An Index of Cryptocurrency Environmental Attention (ICEA)

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Abstract

A concern often expressed in relation to cryptocurrencies is their environmental impact associated with increasing energy consumption, cryptocurrency mining's CO_2 pollution, all of which are currently unregulated. To assist researchers and policy makers, we have developed a new index, called the Index of Cryptocurrency Environmental Attention (ICEA), based on 778.2 million news stories from the LexisNexis News & Business database. This index captures the extent to which environmental sustainability concerns are discussed in alignment with these new assets. We show that the ICEA index, similar to the Cryptocurrency Policy Uncertainty Index and Cryptocurrency Price Uncertainty Index, reacts to major events in the cryptocurrency space. We believe that ICEA can be used for environmental policy development to assess environmental pressure and bring attention to the growing energy-consumption problem of this new digital payment network.

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1. Introduction

How much discussion or engagement is there in mainstream and social media regarding the energy consumption and environmental impact of cryptocurrencies? More so, what drives these discussions? Surprisingly, there exists no simple answer to this. The common perception is that this awareness is high and growing. The problem recently made headlines due to the announcement made by Tesla's CEO Elon Musk, that Bitcoin will no longer be accepted as payment due to its environmental impact[1]. With a global agenda of making our planet greener and more sustainable, surprisingly, the impact of cryptocurrency growth and the growing energy consumption of its networks has not been included in any high-level policy debates yet, and this area remains unregulated. Adoption of Bitcoin as official currency by El Salvador[2] manifests the beginning of legalisation of cryptocurrencies as an official method of payment, therefore the assessment of environmental impacts of this new form of money and investment asset should become one of the main priorities of the United Nations Economic and Social Council and academics worldwide.

Mining cryptocurrency takes more energy than mining gold[3]. It sounds like hyperbole, but it is in fact the truth. How can we find green solutions for the cryptocurrency? Most of the studies are only focus on the electricity consumption and CO_2 emission issues of Bitcoin. However, we can not forget that there are more than 4000 cryptocurrencies available on the market which can pose a significant risk to the environment now. If one were to consider only two of the most popular cryptocurrencies, Bitcoin and Ethereum, the electricity consumption of Bitcoin has increased from 4.8Twh to 73.12Twh over the last two years [Zade et al., 2019]. In October 2019, it was estimated that the energy consumption of Bitcoin mining was significantly more than the energy consumption of Austria [Malfuzi et al., 2020]. As for the carbon footprint of Bitcoin transactions, each Bitcoin transaction can contribute 619 Kwt to the carbon footprint, which is equal to 350,000 bank card transactions, or the energy consumption of an average US family over 20.92 days [Badea and Mungiu-Pupazan, 2021]. China has a huge cryptocurrency market, and Jiang et al. [2020] estimated that without any policy regulations, the annual energy consumption of Bitcoin in China is expected to peak in 2024 at 296.59 Twh. Surprisingly, 296.59 Twh pf energy consumption will generate 130.50 million metric tons of carbon emission output, which is more than the annual carbon emission output of Czechia and Qatar. As for Ethereum, in June 2017, the entire network of Ethereum already consumed a small country's worth of electricity (for example, Cyprus) [Corbet and Yarovaya, 2020].

From a sustainability perspective, cryptocurrency mining's negative impact on the environment is significant [Krause and Tolaymat, 2018]. Motivated by this emerging challenge, we have identified several issues. First, there is very limited existing research on the extent or determinants

[1]More details can be found in: https://www.ft.com/content/1aecb2db-8f61-427c-a413-3b929291c8ac
[2]More details can be found in: https://www.ft.com/content/7b5b1cc4-50bb-437f-aa16-f106d2dbc1c7
[3]More details can be found in: https://www.nature.com/articles/d41586-018-07283-3

of cryptocurrency's growing energy consumption problem, precluding any conclusive scientific confirmation about its contribution to climate change [de Vries, 2020 and Gallersdörfer et al., 2020]. Moreover, the few extant studies concerning the relationship between cryptocurrencies and environmental issues focus on how cryptocurrencies contribute to environmental issues [Stoll et al., 2019; Corbet et al., 2021 and Platt et al., 2021], with few studies comprehensively investigating inverse interactions. Second, no existing studies report on how environmental attention on cryptocurrencies can shock the cryptocurrency markets, not even the literature examining which financial or economic variables are susceptible to shocks transmitted by cryptocurrency environmental attention. Third, no clear and substantial regulations or policies consider the environmental issues related to cryptocurrency [Klein et al., 2019; Chudinovskikh and Sevryugin, 2019; Shanaev et al., 2020 and Riley, 2021][4].

Accordingly, this paper introduces the Index of Cryptocurrency Environmental Attention (ICEA), which aims to capture the relative extent of media discussion surrounding the environmental impact of cryptocurrencies, building, conceptually, on Lucey et al. [2021] and using data from the LexisNexis News & Business database for the period between January 2014 and May 2021, examining a total of 778.2 million news stories. Furthermore, we empirically investigate the impact of cryptocurrency environmental attention on other financial or economic variables, representing cryptocurrency markets using the Cryptocurrency Policy Uncertainty Index (UCRY Policy), Cryptocurrency Price Uncertainty Index (UCRY Price), Bitcoin price. To assess economic price and policy uncertainty, we use the CBOE Volatility Index (VIX) and Global Economic Policy Uncertainty (GlobalEPU). To investigate the relationships between the ICEA and the crude oil markets, we include the Brent crude oil price (BCO). To evaluate the effects of cryptocurrency environmental attention on climate change, we introduce the Global Temperature Uncertainty Index (GTU). Finally, the Industrial Production Index (IP) has been adopted to investigate the relationship between cryptocurrency environmental attention and the real production output of cryptocurrency manufacturing, mining and utilities. We deemed the Vector Error Correction Model (VECM) the most suitable model for testing the effectiveness and validity of the newly issued indices, processing structural shocks analysis between indices, and incorporating macroeconomic and microeconomic variables. Therefore, we selected the VECM and its Structural Vector Error Correction Model (SVECM) as this research's financial econometric methodologies. In addition, we further set ICEA as our explanatory variable. Examining how the ICEA impacts the log change of Bitcoin price, Ethereum price, and UCRY indices by applying a panel pooled OLS regression model. It can provide a more comprehensive understanding of the impact of cryptocurrency environmental attention on the cryptocurrency markets.

