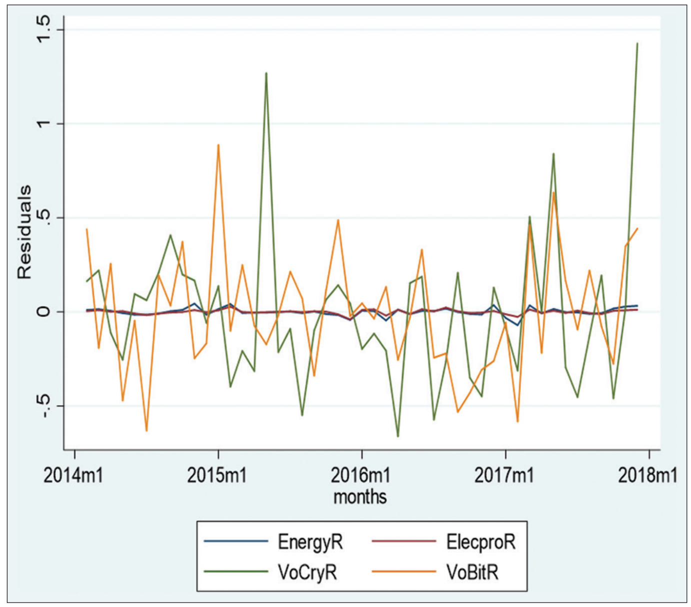

Table 7: Structural break tests and ARCH disturbance tests for unexplained evolutions

Var	Cumulative sum test for parameter stability				
	Test statistic	1% critical value	5% critical value	10% critical value	Conclusions
EnergyR	0.4824	1.143	0.9479	0.850	No Break
ElecproR	0.3594	1.143	0.9479	0.850	No Break
VoBitR	0.5564	1.143	0.9479	0.850	No Break
VoCryR	0.4439	1.143	0.9479	0.850	No Break
Var	**Estimated break date**		**Wald test**		
			Statistic	**P-value**	**Conclusions**
EnergyR	2017 m³		2.7634	0.6046	No Break
ElecproR	2017 m³		0.4604	1.0000	No Break
VoBitR	2017 m³		3.2111	0.5114	No Break
VoCryR	2017 m³		2.0958	0.7620	No Break
Var	**LM test for autoregressive conditional heteroskedasticity (ARCH)**				
		Statistic	**P-value**	**Conclusions**	
EnergyR		1.626	0.2023	No ARCH disturbance	
ElecproR		0.015	0.9038	No ARCH disturbance	
VoBitR		1.055	0.3043	No ARCH disturbance	
VoCryR		0.525	0.4686	No ARCH disturbance	

where *EnergyR* refers to the residuals from equation (2). *VoCryR* is the residual term from the equation (3). We also replace the residuals from equation (4) to examine the effect of the unexplained evolution of the Bitcoin trading volume (*VoBitR*) on the unexplained evolution of the energy consumption[3]. The following section reports and discusses in more detail our findings.

4. RESULTS AND DISCUSSION

The results of our ARDL estimation for the equation (1) are reported in the Table 8 that show the effects of Bitcoin/All cryptocurrencies trading volume on energy consumption in both short-run and long-run.

Firstly, the adjustment term (the lag of dependent variable – *Energy*) has a significant negative effect on the difference energy consumption in the studied period implying that a higher level of energy consumption in the previous month is adjusted in the following month through the long-run level. The value of the coefficient is ranged between -1 and 0 indicating that the results from the ARDL model are consistent.

Secondly, the trading volume of all cryptocurrencies has a significant positive effect on energy consumption in both short-run and long-run meaning that the cryptocurrencies trading causes a higher energy consumption globally. Interestingly, the coefficient of long-run effect (0.011) is much stronger than the coefficient of short-run effect (0.008), which implies a long-run consequence. This observation is a key contribution of our article since, to our knowledge, there is no existing works offering a clear empirical evidence on the long-term deteriorating consequence of the cryptocurrencies trading on the energy consumption. These results are also consistent with our earlier findings according to which the crypto-currenccies trading has a positive correlation with energy consumption. Moreover, cryptocurrency trading has a granger-causality with the energy consumption.

The Table 8 below refers to the results for the case of Bitcoin trading volume and it shows the insignificant positive effects of Bitcoin trading volume on energy consumption in both short-run and long-run. This result is quite consistent with our earlier observation on the correlation and Granger-causality test among the variables. It can be understanding by the fact that, although the bitcoin trading volume is large, it is still relatively less important that the trading volume of all 1636 cryptocurrencies that, together consume more energy than the bitcoin only. Despite this result on the energy consumption, the Table 8 indicates that the bitcoin trading volume has a significant positive influence on the short-run and the long-run production of energy consumption. Such observation confirms that the bitcoin has a problem of sustainability in the long term. The effects of unexplained evolutions of crypto-currencies trading on the unexplained evolutions of energy consumption are reported in the Table 9 shown in the following page.

The findings show that the unexplained evolution of both, the bitcoin trading volume and the trading of all cryptocurrencies have a significant positive impact on the unexplained evolutions of energy consumption. This result confirms our findings about the crypto-currencies trading that increase the global energy consumption. Furthermore our observations indicate that the trading volume of crypto-currencies market might significantly explain the unexplained evolution of the energy consumption. In other words, one might consider that the unexpected evolution of energy consumption can be described by the evolution of cypto-currencies trading.

