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Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability

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Abstract

When Bitcoin (BTC), the first pioneering cryptocurrency was released in 2009, it was considered as an apolitical currency. Besides, the possible effect of BTC and other cryptocurrencies on either financial markets or transactions has been widely discussed. However, the environmental effects of cryptocurrency demand have been ignored. Here, this study examines the nexus between cryptocurrencies and environmental degradation by employing standard and asymmetric causality methods. The Toda-Yamamoto and bootstrap-augmented Toda-Yamamoto test results reveal

Bitcoin and Ethereum (ETH) excluding Ripple (XRP) have causal effects on environmental degradation. The Fourier-augmented Toda-Yamamoto test results show causal effects running from Bitcoin and Ripple to environmental degradation, whereas no causal effect runs from Ethereum to environmental degradation. The asymmetric causality shows causal effects from the positive shock of Bitcoin demand, negative shocks of Ripple and Ethereum demands to positive shocks of environmental degradation. Further discussions and policy implications are provided in the relevant sections of this study.

Keywords: Environmental Sustainability; Cryptocurrency; Asymmetric Causality; Bitcoin (BTC); Ethereum (ETH); Ripple (XRP)

1. Introduction

The demand for energy to mine and transact cryptocurrencies has triggered global debate among academicians, mainstream media, and the public in recent years. The technological innovation behind peer-to-peer electronic currency "blockchain" is considered one of the greatest innovations in the 21st century. Blockchain technology was first proposed in the white paper by Satoshi Nakamoto in 2008, viz. bitcoin—a decentralized digital electronic currency that enables online payment without recourse to any intermediary. Since its inspection, thousands of second generational cryptocurrencies aka alternative coins have emerged including Ethereum, Bitcoin Cash, and Ripple. Currently, the estimated total cryptocurrency market capitalization stands at $1.72 trillion [est. May 26, 2021; 23:21 GMT+2] (CoinMarketCap, 2021). There are more than 2500 cryptocurrencies in global circulation that are generally based on blockchain technology (Goodkind et al., 2020). The process by which new mineable tokens of cryptocurrency enter circulation is called mining whereas miners are participants that perform cryptographic work that adds the new transaction to the ledger (Kosba et al., 2016). For instance, Nakamoto's paper explains in detail the working principles of Bitcoin mining which began in 2009 (Nakamoto & Bitcoin, 2008). Mining requires substantial electricity to power special computers that uses consensus proof-of-work algorithm to validate transactions that are stored in the publication transaction ledger. It is unclear the amount of energy cryptocurrency consumes, as by design, they are hard to track. But the consensus is that Bitcoin mining is energy sensitive. For instance, the report by the University of Cambridge Centre for Alternative Finance (CCAF) shows the estimated Bitcoin total energy consumption between 40 and 445 annual terawatt-hours (TWh) is similar to the total energy used by Netherland (Rowlatt, 2020). When the price of cryptocurrency such as Bitcoin increases, it leads to a rise in energy consumption due to computing power used in creating and mining transactions—this has been the Achilles heel of the cryptocurrency industry (Rowlatt, 2020). Additionally, the halving of Bitcoin rewards and hashing power added to the global mining network

drastically increases the mining difficulty and production cost—which may positively influence the price.

As with any new emerging technology, careful consideration of its environmental and health impacts ought to be investigated. In recent years, emerging literature investigating these impacts—such as quantifying energy consumption and carbon emissions attributed to cryptocurrency mining including Ethereum, Litecoin, Bitcoin and Monero—were responsible for 3-15 million tons of carbon emissions (Krause & Tolaymat, 2018). An attempt to use IP addresses to assess mining locations indicate significant carbon emissions associated with Bitcoin mining contribute more than 20 million tons annually (Stoll et al., 2019). A study revealed carbon emissions associated with Bitcoin mining alone could exacerbate global warming above 2 degree Celsius threshold (Mora et al., 2018). Evidence from the study estimates cryptocurrency mining could be associated with 3-15 million tons of carbon emissions globally (Kahn, 2018). But the transaction per carbon emitted differs by country—for instance, many mining centers are in China due to low setup cost, and heavy reliance on coal energy—which is, unfortunately, the most carbon-intensive place for cryptocurrency mining (Jiang et al., 2021). The volatility movement in cryptocurrency price and the need to minimize operational costs including the cost of energy in order to maximize profit are important drivers in selecting a crypto mining site (Peck, 2017). The use of powerful computers requires large energy sources with machines running continuously. A typical computer server that consumes about 1.5 kilowatts (kW) of power may cost between $3224-$9000 for mining an individual coin (McGeeham, 2018). Findings from the study show that without a direct policy intervention in Bitcoin blockchain mining, energy consumption in China is estimated to reach 296.59 TWh with a corresponding 130.50 million tons of carbon emissions in 2024 accordingly (Jiang et al., 2021). However, the amount of renewable energy sources in Canada is higher relative

to China, and similar amount of cryptocurrency mined in China may generate four times carbon emissions compared to Canada (Krause & Tolaymat, 2018).