We summarise our main findings as follows. First, based on LexisNexis News & Business news

[4] For more details about cryptocurrency regulatory events, please find in [Shanaev et al., 2020].

coverage, we developed a new index for cryptocurrency environmental attention for the period 2014–2021, namely, the ICEA. This new index captures cryptocurrency environmental attention in terms of the cryptocurrency response to major related events. For example, ICEA spiked alongside new developments in cryptocurrency regulation and cryptocurrency flash news. Second, investigations of the impact of the ICEA on financial markets and economic developments using SVECM structural shock analysis revealed that it significantly impacted the UCRY Policy, UCRY Price, Bitcoin price, VIX, and BCO, as well as having a significantly negative impact on the GlobalEPU and GTU. Moreover, our empirical findings suggest that the ICEA significantly positively impacted the IP in the short term while having a significant negative impact in the long term. Third, reassuring news items and positive government policies were revealed to significantly negatively affect the ICEA's historical decomposition results. Additionally, ICEA historical decomposition results significantly spiked near significant events concerning cryptocurrencies. Ultimately, we have been able to conclude that overall attention on environmental issues concerning cryptocurrency increases cryptocurrency price fluctuations, a single-unit ICEA log change can contribute a 147.67 Bitcoin price log change, a 206.58 Ethereum price log change, a 0.91 UCRY Policy log change and a 1.04 UCRY Price log change. And the public is growing more concerned with the energy consumption of these innovative assets.

This paper contributes to the existing literature in three ways. First, our study provides an efficient new proxy for cryptocurrency and robust empirical evidence for future research concerning the impact of environmental issues on cryptocurrency markets. Second, this study successfully links cryptocurrency environmental attention to the financial markets, economic developments and other volatility and uncertainty measures, which has certain novel implications for the cryptocurrency literature. Third, our empirical findings offer useful and up-to-date insights for investors, guiding policymakers, regulators and media, enabling the ICEA to evolve into a barometer in the cryptocurrency era and play a role in, for example, environmental policy development and investment portfolio optimisation.

The remainder of this paper is structured as follows. section 2 outlines previous literature related to the effects of environmental issues on economic and the existing methodologies for the effects of one or more variables on other financial variables. section 3 describes the construction of the indices and the data for the empirical analysis, while this section also describes the econometric methods used. section 4 presents the empirical results and robustness tests, and section 5 concludes the main findings of this research and discusses the implications.

2. Literature review

Although the environmental impact of cryptocurrencies has been discussed widely in the literature, awareness of this problem among cryptocurrency investors and the general public varies, and opinions are mixed. Both mainstream and scientific literature have investigated the energy and environmental footprint of cryptocurrencies, dating back to the seminal work of O'Dwyer and Malone [2014], which focused on energy consumption and concluded that the electric power then used for Bitcoin mining was comparable to Ireland's electricity consumption. However, this does not indicate that scholars considered cryptocurrency mining activities wasteful. For example, Wimbush [2018] suggested that mining cryptocurrencies seems significantly less wasteful because they can create more value than they consume. The development of an electricity consumption index by the Cambridge Center for Alternative Investments is also a seminal piece of work in the field[5]. Meanwhile, Krause and Tolaymat [2018] indicated that cryptocurrency mining activities consumed more energy than mineral mining to create an equivalent market value (with the exception of aluminium mining) and also introduced CO_2 emission issues. Elsewhere, Stoll et al. [2019] examined the carbon footprint issue caused by Bitcoin, reminding the public that it could not ignore the environmental risks when evaluating the anticipated benefits of Bitcoin, and Gallersdörfer et al. [2020] selected more than 500 mineable crypto coins and tokens for comprehensive and systematic research on the associated energy consumption, concluding that Bitcoin consumed two-thirds of the entire energy consumption of cryptocurrencies, with the other cryptocurrencies accounting for the remaining third. Notably, studies on cryptocurrencies and energy consumption and environmental pollution issues have continued to advance, with more recent studies considering the relationship between attention on cryptocurrency energy consumption and the performance of financial markets [Corbet et al., 2021] and [Naeem and Karim, 2021]. Interestingly, Corbet et al. [2021] applied the DCC-GARCH model to investigate the effects of Bitcoin's volatility and cryptocurrency mining activities on energy markets and utility companies, producing results suggesting that cryptocurrency energy usage has a significantly positive relationship with the performance of some companies. Naeem and Karim [2021] further probed the interdependence of Bitcoin and green financial assets through application of time-varying optimal copula, concluding that all green assets could demonstrate Bitcoin hedge capacity.

The existing literature reviewed confirms that cryptocurrencies – including both transactions and mining activities – are significantly associated with environmental issues, including energy consumption, environmental pollution and CO_2 emissions. However, there remains controversy regarding how environmental attention and public concerns adversely affect cryptocurrency prices.

This research gap is characterised by the lack of data or proxies capable of reflecting and capturing attention on cryptocurrency environmental issues, hindering analyses of the impact of cryptocurrency environmental attention on financial markets and economic development. Therefore, building on the literature on the role of media coverage, public environmental awareness and government policy in financial markets, this paper develops an index (the ICEA) capable of capturing aware-

[5]More details can be found in: https://cbeci.org/faq/

ness of cryptocurrency energy consumption and sustainability issues and the consequent impacts on financial markets and economic developments. First, we draw on work concerning environmental awareness drivers. Both Lee et al. [2015] and Brulle et al. [2012] have observed that the changing climate and environmental issues, alongside general social educational attainment, drive awareness of climate and environmental risks in financial markets, findings that align with [Capstick et al., 2015]. Second, Duijndam and van Beukering [2020] have observed that the importance of climate change and environmental issues strongly correlates with future economic and financial market uncertainty, echoing the findings of Pidgeon [2012]. Third, Pianta and Sisco [2020] have demonstrated that the lagged values of extreme climate events can drive media coverage, causing financial market panic. However, many of the studies on awareness of and sensitivity to climate and environmental issues have been undertaken at individual, organisational or governmental levels, with few papers addressing longer-term macro-level drivers. For example, evaluating the effects of low-energy-consumption tax reduction policies, Dongyang [2021] observed that positive policies can improve the innovation investments of companies by alleviating financial constraints. Elsewhere, empirical findings from Zhang et al. [2021] provided evidence that air pollution in a city has a significantly positive relationship with an IPO under-pricing a company that is located in the city. Based on this gap, this paper will further examine the effects of the ICEA on financial markets or economic developments.