For the robustness check, our study also checked the correlation, the Granger-causality, and the co-integration among cryptocurrencies trading volume as well as the unexplained evolutions in energy consumption. Our analysis shows shows that there is a significant positive correlation between all cryptocurrencies trading volume and the unexplained evolution in energy consumption. Moreover, there are co-integrations between them. The ARDL model is mobilized for the stationary of variables at different levels

3 As the evidence of no ARCH disturbance, no structural break, and all variables are stationary at the level, the equation (4) is estimated by OLS and checked the robustness by Robust OLS.

Table 8: The cryptocurrency trading volume and energy consumption: ARDL estimations

ARDL model		D.Energy		D.Elecpro	
The effects of:		Bitcoin volume	Total cryptocurrency volume	Bitcoin volume	Total cryptocurrency volume
Adjustment	L.Energy/L.Elecpro	**−0.668*****	**−0.724*****	**−0.671*****	**−0.600*****
		[0.147]	[0.144]	[0.139]	[0.139]
Long-run	L.VoBit	**0.008**		**0.009*****	
		[0.006]		[0.003]	
Short-run	D.VoBit	**0.005**		**0.006*****	
		[0.004]		[0.002]	
Long-run	L.VoCry		**0.011****		**0.007***
			[0.005]		[0.004]
Short-run	D.VoCry		**0.008****		**0.004***
			[0.004]		[0.002]
	Constant	1.320***	1.309***	9.085***	8.092***
		[0.315]	[0.302]	[1.898]	[0.139]
	N	46	46	46	46
	R-squared	0.344	0.385	0.362	0.311

*, **, *** are significant levels at 10%, 5%, and 1%, respectively

Table 9: The effects of unexplained evolutions in cryptocurrency trading on unexplained evolutions in energy consumption

Part A: dep. Var: EnergyR	(1)	(2)	(3)	(4)
Model	**OLS**	**Robust OLS**	**OLS**	**Robust OLS**
VoCry	**0.012**	**0.012***		
	[0.008]	[0.007]		
VoBit			**0.017***	**0.017***
			[0.010]	[0.010]
Constant	−5.2e-11	−1.2e-10	−1.2e-10	−5.2e-11
	[0.003]	[0.003]	[0.003]	[0.003]
N	47	47	47	47
R-squared	0.055	0.055	0.069	0.069
Part B: dep. Var: ElecproR	(1)	(2)	(3)	(4)
Model	**OLS**	**Robust OLS**	**OLS**	**Robust OLS**
VoCry	**0.001**	**0.001**		
	[0.004]	[0.003]		
VoBit			**0.006**	**0.006**
			[0.005]	[0.005]
Constant	0.000	0.000	−0.000	−0.000
	[0.002]	[0.002]	[0.002]	[0.002]
N	47	47	47	47
R-squared	0.001	0.001	0.028	0.028

*, **, *** are significant levels at 10%, 5%, and 1%, respectively

(unexplained evolution of energy consumption is stationary at the level, while the trading volume of cryptocurrency is stationary at the 1st difference). The results of ARDL estimations confirm that the trading volume of cryptocurrencies has a significant positive impact on the unexplained evolutions of energy consumption in the short-run and the long-run.

5. CONCLUSION

This study deals with the environmental aspects of crypto-currencies trading through its statistical relationship with the energy consumption. This article examines the effects of cryptocurrencies trading on the energy consumption over the period 2014M1-2017M12. The data for the Bitcoin and 1636 cryptocurrencies trading volume combined with primary energy consumption were collected for an analysis of time series through the application of econometric techniques. In this study, we also investigate the effect of the unexplained evolution of cryptocurrencies trading volume on the unexplained evolution of energy consumption.

Our empirical analysis provides three different contributions. First, we show the positive influence of the trading of cryptocurrencies on the energy consumption by generating a higher unexplained level of energy consumption. Second, the trading volume of all cryptocurrencies has a significant positive impact on the energy consumption in both short-run and long-run indicating a long-run deteriorating impact of the consumption of energy. Finally, the trading of bitcoin appears to have a long-run positive influence on the production of energy emphasizing its limitations in terms of sustainability. In this research, we did not distinguish the proof-of-work based crypto-currencies from the other algorithms based ones - this could be a limitation of our study – but still acceptable since the vast majority of the crypto-currencies are now traded through the energy consuming Proof-of-Work consensus (Goodkind et al. 2020), we simply use the data related to the trading of all crypto-currencies in our analysis. Another methodological aspect can be mentioned here: in line with the existing literature, we associated here the electricity consumption with the trading volume of cryptocurrencies – it is worth mentioning that some studies (Dittmar and Praktiknjo 2019; Masanet et al., 2019) claim that the Bitcoin's electricity consumption should be analyzed in relation with the hashrate (i.e. the network computational power). Due to the limitation of data (the past evolution of the hashrate is available only for the Bitcoin), we decided to use the trading volume (number of transactions) to proxy the activity of all cryptocurrencies. Furthermore, our study can easily be replicated with the hashrate as major indicator (instead of the trading volume). More generally, our study paves the way for future research that will categorize the crypto-currencies based on their validating algorithms to identify which ones offer the most sustainable option for the future of digital currencies.

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