Energy consumption in the mining of cryptocurrency is significant and growing at alarming rate. For instance, a study using vector error correction model (VECM) indicates the short-run and long-run bidirectional causality between cryptocurrency volume and environmental degradation (Mohsin et al., 2020). Evidence from the study suggests ~13 million metric tons of carbon emissions can be attributed to Bitcoin blockchain technology expanding between the period spanning 2016-2018 (Krause & Tolaymat, 2018). Empirical findings using the novel ARDL reveal the volume of trading all cryptocurrencies has significant positive effect on energy consumption in both short-run and long-run—with long-term consequence on the energy sector and environment (Schinckus et al., 2020). The author of the study suggests the reduction in production cost drivers of cryptocurrencies—that improves energy efficiency of mining hardware, have cheaper worldwide electricity prices, and lower mining difficulty could indirectly have a negative impact on the price of cryptocurrencies (Hayes, 2017). A study suggests the average mining efficiency was 500 W per GH/s throughout 2010-2013 (Garcia et al., 2014). However, another study shows the average mining energy efficiency across different mining networks is around 0.40 W per GH/s (Hayes, 2017). The study shows cryptocurrency mining consumes significant amount of energy for proof-of-work to add new blocks to the chain. Each $1 Bitcoin value created is reported to cause health and climate damages of $0.49 and $0.37 in the United States and China, respectively (Goodkind et al., 2020).

Recently, CEO of Tesla Motors, Elon Reeve Musk announced the suspension of using Bitcoin as mode of purchasing Tesla vehicles—citing unsustainable use of fossil fuel energy (i.e., coal) for mining and transacting Bitcoin.

The tweet reads,

> "Tesla has suspended vehicle purchases using Bitcoin. We are concerned about 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 promising future, but this cannot come at 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% of Bitcoin's energy/transaction. (Elon, 2021)"

Although energy consumption attributed to cryptocurrency market has gained much interest in recent years, however, literature is limited in the scope of assessing the effects of mining and transacting cryptocurrencies on environmental degradation. Motivated by this, we extend the literature to investigate the impact of cryptocurrencies on environmental degradation using the novel standard and asymmetric causality test proposed by Toda and Yamamoto.

2. Data, Methodology, and Empirical Results

Due to lack of data measurement, we used monthly data of global carbon dioxide emissions (parts per million) from 2010 (M8) to 2021 (M1), and monthly prices of—Bitcoin (BTC) from 2010 (M8) to 2021 (M1), Ripple (XRP) 2015 (M2)-2021 (M1), and Ethereum (ETH) from 2016 (M4) to 2021 (M1) to test causality among cryptocurrency demand and environmental degradation. According to Investing (2021), the daily trade volume of the total cryptocurrency trade is approximately 1.562 billion U.S. Dollars (USD), whereas the daily trade volume of BTC, XRP, and ETH is almost 1.166 billion USD. In this manner, the share of BTC, XRP, and ETH is approximately 71.96% of total traded cryptocurrencies. Besides, BTC, XRP, and ETH are among the oldest and well-known cryptocurrencies, thus, cryptocurrency demand was proxied by using the prices of BTC, XRP, and ETH, while data on carbon dioxide emissions were used as indicator of environmental degradation.

Data on carbon dioxide emissions were obtained from Global Monitoring Laboratory (2021) whereas cryptocurrency price data were obtained from Investing (2021). In Fig. 1, we applied seasonal-adjustment procedures to the monthly data using Census X-13 procedure. The trend of carbon dioxide emissions shows seasonality as expected. All variables were converted into logarithmic values.