Thus, we have identified two research gaps in the existing literature. First, there is no proxy that reflects cryptocurrency environmental attention. Second, the impact of cryptocurrency environmental attention on long-term macro-financial markets and economic developments remains an undeveloped research field. In bridging these gaps, this paper represents three broad novelties. First, we develop a cryptocurrency environmental attention index based on news coverage that captures the extent to which environmental sustainability concerns are discussed in conjunction with cryptocurrencies. Second, we empirically investigate the impacts of cryptocurrency environmental attention on other financial or economic variables. Third, we provide insights into making the most effective use of online databases in the development of new indices for financial research.

3. Research design

As discussed, there is no existing literature demonstrating the effects of cryptocurrency environmental attention on cryptocurrency markets, other financial markets or economic development. This is due to the lack of a proxy representing cryptocurrency environmental attention. Accordingly, we have developed the ICEA to capture the extent to which environmental sustainability concerns are discussed in conjunction with cryptocurrencies using the theoretical frameworks introduced by [Baker et al., 2016; Huang and Luk, 2020 and Lucey et al., 2021]. Although the ICEA was developed on the basis of media coverage, our methodology differs from Baker et al. [2016] and Huang and Luk [2020], who used US and Chinese newspapers, respectively, as databases in the construction of their indices. In contrast, we adopted LexisNexis News & Business, a digital source, as our database because its overall article volume varies across publication sources and over time.

3.1. Index construction methodology

A difficult and doubtful point of the raw observed value of news articles from the LexisNexis News & Business database is that the overall volume of articles varies across publication sources and time. For constructing a useful index, this research draws on the index construction methodology of [Baker et al., 2016; Huang and Luk, 2020; Rice et al., 2020 and Lucey et al., 2021] and tries to scale the raw data of the observed total number of articles in the same publication source at the same time. Therefore, the standardisation and normalisation process is applied to the raw counts' data because it allows for sorting different variables on the same scale. In detail, firstly let N_t denotes the weekly observed value of news articles from LexisNexis News & Business in time (minute/day/week/month/year) t. Secondly, compute μ, the mean of the raw counts of the overall articles. Thirdly, compute the time-series standard deviation, σ. Fourth, perform N_t minus μ and then divide by σ to complete the raw counts standardization process, Z_t. In the end, add 100 for all t in Z to obtain the final normalised time-series index. This index construction methodology is used for all index constructions in this research.

3.1.1. ICEA construction

In spirit, this index is similar to Lucey et al. [2021], albeit focused not on uncertainty but on attention. This database covers a very wide variety of newspapers and news-wire feeds. Traditionally in this form of index construction the focus is on 'major' news publications (see for example Rice et al. [2020]). However, the rationale for using LexisNexis News & Business is that it covers a rather wide range of sources, including but not limited to news-wire feeds (breaking news) and media news transcripts (broadcast journalism), to acknowledge an aspect of the 'social' nature of cryptocurrencies. As new phenomena, these currencies have become subject to extensive discussion via not just traditional media, but alternative and social media, where the response to environmental concerns expressed by industry players have been especially pronounced on social media. There are papers such as [Phillips and Gorse [2017]; Subramaniam and Chakraborty [2020] and Nasekin and Chen [2020]] that discuss the role of both social and general media in analysis and specifically stress the importance of social sentiment in the cryptocurrency space.

To collect the relevant news stories, we ran the following queries on LexisNexis News & Business. The search string is as follows:

[("cryptocurrency" or "bitcoin" or "ethereum") and atl1("energy" or "energy consumption" or "energy footprint" or "carbon footprint" or "environment" or "environmental" or "environmental impact" or "climate change")] .

In terms of our search string design methodology, our index relates to the cryptocurrency environmental attention. Therefore, our search string design should focus on the 'cryptocurrency' and 'environment'. First, there is no doubt that 'cryptocurrency' was set as our first search term. Second, as the two most popular cryptocurrencies [Corbet et al., 2018; Ji et al., 2019; Bouri et al., 2019 and Conlon et al., 2020], 'Bitcoin' and 'Ethereum' were also selected as our key search terms to represent the cryptocurrency market. Third, we searched for the most popular synonyms for 'environmental' to represent 'environmental attention', based on the literature review of the relationship between cryptocurrencies, environmental issues and energy consumption concerns. We picked up 'energy', 'energy consumption', 'energy footprint', 'carbon footprint', 'environment', 'environmental', 'environmental impact' and 'climate change' to represent 'environmental attention'. In the end, compiling these key search terms together can successfully generate our search string for ICEA.

In addition, we set the option for Group Duplicate to HIGH so as to avoid duplicate results as much as possible. The queries were performed for each week from January 2014 to the beginning of May 2021[6].

The index is calculated as in Equation 1,

$$ICEA_t = (\frac{N_{1t} - \mu_1}{\sigma_1}) + 100, \tag{1}$$

where $ICEA_t$ is the value of the Index in the weeks t between $30/12/2013 - 02/05/2021$. N_{1t} is the weekly observed value of news articles on LexisNexis News & Business matching the search string above, μ_1 is the mean number of these same articles and σ_1 is the standard deviation of such.

The weekly ICEA is annotated in Figure 2, highlighting major changes as they map to events in the cryptocurrency and environmental sustainability concerns related spaces. Some clear spikes around the Mt.Gox occur in February. Mt.Gox went offline, suspended transactions, shut down its official website and exchange service at this time. Even more notably, Mt.Gox filed for bankruptcy protection from creditors. At the end of the month of June 2017, Ethereum had already used a small country's worth of electricity. At the end of November 2017 and in early December 2017, Bitcoin broke the $10,000 barriers, and at the same time, Bitcoin's Carbon Footprint issue and Bitcoin's Energy Consumption issue were proposed again. At the end of January 2018, Smartcool proved that new technology could lower the energy consumption and cost for cryptocurrencies. In February 2018, many research institutions and scholars identified that Bitcoin is an absolute energy and environmental disaster, and the Bitcoin Energy Consumption Index was issued. In July 2018, the United Nations supported a start-up that aimed to eliminate the carbon footprint produced by blockchains. In December 2018, the EOSIO fulfilled blockchains' promise on social and environmental sustainability. In June 2019, Bitcoin mining pumped out as much CO_2 per

[6] Weekly values can be downloaded from here: https://sites.google.com/view/cryptocurrency-indices/home?authuser=0

year as Kansas City, and Bitcoin CO_2 emissions were comparable to Las Vegas or Hamburg. At the end year of 2019, the COVID-19 outbreak strongly shocked the cryptocurrency market and ICEA. In July 2020, the Restart Energy MWAT (MWAT) market cap hit $1.49m. Around August 2020, the bullish market of cryptocurrency began. On April 13, 2021, Bitcoin surpassed $63,000 in a record high, rallying further growth and bringing back the heated discussion of environmental issues associated with cryptocurrency yet again.