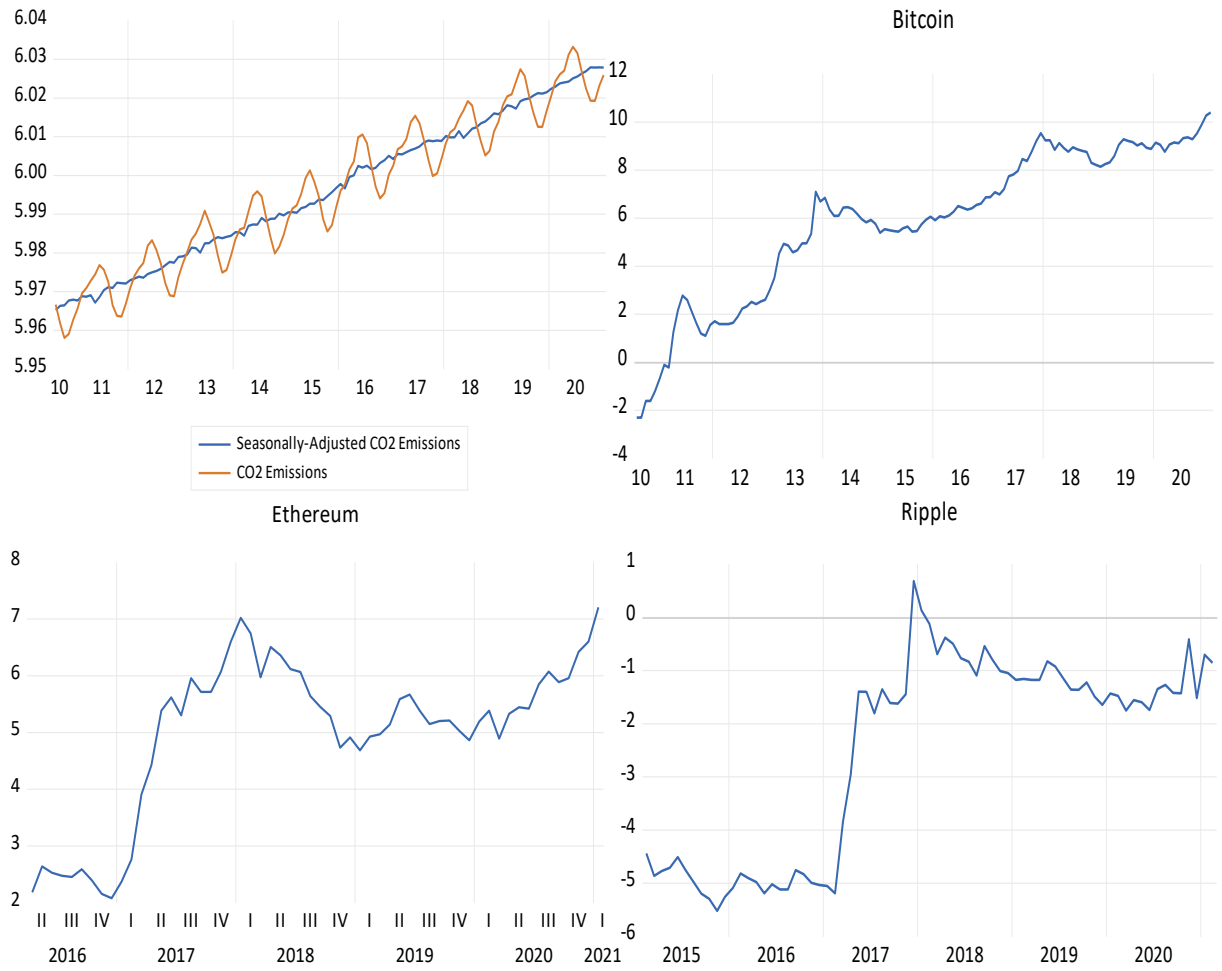


Fig.1: CO_2 Emission from 2010 (M8) to 2021 (M1) and Cryptocurrency Prices

We began our analysis by employing the causality test proposed by Toda and Yamamoto (1995). Toda-Yamamoto causality test can be implemented regardless of integration and cointegration properties of the data. Hence, preliminary analysis for determining the integration level of variables and existence of cointegration are not require. Toda-Yamamoto causality approach is simply based on the idea of estimation following Vector Autoregressive (VAR) model expressed as:

$$y_t = \alpha + \beta_1 y_{t-1} + ... + \beta_{p+d} y_{t-(p+d)} + \varepsilon_{1t} \quad \textbf{(1)}$$

Where y_t is formed by *K* endogenous variables, *p* is the lag length, d is the maximum integration level of the variables, α is the intercept term, β are coefficient matrices, and ε_{1t} is the error term. The Toda-Yamamoto causality test adopts the null hypothesis of Granger non-causality $(H_0 : \beta_1 = ... = \beta_p = 0)$, with estimated test statistic based on Wald statistic and asymptotic χ^2 distribution with *p* degrees of freedom (Nazlioglu et al. 2016; Toda and Yamamoto 1995). However, Hacker and Hatemi-J (2006) reported that size properties of the Toda-Yamamoto causality approach perform relatively weak in the case of asymptotic distribution (χ^2). Moreover, utilization of the leveraged bootstrap distribution could give satisfying results on minimizing size distortions. Therefore, proposing the use of bootstrap-augmented Toda-Yamamoto (Hacker and Hatemi-J 2006) causality test.

The economic data generally exhibit structural changes, thus, ignoring such changes could lead to biased inferences in testing hypothesis (Erdogan et al. 2020). Additionally, failure to account for structural changes in data can cause false rejection of the null of non-causality (Enders and Jones 2016). Hence, Nazlioglu et al. (2016) extended the traditional Toda-Yamamoto procedure to include Fourier approximation that control for structural changes. Like the standard Toda-Yamamoto procedure, the Fourier Toda-Yamamoto procedure does not require any prior knowledge on variables including integrational level and cointegration. The data generation procedure of the Fourier Toda-Yamamoto test can be given as (Nazlioglu et al. 2016):

$$y_t = \alpha(t) + \beta_1 y_{t-1} + ... + B_{p+d} y_{t-(p+d)} + \varepsilon_{2t} \quad \textbf{(2)}$$

Where $\alpha(t)$ is a function of time, and represents the structural shifts in the dependent variable. Eq. 2 can be extended by using Fourier functions as follows:

$$\alpha_t = \alpha_0 + \sum_{k=1}^{n} \gamma_{1k} \sin(2\pi kt/T) + \sum_{k=1}^{n} \gamma_{2k} \cos(2\pi kt/T) \quad \textbf{(3)}$$

Where n is the number of frequencies. Eq. 3 can be modified by including frequency as follows:

$$\alpha_t = \alpha_0 + \gamma_1 \sin(2\pi kt/T) + \gamma_2 \cos(2\pi kt/T) \quad \textbf{(4)}$$

Where k is the number of Fourier frequency. The general procedure of the Fourier Toda-Yamamoto can be expressed by utilizing Eq. 2 and 4 as:

$$y_t = \alpha_0 + \gamma_1 \sin(2\pi kt/T) + \gamma_2 \cos(2\pi kt/T) + \beta_1 y_{t-1} + ... + B_{p+d} y_{t-(p+d)} + \varepsilon_{2t} \quad \textbf{(5)}$$

Nazlioglu et al. (2016) adopted the null hypothesis of non-Granger causality, and employed bootstrap procedure to obtain more powerful test statistics that satisfies small sample properties. Such technique is robust in the case of the existence of unit root and cointegration. In traditional causality literature, no separation is made between the causal impact of positive and negative shocks, and such an assumption might be hard to satisfy. Hatemi-j (2012) proposed an asymmetric causality approach to address this issue. The data generation process of asymmetric causality test is based on the idea of causality between two integrated variables as follows (Hatemi-j 2012; Destek 2016):

$$y_{3t} = y_{3t} + \varepsilon_{3t} = y_{30} + \sum_{i=1}^{t} \varepsilon_{3i} \quad \textbf{(6)}$$

$$y_{4t} = y_{4t} + \varepsilon_{4t} = y_{40} + \sum_{i=1}^{t} \varepsilon_{4i} \quad \textbf{(7)}$$

Where y_{1t} and y_{2t} are constant, ε_{3i} and ε_{4i} are residuals. Positive and negative shocks can be defined as $\varepsilon_{3i}^{+} = \max(\varepsilon_{3i}, 0), \varepsilon_{4i}^{+} = \max(\varepsilon_{4i}, 0), \varepsilon_{3i}^{-} = \max(\varepsilon_{3i}, 0), \varepsilon_{4i}^{-} = \max(\varepsilon_{4i}, 0)$, respectively. Hence, ε_{3i} and ε_{4i} can be extended as $\varepsilon_{3i} = \varepsilon_{3i}^{+} + \varepsilon_{3i}^{-}$ and $\varepsilon_{4i} = \varepsilon_{4i}^{+} + \varepsilon_{4i}^{-}$, respectively. Therefore, Eq. 6 and Eq. 7 can be shaped as:

$$y_{3t} = y_{3t-1} + \varepsilon_{3t} = y_{3,0} + \sum_{i=1}^{t} \varepsilon_{3i}^{+} + \sum_{i=1}^{t} \varepsilon_{3i}^{-} \quad \textbf{(8)}$$

$$y_{3t} = y_{4t-1} + \varepsilon_{4t} = y_{4,0} + \sum_{i=1}^{t} \varepsilon_{4i}^{+} + \sum_{i=1}^{t} \varepsilon_{4i}^{-} \quad \textbf{(9)}$$

The cumulative form of the positive and negative shocks of the variables can be expressed as $y_{3t}^{+}=\sum_{i=1}^{t}\varepsilon_{3i}^{+}, y_{3t}^{-}=\sum_{i=1}^{t}\varepsilon_{3i}^{-}$ and $y_{4t}^{+}=\sum_{i=1}^{t}\varepsilon_{4i}^{+}, y_{4t}^{-}=\sum_{i=1}^{t}\varepsilon_{4i}^{-}$. In the next step, causality among variables is determined by using the Vector Autoregressive model. For instance, positive cumulative shocks between variables can be tested by the following specification:

$$y_t^{+}=\theta+\delta_1 y_{t-1}^{+}+...+\delta_p y_{t-1}^{+}+v_t^{+} \qquad \textbf{(10)}$$