[INSERT Figure 2 HERE]

3.2. Data

We derived our explanatory variables, which are the UCRY Policy, the UCRY Price, the GlobalEPU, the VIX, the BCO, the price of Bitcoin, the GTU[7] and the IP. The reasons why we choose these explanatory are justified as follows:

3.2.1. Financial and economic variable selection

To justify the selection of financial or economic variables for our sample, we evaluated previous studies reporting variables substantially correlated with cryptocurrency environmental attention or that were susceptible to shocks transmitted by environmental concerns or, inversely, that were immunised from these shocks.

First, one of this study's research aims is to investigate the effects of the ICEA on cryptocurrency markets. Accordingly, we selected the most important cryptocurrency assets [Corbet et al., 2020], Bitcoin price, as one of our financial variables. As the most popular digital currency, Bitcoin is often chosen as a proxy to reflect trends and volatility within cryptocurrency markets [Klein et al., 2018; Corbet et al., 2020 and Hudson and Urquhart, 2021]. Although there is an index that can represent the whole cryptocurrency market, the Bloomberg Galaxy Crypto Index [Umar and Gubareva, 2020], we chose not to use it because it only began in 2017, thus not representing our entire research period.

Second, the ICEA is a cryptocurrency index that captures environmental attention on cryptocurrencies, enabling the assumption that the ICEA affects cryptocurrency prices and policy uncertainty. Accordingly, we also included UCRY Policy and UCRY Price indices in our variable systems.

Third, several studies have made overwhelmingly clear that the environmental issues caused by crude oil exploration [Poizot and Dolhem, 2011 and Zhang and Kong, 2021] can impact crude oil market volatility [Yu et al., 2015 and Soliman and Nasir, 2019], leading to the selection of Brent Crude Oil price to represent the crude oil market [Kanamura, 2020] to examine the effects of cryptocurrency environmental attention on crude oil markets.

[7] The GTU measure is taken from and represents the 95% confidence interval of the global temperature anomaly.

Fourth, to analyse the relationship between the ICEA and other popular global economic or policy uncertainty measures, we selected the VIX and the GlobalEPU indices, using the VIX as a "fear index" [Whaley, 2009] representing the financial price uncertainty [Adrian and Shin, 2010; Whaley, 2000 and Reboredo and Uddin, 2016] and the GlobalEPU to capture economic policy uncertainty [Mensi et al., 2014; Long et al., 2021 and Ghosh and Kumar, 2021]. From our literature review, no studies can directly link VIX to environmental issues and energy consumption. Only Arslan-Ayaydin and Thewissen [2016] indicated that markets do not show a positive attitude to the environmental performance of energy sector companies by using VIX. As for GlobalEPU, Ahmed et al. [2021] suggested that the GlobalEPU has a significantly negative relationship with pollutant emissions. However, the GlobalEPU has a significantly positive relationship with the CO_2 emissions. Yu et al. [2021] indicated that China Provincial EPU has a positive impact on the carbon emission intensity of a company. And companies prefer to use cheap and dirty fossil fuels against the rising EPU. Liao et al. [2021] selected 175 companies from Shanghai and Shenzhen 300 index. Their empirical findings inferred that compared with the companies with a low corporate environmental responsibility, the EPU has a lower negative impact on the stock returns of the companies with a high corporate environmental responsibility.

Fifth, the effects of the ICEA on the output of the economy's industrial sector is captured by including the OECD industrial production index [Davis and Weinstein, 1999, Fernandez, 2016 and Feng et al., 2021]. Marques et al. [2019] suggested that the investments related to ensuring a clean and safe environment can increase energy efficiency and reduce greenhouse gas emissions by using the IP. Bozkus et al. [2020] investigated the relationship between atmospheric carbon emissions and the IP. Their empirical findings suggested that IP can cause long and short-term environmental costs. Moreover, these two variables have a strong correlation between the time domain.

Finally, we included the GTU index to confirm the findings of previous studies regarding the environmental issues caused by cryptocurrency mining and transactions.

3.2.2. Unit root test and cointegration test

To achieve the mentioned analyses and results, we proceeded as follows. Firstly, a unit root test was performed on the data, in this case the Augment Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were applied[8]. Table 3 shows that the p-value of each variable was more significant than 0.05 in the ADF test and also less significant than 0.05 in the KPSS test. This evidence shows that there are unit roots in all variables and that all variables are nonstationary. Secondly, further investigation shows that stable cointegrating relationships are present in the variable system, motivating the use of a VECM. From Table 4, $r = 0$, tested for the presence of cointegration. Since the tested statistic exceeded the 1% level significantly ($285.27 > 215.74$),

[8]The reasons why we choose these two unit root tests are available on demand.

we have strong evidence that our variables forms are cointegrated. To prove that our results are robust, we also processed a Johansen maximum eigenvalue test, too. The results also can be found in Table 4. As previously displayed, $r = 0$, tested for the presence of cointegration. Since the tested statistic exceeded the 1% level significantly ($68.01 > 63.71$), we also have strong evidence that our variables forms are cointegrated.