Where y_t^{+} denotes 2x1 vector of the variables, θ is 2x1 vector of the constant terms, and v_t^{+} is 2x1 vector of the residuals. δ_r represents 2x2 matrix of coefficients for the lag order r(r=1,…,*p*). The VAR_p model can be expressed as:

$$Y=DZ+\lambda \qquad \textbf{(11)}$$

Where $Y=(y_1^{+},...,y_T^{+})(nxT)matrix, D=(\theta,A_1,...A_p)(nx(1+np))matrix, \lambda=(u_1^{+},...u_T^{+})$, and Z_t can be defined as follows:

$$Z_t=\begin{bmatrix}1\\ y_t^{+}\\ y_{t-1}^{+}\\ .\\ .\\ y_{t-p+1}^{+}\end{bmatrix}((1+np)x1)\,matrix, for\, t=1,...T, \qquad \textbf{(12)}$$

Where $Z=(Z_0,...Z_{T-1})((1+np)xT)matrix.$. Finally, the null hypothesis of non-Granger causality $(H_0:C\varphi=0)$ can be tested by the following specification:

$$Wald=(C\varphi)'\left[C((Z'Z)^{-1}\otimes S_U)C'\right]^{-1}(C\varphi) \qquad \textbf{(13)}$$

Where $\varphi=vec(D)$ and *vec* represent the column-stacking operator; $\otimes$ represents Kronecker product, *C* is $pxn(1+np)$ indicator matrix, and S_U represents covariance matrix of the

unrestricted estimated VAR model. Besides, Hatemi-j (2012) conducted a bootstrap simulation with leverage adjustments to obtain more precise critical values.

We began our analysis by conducting Toda-Yamamoto and Bootstrap-Augmented Toda-Yamamoto causality test. According to the findings (Table 1), the null hypothesis of non-Granger causality running from XRP to environmental degradation is accepted, whereas null hypotheses of non-Granger causality running from BTC and ETH to environmental degradation are rejected. This implies causal effects running from BTC and ETH to environmental degradation, whereas no causal nexus is observed from XRP to environmental degradation.

The standard Toda-Yamamoto and Bootstrap-Augmented Toda-Yamamoto causality tests do not consider possible structural changes in the nature of the data. Enders and Jones (2016) reported that ignoring such structural shifts in series could lead to false rejection of the null of non-causality in the case of non-existence of causal linkages among variables. It can be observed in Fig.1 that cryptocurrencies frequently exhibit volatile behaviors and sensitive to both economic and political events. Therefore, it would be more rational to check the robustness of the estimations by employing a causality approach that controls structural changes in data. To this end, we employed Fourier Toda-Yamamoto proposed by Nazlioglu et al. (2016). The Fourier Toda-Yamamoto causality test with single and cumulative frequency results (Table 1) suggest the null hypothesis of non-Granger causality running from ETH to environmental degradation is accepted, while the null hypotheses of non-Granger causality running from BTC and XRP to environmental degradation are rejected. Thus, the assessment finds causal effects running from BTC and XRP to environmental degradation, whereas no causal nexus is observed from ETH to environmental degradation.

Table 1: Causality Tests Results

Toda-Yamamoto & Bootstrap-Augmented Toda-Yamamoto Tests					
Hypothesis	**Test Stat.**	**Asymptotic Prob.**	**Bootstrap Prob**	**k**	ρ
BTC ≠> ENV	25.592	0.019	0.032	-	13
XRP ≠> ENV	0.172	0.917	0.934	-	2
ETH ≠> ENV	18.480	0.010	0.022	-	7
Fourier Toda-Yamamoto Test with Single Frequency					
Hypothesis	**Test Stat.**	**Asymptotic Prob.**	**Bootstrap Prob**	**k**	ρ
BTC ≠> ENV	25.118	0.022	0.043	3	13
XRP ≠> ENV	2.973	0.085	0.094	1	1
ETH ≠> ENV	10.142	0.181	0.209	1	7
Fourier Toda-Yamamoto Test with Cumulative Frequency					
Hypothesis	**Test Stat.**	**Asymptotic Prob.**	**Bootstrap Prob**	**k**	ρ
BTC ≠> ENV	24.714	0.025	0.045	3	13
XRP ≠> ENV	9.829	0.020	0.060	3	3
ETH ≠> ENV	5.195	0.636	0.657	3	7

Note: ρ: optimal lag, k: number of Fourier frequency. Optimal lag lengths were determined by using the Schwarz information criterion. Bootstrap critical values were obtained by utilizing 1000 bootstrap replications.

The price fluctuations in financial markets can cause investors to act in several ways — in the case of price decrease, investors either stop-loss or take long position whereas in the case of price increase, investors either take profits or invest more. Hatemi-j (2012) noted investors could respond differently to positive shocks compared to negative shocks of absolute magnitudes in the financial market. In this manner, investment behavior is more sensitive to negative shocks than positive ones. Therefore, asymmetric causal effects could occur in financial markets. Furthermore, the existence of asymmetric information on financial markets can cause the occurrence of asymmetric causal effects (Stiglitz 1974; Akerlof 1978; Hatemi-j 2012). It can be said that cryptocurrencies remain one of the markets with asymmetric information. Business Insider (2021a) reported nearly 1,000 individuals known as "whales", who hold almost 40% of the cryptocurrency market—easily manipulating cryptocurrency valuation, hence, causing serious price fluctuations. In such a case, the investment decisions of ordinary investors can easily be manipulated—by taking long-position after selling huge amount of cryptocurrencies and vice versa, hence, small investors easily make a loss due to asymmetric information of behaviors of whales in cryptocurrency market.

Therefore, asymmetric causal effects may easily occur in cryptocurrency market. To consider asymmetries in cryptocurrency market, we utilized an asymmetric causality test to investigate the effects of positive and negative demand shocks of cryptocurrencies on the environment.

Table 2: Asymmetric Causality Test Results

		Bootstrap Critical Values		
Hypothesis	**Test Stat.**	**1%**	**5%**	**%10**
$BTC^{+} \neq> ENV^{+}$	5.516*	9.697	6.030	4.497
$BTC^{+} \neq> ENV^{-}$	1.217	9.483	6.295	4.626
$BTC^{-} \neq> ENV^{-}$	0.529	9.041	3.904	2.743
$BTC^{-} \neq> ENV^{+}$	0.288	10.860	6.672	5.153
$XRP^{+} \neq> ENV^{+}$	1.064	11.296	4.446	2.918
$XRP^{+} \neq> ENV^{-}$	5.066	25.771	15.468	12.355
$XRP^{-} \neq> ENV^{-}$	0.101	12.535	4.881	3.012
$XRP^{-} \neq> ENV^{+}$	39.564***	27.519	16.849	13.753
$ETH^{+} \neq> ENV^{+}$	15.020	154.623	64.736	38.166
$ETH^{+} \neq> ENV^{-}$	11.528	36.993	18.456	14.056
$ETH^{-} \neq> ENV^{-}$	0.004	13.575	5.281	2.845
$ETH^{-} \neq> ENV^{+}$	37.398**	43.308	22.681	16.390

Note: Optimal lag lengths were determined by using Akaike information criterion *, **, and *** show statistical significance at 10, 5, and 1% level, respectively. Critical values were obtained by utilizing 1000 bootstrap replications.

The asymmetric causality test results (Table 2) validate the null hypothesis of non-Granger causality from positive shocks of BTC to positive shocks of environmental degradation (i.e., *p-value<0.10*), whereas the null hypothesis of non-Granger causality is accepted other three hypotheses regarding BTC and environmental degradation. Therefore, positive shock in BTC demand causes positive shocks to environmental pollution. Moreover, the null hypothesis of non-Granger causality from negative shocks of XRP and ETH to positive shocks of environmental degradation is rejected at 1% and 5% significance levels, respectively, whereas the null hypothesis of non-Granger causality is accepted for other three hypotheses regarding XRP-ETH and environmental degradation. Thus, negative shocks in XRP and ETH demand cause positive shocks to environmental pollution.

3. Discussion

Cryptocurrencies are regarded as decentralized, secure, low-cost payment tools for financial transactions. Therefore, it is asserted that the value of any cryptocurrency would be determined by the market forces without exogenous intervention such as central banking policy. The idea of decentralized currency has increasingly been adopted by individuals, hence, increasing cryptocurrency demand and mining activities across the globe. Besides, the adoption of cryptocurrencies is reported to have increased during the global pandemic, viz. COVID-19—when social distancing measures were enforced (Sarkodie et al. 2021). However, the environmental cost of cryptocurrency markets are often ignored in the existing literature.