[INSERT Table 3 and Table 4 HERE]

3.2.3. Descriptive statistics

Time series plots of each variable are shown in Figure 1. Monthly frequency data is considered for further empirical analysis, and the empirical study period runs from January 01, 2014, to February 01, 2021. The ICEA, UCRY Policy and UCRY Price indices were generated by LexisNexis News & Business. GlobalEPU was obtained from policyuncertainty.com. GTU was obtained from Berkeley Earth[9], and IP was collected from OECD and other financial indices from Yahoo Finance. Table 1 shows the descriptive statistics for the indices of ICEA, UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin price, GTU and IP. Table 1 shows that Bitcoin price has the largest mean value (5464.53), standard deviation (7454.22), trimmed mean (4114.64), mean absolute deviation (4226.66), and range (44908.10), which indicates the high fluctuations and uncertainty. Furthermore, the mean value of Bitcoin price is significantly different from zero, while the standard deviation value is larger than the mean value. The skewness and kurtosis values of Bitcoin price are large and positive, indicating the Bitcoin price has a skewed left, fat-tailed and leptokurtic distribution. As for the protagonist, ICEA, it features lesser fluctuations than its family members, the UCRY Policy, UCRY Price and Bitcoin price. The mean of the ICEA is 99.88, lesser than the 99.89 of the UCRY indices. The standard deviation of ICEA is 0.62, also lesser than the UCRY Policy Index (0.67) and UCRY Price Index (0.71). Furthermore, ICEA has excess skewness and kurtosis values. These findings show a certain volatility, uncertainty and overall risky related with this index. In addition, all the variables in Table 1 can reject the normal distribution confirmed by Jarque-Bera (J.-B.) tests because the p-values of these tests are all less than 0.01. That is, all except for the GlobalEPU and GTU. The p-value of GlobalEPU is equal to 0.0186 and less than 0.05. The p-value of GTU is equal to 0.02852 and also less than 0.05.).

[INSERT Table 1, Figure 1 HERE]

Table 2 shows the Pearson correlation matrix, and reveals that ICEA is positively and significantly correlated with UCRY Policy Index, UCRY Price Index, GlobalEPU, VIX, BCO, Bitcoin price, GTU and IP. Additionally, ICEA correlates with UCRY Policy, UCRY Price, Bitcoin price

[9]Data can be downloaded from: `http://berkeleyearth.lbl.gov/auto/Global/Complete_TAVG_complete.txt`

and IP with a 1% significant level. UCRY Policy Index (86.99%), UCRY Price Index (90.46%), Bitcoin price (81.90%) and IP (46.26%) are the four indices which display a high Pearson correlation relationship with the ICEA. It is worth noting that the correlation value of UCRY Policy and ICEA is 0.8699 with a 1% significance level, and the correlation value of UCRY Price and ICEA is 0.9046 with a 1% significance level. These results indicate that UCRY Policy, UCRY Price and ICEA have a strong positive correlational relationship.

[INSERT Table 2 HERE]

3.3. Methodology

This paper develops a new index, the ICEA, and investigates the effects of the ICEA on financial and economic variables. However, it is necessary to consider the most suitable methodology for checking the effectiveness and validity of a newly issued index and further analysing the dynamic connections between the newly issued index and other variables. For this purpose, Baker et al. [2016] introduced the Economic Policy Uncertainty (EPU) Index and applied the vector autoregression model (VAR) to exploit time-series variation at log change of S&P500, the federal funds rate, log change of employment, log change of industrial production. Elsewhere, Huang and Luk [2020] developed the China Economic Policy Uncertainty Index (China EPU) based on Chinese newspapers and using a structural vector autoregression (SVAR) model based on the VAR model used to study the responses of macroeconomic variables (e.g. log change of Shanghai Composite Index, log change of benchmark interest rate, log change of unemployment rate, log change of real GDP) to shocks in the China EPU. Meanwhile, Rice et al. [2020] developed the Ireland Economic Policy Uncertainty Index (Ireland EPU) based on the two leading Irish newspapers (Irish Times and Irish Independent) and processed historical decomposition using a SVAR model to examine the co-movement of Irish economic activities (e.g. investment, CPI, consumption, employment, financial uncertainty and European Central Bank shadow rate) with the Ireland EPU.

Building on these studies, we selected the VAR model as our main financial econometric methodology for investigating the effects of the ICEA on financial and economic variables. However, the standard VAR is a reduced form model designed for stationary data [Lütkepohl, 2005]. Unit-root tests in Table 3 and cointegration texts in Table 4 enabled confirmation that there were unit-roots for all variables and our variable forms were cointegrated. Given these conditions, the VAR model did not perfectly suit our data and. Moreover, data processing would have broken the original characteristics of variables. Thus, we decided to not further calculate the log return, continuously compounded return or return variance (among other outcomes) of our variables, making our sample smoother. This led to application of the VECM, which is based on the VAR [Durlauf and Blume, 2016] but adds error correction features [Kočenda and Černỳ, 2015]. The VECM is designed for the non-stationary but cointegrated sets of variables [Maronna et al., 2019]. Lucey et al. [2021] applied the SVECM, which is based on the VECM, to investigate the shocks from UCRY Policy on financial markets. Our VECM comprises nine variables, and our sample runs from 2014-01-01 to 2021-05-01. We added one lag to the VECM based on the number of variables, observation period and the Akaike information criteria.

3.3.1. Econometric model specification

The VECM can be expressed as Equation 2:

$$\Delta y_t = \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1}\Delta y_{t-p+1} + \Xi^+ D_t + u_t, \tag{2}$$

where y_t is a $K \times 1$ dimensional vector of variables observed at time t. The decomposed cointegrated model $\alpha\beta^{'}$ has reduced rank $r = rk(\alpha\beta^{'}) < K$. Also, α is a $K \times r$ matrix containing the loading coefficients, β is also a $K \times r$ matrix containing the cointegrated vectors. Γ_j is a $K \times K$ short-run coefficient matrix with $j = 1, \cdots, p-1$. u_t is a k-dimensional unobservable zero mean vector white noise process, and has covariance matrix Σ_u. u_t also denotes the reduced form disturbance (forecast errors). D_t is a vector of deterministic terms, and Ξ^+ is the coefficient matrices correspond with D_t.

Based on VECM Equation 2 described above, we ordered variables as indicated by Equation 3. Each series was identified and recorded in Table 1.

$$\mathbf{Y}_{t-1} = \begin{bmatrix} ICEA_{t-1} \\ UCRY\ Policy_{t-1} \\ UCRY\ Price_{t-1} \\ GlobalEPU_{t-1} \\ Vix_{t-1} \\ BCO_{t-1} \\ Bitcoin_{t-1} \\ GTU_{t-1} \\ IP_{t-1} \end{bmatrix} \tag{3}$$

where, this research examines the impact of ICEA on the variable system Equation 3. To further isolate the effect of ICEA, ICEA was ordered first, since it captures the cryptocurrency environmental attention, while the UCRY Policy Index, the UCRY Price Index, GlobalEPU, VIX, BCO, Bitcoin price, GTU and IP can react contemporaneously to the attention shocks.

Structural shocks on the system variables y_t based on the VECM can be calculated as Equation 4:

$$\bar{A}_0 y_t = \bar{A}_1 y_{t-1} + \bar{A}_2 y_{t-2} + \cdots + \bar{A}_{p-1} y_{t-(p-1)} + \bar{A}_p y_{t-p} + \bar{\Xi} D_t + \varepsilon_t, \tag{4}$$

where ε_t is a $K \times 1$ dimensional vector white noise process with covariance matrix Σ_ε, which also means structural shocks. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. Premultiplying the

Equation 2 by $\bar{A}_0^{-1}$ can link the reduced form disturbance (forecast errors) u_t to the underlying structural shocks ε_t. The normal distribution $(0, I_K)$ is subject to ε_t.

From the above, we derive Equation 5:

$$u_t = \bar{A}_0^{-1}\varepsilon_t, \tag{5}$$

Stationary VECM [10] allows for three tools, which are Impulse Response Function (IRF), Forecast Error Variance Decomposition (FEVD) and Historical Decomposition (HD) to capture the dynamic and instantaneous impacts of structural shocks within the variable system, see Equation 3. The three elements can be broadly defined as follows.

3.3.1.1. Impulse Response Function. /
The Impulse Response Function is designed for presenting the variables' relationships in the ICEA VECM model because variables' relationships are hard to identify just from the coefficient matrices (all the variables in VECM model are a priori endogenous).

When a VECM process is stationary, it can be said that the VECM process has a Moving-average (MA) representation. The MA representation can be expressed as Equation 6:

$$y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k, \tag{6}$$

where u_t is a K-dimensional unobservable zero mean vector white noise process, and has covariance matrix Σ_u. $\Phi_i = JA^iJ'$ and $J = [I_k : 0 : 0 : \cdots : 0]$. A^i are summable.

In the Equation 6, the IRF can work when tracing the marginal effect of a shock to one variable by counterfactual experiment. The IRF shows how each variable reacts to shocks or changes in each other variable, and can be used to evaluate the sensitivity of variables to each other.

3.3.1.2. Forecast Error Variance Decomposition. /
Like the IRF, the Forecast Error Variance Decomposition (FEVD) is also designed to reveal and interpret the variables' relationships in a stationary process VECM. The forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 7[11]:

$$E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2), \tag{7}$$

[10] Detailed results of model stationary are not reported here for the sake of brevity. All test results are available upon reasonable request.

[11] The detailed processes of how the Equation 7 can be calculated are not discussed here for the sake of brevity. All the calculation processes are available upon reasonable request.

where $\theta^2_{jk,0} + \cdots + \theta^2_{jk,h-1}$ can stands for the contribution of the j-th ε_t innovation to the h-step forecast error variance of variable k. $\frac{\theta^2_{jk,0}+\cdots+\theta^2_{jk,h-1}}{E(y_{j,t+h}-y_{j,t}(h))^2}$ can compute the contribution % of the j-th ε_t innovation to the h-step forecast error variance of variable k. $\omega_{kj,h}$ can decompose the contribution of the j-th ε_t innovation to the h-step forecast error variance of variable k.

The FEVD can show the decomposition of changes in a variable arising from changes in other variables.

3.3.1.3. Historical Decomposition. /

Historical decomposition is the third tool used for the VECM structural shock analysis, and allows for the gathering of information on the contribution of structural shocks over time to a system of variables. Impulse Response Function can only trace the response to a one-time positive or negative shock, while the variation of indices in Equation 3 are driven by a sequence of shocks from different levels. The historical decomposition can measure the effect of target variable shocks on the variation of Equation 3 under a dynamic economic environment. Furthermore, compared with the forecast error variance decomposition, the historical decomposition can analyse the relative importance of shocks in different time periods of a system's variables. However, historical decomposition can only do this kind of analysis on a specific forecasting horizon.

In short, u_t can be decomposed into different structural components in the historical decomposition. In details, as what has been analysed above. Equation 6, the Moving-average (MA) representation can be further denoted as Equation 8:

$$y_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i} + \sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i}, \tag{8}$$

where the time series can be decomposed into the estimate structural shocks ε from time 1 to time t, and the inestimate structural shocks ε antedating the start point of the dataset.

In a stationary VECM process, the $\sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i}$ can have a constantly diminishing impact on the y_t as time t increases, which can contribute to a reasonable approximation. This process can be denoted as Equation 9:

$$\hat{y}_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i}, \tag{9}$$

Therefore, the historical decomposition is equal to the weighted sums, which can be measured as the contribution of shock j on variable k in the stationary VECM process. Now, the historical decomposition can be denoted as Equation 10:

$$\hat{y}^{(j)}_{kt} = \sum_{i=0}^{t-1} \Phi_{kj,t} u_{j,t} \tag{10}$$

The relationship between reduced form residuals u and structural shocks of ε the variables system (see Equation 3) are shown in Equation 11,

$$\begin{bmatrix} u_{t-1}^{ICEA} \\ u_{t-1}^{UCRY\,Policy} \\ u_{t-1}^{GlobalEPU} \\ u_{t-1}^{Vix} \\ u_{t-1}^{BCO} \\ u_{t-1}^{Bitcoin} \\ u_{t-1}^{GTU} \\ u_{t-1}^{UCRY\,Price} \\ u_{t-1}^{IP} \end{bmatrix} = \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 & 0 & 0 & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 & 0 & 0 & 0 & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} & 0 & 0 & 0 & 0 \\ S_{61} & S_{62} & S_{63} & S_{64} & S_{65} & S_{66} & 0 & 0 & 0 \\ S_{71} & S_{72} & S_{73} & S_{74} & S_{75} & S_{76} & S_{77} & 0 & 0 \\ S_{81} & S_{82} & S_{83} & S_{84} & S_{85} & S_{86} & S_{87} & S_{88} & 0 \\ S_{91} & S_{92} & S_{93} & S_{94} & S_{95} & S_{96} & S_{97} & S_{98} & S_{99} \end{bmatrix} = \begin{bmatrix} \varepsilon_{t-1}^{ICEA} \\ \varepsilon_{t-1}^{UCRY\,Policy} \\ \varepsilon_{t-1}^{GlobalEPU} \\ \varepsilon_{t-1}^{Vix} \\ \varepsilon_{t-1}^{BCO} \\ \varepsilon_{t-1}^{Bitcoin} \\ \varepsilon_{t-1}^{GTU} \\ \varepsilon_{t-1}^{UCRY\,Price} \\ \varepsilon_{t-1}^{IP} \end{bmatrix} \tag{11}$$

where, u_t denotes the reduced form disturbances (forecast errors) at time t-1. ε_t denotes the structural shocks at time t-1.