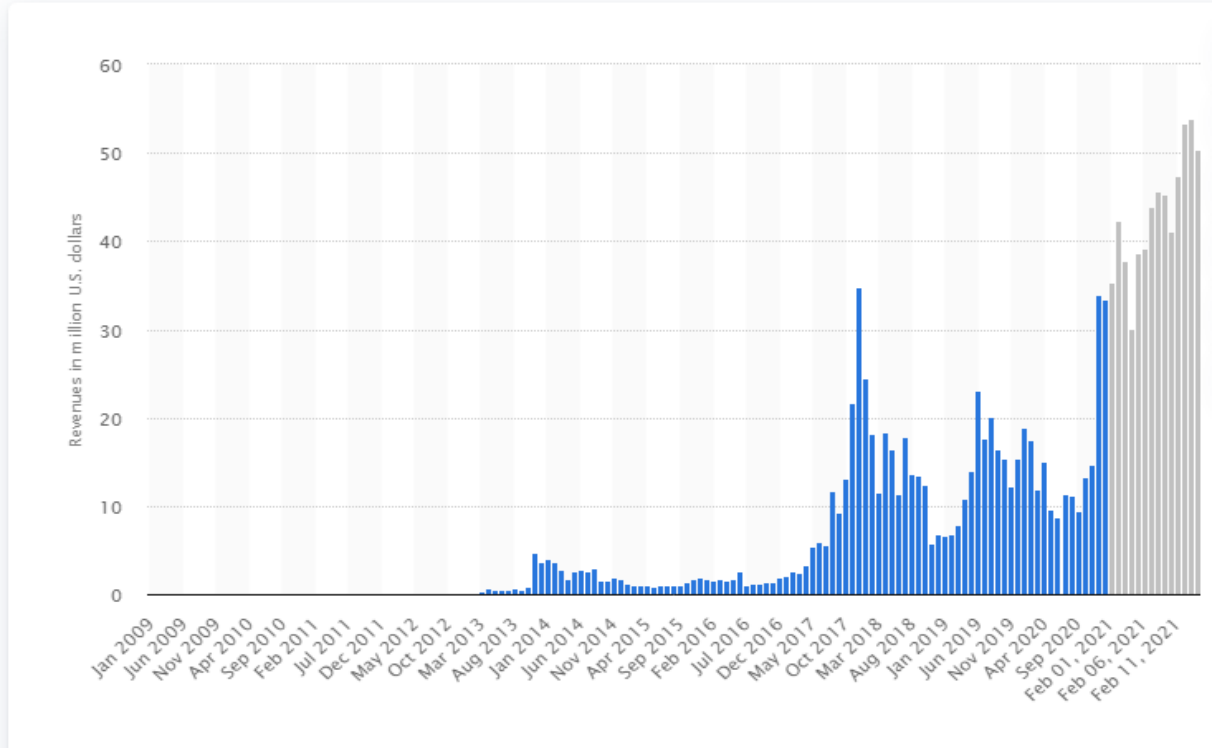
In this study, we aimed to unveil how cryptocurrency demand affects environmental sustainability via empirical assessment. The empirical results provide broad insights into the cryptocurrency market and environmental quality interaction. The standard causality test results suggest the existence of causal effects running from cryptocurrency demand to environmental degradation, but unable to separate the causal impact of positive and negative shocks of bitcoin demand on environmental degradation (Hatemi-J, 2012). To address this issue, we utilized an asymmetric causality approach. The results suggest positive shocks on BTC and negative shocks on XRP and ETH demand predict environmental degradation. First, this might be linked to increasing number of cryptocurrency transactions and mining activities during the period of volatility—either for having speculative profit or avoiding loss of investment—a typical intuition of cryptocurrency investors. Second, due to future expectations of price and revenue increase as same as BTC, negative price shocks on alternative cryptocurrencies such as XRP and ETH may induce investors to demand and mining activities of these alt coins (Katsiampa, 2017). Third, due to unregulated crypto market, transactions could be done with nearly low or no cost without taxes (Stone, 2021). In such a case, the number of cryptocurrency transactions may easily increase, hence, inevitably inducing more energy consumption from fossil fuels—with long-term implications on

292 environmental pollution. For instance, due to the nature of blockchain technology, a huge number
293 of third parties are involved to make a BTC transaction even if it includes lower quantities of
294 cryptocurrency. In this process, the existence of related cryptocurrency is verified by blockchain
295 technology through controlling formerly recorded blocks—verifying the accuracy of a new
296 transaction and recording unalterable records on the accounts of parties existing in the network
297 (Martin and Nauman, 2021).

298 If it is considered that high-performance computers such as gaming computers are widely used in
299 cryptocurrency markets, the environmental results of cryptocurrency demand could be more
300 dramatic. Mills and Mills (2016) reported the average electricity consumed by gaming computers
301 as ~1,394 kilowatt-hours (kWh)/year. This implies gaming computer consumes an average of 3.82
302 kWh of electricity per day. Business Insider (2021b) reported that the number of cryptocurrency
303 users surpassed 100 million by February, 2021. Thus, one-hour cryptocurrency trade of 100 million
304 investors is almost equal to 15,913,242.01 kWh/day and 5,808,333,333.33 kWh/year electricity
305 consumption. This can further be estimated in terms of emissions by using the estimation method
306 of Sibelga (2021)—where the amount of electricity consumption is nearly equal to 1,694,097,222.22
307 kg/year carbon emissions, viz. 1,694,097.22 metric tons/year of CO_2 emissions. This infers each
308 cryptocurrency investor emits ~0.0169 metric tons/per capita year of CO_2 emissions—assuming
309 one-hour daily cryptocurrency trade. The emission value is almost equal to 0.37% of global average
310 CO_2 emissions per capita (metric tons). In another scenario, if cryptocurrencies are traded on the
311 digital platforms by using mobile phones, tablet PCs, and laptops, the amount of CO_2 emission
312 could increase (Martin and Nauman, 2021).