4. Empirical analysis and findings

4.1. IRF analysis results

To gain a more comprehensive understanding of the dynamic interaction between variables, we calculated the IRF from the SVECM with regards to ICEA shocks to the variable system Equation 3. Due to the variable system, Equation 3 shocks to the ICEA are not the main focus of the paper, this part will not be fully explained in the main context[12]. The plots of ICEA shocks to its variable system, which contains UCRY Policy, UCRY Price, GlobalEPU, VIX, BCO, Bitcoin price, GTU, and IP can be found in Figure 3. More statistics can be found in Table 5.

Figure 3a presents the response of UCRY Policy after ICEA impulses unit shocks, and UCRY Policy has a positive response. The peak response value is present at the premier point, which is equal to 1.9672×10^{-1}. The response values show a decreasing tendency with the elapsing of the time period. From the 8th period, the UCRY Policy responses tend to converge and move closely around the x=0 axis. This empirical finding verifies that ICEA shocks can significantly increase the UCRY Policy Index. In other words, the ICEA shocks can increase the cryptocurrency policy uncertainty. Figure 3b presents the results after ICEA impulses unit shocks occur to UCRY Price, and UCRY Price responses show a similar response to that if εICEA to UCRY Policy. The peak response value is present at the start point, which is 1.5739×10^{-1}. UCRY Price response values show a decreasing tendency with the elapsing of the time period. From the 8th period, the UCRY

[12]Detailed results and statistics of the variable system Equation 3 shocks to the ICEA are not reported here for the sake of to brevity. All test results are available upon reasonable request.

Price responses tend to converge and move closely around the x=0 axis. This empirical finding verifies that ICEA shocks can significantly increase the UCRY Price Index. In other words, the ICEA shocks can increase the cryptocurrency price uncertainty. Figure 3f presents that after ICEA impulses unit shocks to Bitcoin price, then Bitcoin price has a positive response. The peak response value shows on the start point, which is equal to 4.5325. Then, the response values begin to decay with the elapsing of the period. From the 8th period, the Bitcoin price responses tend to converge. This empirical finding verifies that the ICEA shocks can increase the Bitcoin price index.

It is worth noting that when comparing εICEA to UCRY Policy, with εICEA being inclusive of UCRY Price, UCRY Policy responses are slightly stronger than the UCRY Price responses. One possible explanation for this phenomenon is that the ICEA is an index focusing on environmental impacts on the cryptocurrency market. One of the most powerful tools to mitigate the environmental issues caused by cryptocurrencies is policy adjustments. Therefore, the UCRY Policy should be expected to be more sensitive to the ICEA shocks.

Because the ICEA focuses on cryptocurrencies, it is worth further investigating why it can increase the UCRY indices and Bitcoin price. As such, a number of potential explanations of this phenomenon are presented thusly. The rise in the ICEA can instigate speculation amongst cryptocurrency traders. These cryptocurrency speculators may increase their net long position because they believe to a certain extent in their own intellectual capabilities in the industry, and will attempt to avoid being the last to take the "hot potato" [Mnif et al., 2020]. Secondly, the high cryptocurrency environmental attention can reflect the awareness of the general public's environmental consciousness. Therefore, cryptocurrency miners may reduce the amount of cryptocurrency mining [Corbet et al., 2021]. Also, new policies may be issued to regulate cryptocurrency mining activities. In this case, the decrease in the cryptocurrency supply will lead to an increase in the cryptocurrency price.

Figure 3c presents the results after ICEA impulses unit shocks occur to GlobalEPU, and as displayed, GlobalEPU has a negative response. The lowest response value appears in the 1st period, which is equal to -3.6055. Then, the GlobalEPU response values gradually rise with the elapsing time period. In the front-middle period, which is the 3rd period, the GlobalEPU response shows a positive value of 0.0789. However, the general trend of the GlobalEPU response to εICEA is still negative. The GlobalEPU responses tend to converge after the 6th period. This empirical finding verifies that the ICEA shocks can decrease the Global Economic Policy Uncertainty Index. This conclusion is consistent with Ahmed et al. [2021], who suggested that the GlobalEPU has a significantly negative relationship with the pollutant emissions but is different from Yu et al. [2021], who found that the China Provincial EPU has a positive impact on the carbon emission intensity. The reason for the inconsistent conclusion is the different characteristics of the GlobalEPU and the China Provincial EPU. One possible explanation for this phenomenon is that the GlobalEPU is spiked by negative news or policy adjusting, for example, 9/11, the Global Financial Crisis, and the

Federal Reserve interest rate hike. This means, conversely, positive news or policy adjusting can significantly cool the EPU index. Substantial cryptocurrency environmental attention is likely to urge governments to launch new policies to protect the environment and mitigate pollution, which can be considered positive policy adjusting. Accordingly, the ICEA has a significantly negative relationship with the GlobalEPU.

Figure 3d presents the results after ICEA impulses unit shocks occur VIX, and evidently, VIX has a positive response. The VIX response values increase gradually from the start point, where the value is 0.5646, to the peak of responses in the 2nd period, equal to 3.2476. Then, the VIX response values begin to decrease until they converge. This empirical finding verifies that the ICEA shocks can increase the VIX index. This empirical evidence reconfirms the notion of Arslan-Ayaydin and Thewissen [2016], who indicated that financial markets does not reward environmental performance of energy sector. VIX is related to the market's expectations for the volatility in the S&P 500 over the coming 30 transaction days [Wang et al., 2019]. From the characteristics of the ICEA, we see that the ICEA comprises the public's concerns about environmental and energy consumption. The financial market is conductive [Leung et al., 2021 and Shehadeh et al., 2021]. Therefore, the concerns and panic about cryptocurrency environmental factors can be transmitted to the traditional financial markets. Moreover, the high environmental attention values reflect the deterioration of environmental Khan et al. [2020] and will affect the demand for some traditional energy forms Hu [2014], such as crude oil, coal and natural gas, among others. Both of the points mentioned above can cause financial market-price fluctuations. That is why ICEA can have a significantly positive relationship with the VIX.