313 A similar approach can be adopted for CO_2 emissions emitted from cryptocurrency mining
314 activities. According to statistics from Slushpool (2021), the world's first BTC mining pool, there
315 are approximately 147,500 BTC miners actively working. Assuming mining activities are executed
316 on full-time basis, one-day of mining BTC by ~147,500 miners is almost equal to 563,328.77

317 kWh/day and 205,615,000.00 kWh/year electricity consumption. Similarly, the estimated amount
318 of electricity consumption is nearly equal to 59,971,041.67 kg/year of CO_2 emissions, or 59,971.04
319 metric tons/year CO_2 emissions from only one cryptocurrency-mining activity. This means each
320 BTC-miner emits almost 0.406 metric tons/year CO_2 emissions per capita, which is almost equal
321 to 8.92% of global average CO_2 emissions per capita (metric tons). CoinMarketCap (2021) reports
322 more than 10,329 (est. June 8, 2021) different cryptocurrencies in circulation, thus, CO_2 emissions
323 emitted by cryptocurrency mining activities and transactions could dramatically increase.



324

325 **Fig.2:** Revenue raised from cryptocurrency mining worldwide**. Source:** Statista (2021)

326 Though most countries are suffering from lack of legislation on cryptocurrency markets, however,
327 considering the statistics provided, it implies immediate action required to regulate cryptocurrency
328 markets at the global level to internalize the environmental externalities associated with
329 cryptocurrency activities. Considering the influx of cryptocurrency mining revenues (Fig.2),
330 overshooting of cryptocurrency prices, unusual profits, and expectations related to increasing
331 cryptocurrency values in the future; due to high level of energy use, the environmental cost of
332 crypto market has the potential to exhibit a sharp increase (University of Cambridge, 2021).

333 Moreover, the number of cryptocurrencies and its corresponding users are increasing day-by-day,
334 thus, policymakers could immediately focus on diminishing the environmental burden of
335 cryptocurrency mining activities and transactions at national and international levels. Failure to
336 regulate the budding potential of cryptos could thwart the environmental aims determined by
337 international initiatives such as Kyoto Treaty, Paris Summit, Sustainable Development Goals,
338 hence, affecting climate change.

339 **4. Conclusion and Policy Implications**

340 In this study, we investigated whether the causal effects run from cryptocurrency demands to
341 environmental degradation by employing a set of symmetric and asymmetric causality tests.
342 According to the Toda-Yamamoto and bootstrap-augmented Toda-Yamamoto test results, Bitcoin
343 and Ethereum excluding Ripple have causal effects on environmental degradation. The Fourier-
344 augmented Toda-Yamamoto test results validate the causal effects running from Bitcoin and Ripple
345 to environmental degradation, whereas no causal effect runs from Ethereum to environmental
346 degradation. The asymmetric causality test results indicate causal effects from the positive shock
347 of Bitcoin demand, negative shocks of Ripple and Ethereum demands on positive shocks of
348 environmental degradations.

349 The results reveal the exigency of policy implementations on cryptocurrency markets. First,
350 politicians could immediately focus on establishing financial and environmental legislation to
351 regulate cryptocurrency market and stabilize demand. Second, policymakers could consider
352 licensing bulk cryptocurrency mining facilities and place environmental tax on revenues of mining
353 facilities within the scope of the "polluter pays" principle. The license implementation will allow
354 controlling environmental harms of mining activities whereas environmental taxes could help the
355 internalization of the negative externalities caused by mining activities and transactions. Third,
356 policymakers could consider making a tax break for bulk cryptocurrency mining facilities, which
357 could establish renewable energy technologies such as solar panels and (or) wind turbine to produce

electricity required for mining activities. This could help to lessen pressures of resource use of mining activities on the environment. Fourth, policymakers may consider placing an environmental tax on cryptocurrency revenues. This may help reduce the environmental burden of cryptocurrency trade by preventing speculative profit expectations from crypto markets.

This paper has several limitations. Due to the lack of data on cryptocurrencies, we could include widely known cryptocurrencies into the analysis. The cryptocurrency market is experiencing unprecedented growth and number of cryptocurrencies increasing day by day. Therefore, future studies may consider including other cryptocurrencies in the analysis. Moreover, due to existence of relatively small number of observation of data, we did not conduct an analysis to make inferences for the long-run such as cointegration and cointegration estimation. Therefore, future studies could focus on the magnitude of long-run effect of cryptocurrency demand on the environment. Last, it is widely known that the size and power properties of empirical methods increase with time dimension, hence, future studies may consider analyzing with a longer time span.

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381 Writing - review & editing, ***MYA:*** Investigation, Writing - original draft; Writing - review &
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