Figure 3e presents the results after ICEA impulses unit shocks occur BCO, and as present in such figure, BCO has a positive response. The peak response value is present at the start point, which is equal to 2.4319. Then, the response values begin to decay over the elapsed period of time. From the 6th period, the UCRY Policy responses tend to converge. This confirms that the ICEA shocks can increase the BCO index. This phenomenon also can be explained by the ICEA can decrease the supply of BCO and provoke more BCO speculative trading activities. Moreover, εICEA impulses to BCO show a similar response trend as the εICEA impulses to Bitcoin. The only difference of note between BCO and Bitcoin's responses is that those of Bitcoin are more violent. There are several possible reasons that can aid the explanation of this difference. Firstly, both BCO and Bitcoin are financial assets. They therefore have close relationships with cryptocurrencies and environmental pollution. Secondly, Bitcoin markets contain more price bubbles and fluctuate more frequently than the BCO market. Thirdly, ICEA is designed to capture the attention of environmental issues to cryptocurrencies. Bitcoin markets hold a significant position in cryptocurrency markets,therefore, the Bitcoin price index is expected to be more sensitive and responsive to the ICEA.

In a similar fashion to from the εICEA on the Global Economic Policy Uncertainty Index. Global Temperature Uncertainty also shows a generally negative response trend to the εICEA shock. In

Figure 3g, the lowest response value is present in the 1st period, which is equal to -2.2639. Then, the GTU responses slightly rise to the peak value, which is equivalent to 0.0447. In general, the GTU responses show a "Wave-type" trend in the negative interval. From this data we can confirm that ICEA shocks can decrease the Global Temperature Uncertainty. Meanwhile, a high ICEA value indicates that people and governments are paying more attention to environmental issues and can reflect enhanced environmental awareness among the population. Governments promulgate new environmental protection policies to push entire societies to become more environmentally friendly, and heightened public environmental awareness guides more environmentally friendly behaviours. These significant steps are likely to reduce energy consumption and CO_2 emissions and achieve waste reduction, helping to mitigate the frequency and intensity of extreme weather events. Accordingly, the ICEA also demonstrates a significantly negative relationship with the GTU.

Figure 3h displays results after ICEA impulses unit shocks are applied to IP. As presented, IP has a positive response in the early period (1st to 2nd), and the peak value is 0.2070. However, the IP shows a negative response in the early-mid period (around the 3rd), and the lowest value is -0.0690. After the 7th period, the IP responses tend to converge. From this, we can state with confidence that the ICEA can increase the Industrial Production Index in the short-term, and the ICEA can also decrease the Industrial Production Index in the long-term. Importantly though, the short-term significantly positive relationship between the IP and the ICEA is leading. This empirical evidence can echo the findings of Bozkus et al. [2020] that IP can contribute to the long and short-term environmental costs. Industrial production is generally accompanied by pollution and consumption, with high industrial production values indicating high levels of pollution and consumption. The ICEA spiked in response to extreme energy consumption and pollution events, indicating it can demonstrate a significantly positive short-term relationship with the IP. However, as the environment deteriorates, governments are likely to promulgate new environmental protection policies to regulate industrial production activities, forcing enterprises to abandon high-energy-consumption and high-pollution activities and become more environmentally friendly [Vu and Dang, 2021]. Moreover, the ICEA can be cooled by new environmental protection policies, explaining its significantly negative long-term relationship with the IP.

[INSERT Figure 3, Table 5 here]

4.2. FEVD analysis results

To evaluate the importance of different shocks and decompose the forecast error variance into the contributions from exogenous shocks, we calculate the FEVD for ICEA. Figure 4 depicts the FEVD of ICEA decomposition results[13].

[13] Plots and statistic results about the FEVD of other variables are not reported here due to brevity. All test results are available upon reasonable request.

In Figure 4 and Table 6, we see the FEVD of ICEA plot and FEVD of ICEA statistics. In the first period, approximately 60% of the variation in ICEA is from shocks to ICEA itself, and most of the remaining approximately 40% is from UCRY Policy (19.17%), GlobalEPU (10.86%), Bitcoin price (4.71%) and IP (4.5%). It is surprising that UCRY Price can only contribute 0.187‰. The contribution of ICEA to the variations in the ICEA quickly dies after the first period and becomes stable after the sixth period, as is the case with the contribution of UCRY Policy to the variations in the ICEA. However, the contribution of Bitcoin price to variations in the ICEA changes fairly rapidly over the first period and eventually seems to converge at around 50%. As for the contribution of UCRY Price to variations in the ICEA, this begins to rise after the first period, and the growth rate gradually accelerates with the increase of the time period. In the end, UCRY Price to variations in the ICEA can converge at around 2.8%. These findings are also comparable to results in Lucey et al. [2021], which find that UCRY Policy and UCRY Price are more important in the short run, and the Bitcoin price is more important in the long run. The system becomes stable after the eighth period. In the end, the contribution of UCRY Policy, GlobalEPU, Vix, BCO, GTU, IP and ICEA can converge at around 11.08%, 6.73%, 1.45%, 4.15%, 1.55%, 1.87% and 20.46%, respectively.

[INSERT Figure 4, Table 6 HERE]

4.3. HD analysis results

The historical decomposition is most interesting here as it shows how, accumulating over time, the ICEA has changed as a consequence of changes in other variables, providing an interpretation of the relative importance over time of the various drivers.

The historical decomposition of the ICEA is shown in Figure 5 with annotated events appended. The contribution of ICEA shocks to the historical decomposition in ICEA is given in green. These shocks match the expectations of public concerns on the environment to a certain extent. ICEA and UCRY Price have a significantly positive relationship. In other words, the greater the media's attention to cryptocurrency's effects on the environment, the higher the cryptocurrency market value. For example: Ethereum is already using the equivalent of a small country's worth of electricity with the rise of cryptocurrency markets' price. Bitcoin's Carbon Footprint and energy consumption issues gained significant attention when cryptocurrency market value reached $10k. The ICEA increases with the start of the cryptocurrency bull market. Regulatory discussions, like UN aims to wipe out the Carbon Footprint of blockchains, negatively contributed to only small shifts in the ICEA. In contrast, technology's type policy adjustment events - for example: Smartcool proves that technologies can lower energy consumption and costs for cryptocurrency and the creation of the Bitcoin Energy Consumption Index - positively impacted the ICEA. As for the shocks in historical decomposition from other variables, VIX and Bitcoin price have a significantly positive impact on ICEA in general. We can hedge that this is potentially due to the extreme uncertainty and volatility of Bitcoin and other financial assets. These empirical findings from the historical decomposition match the findings in the impulse response function analysis. In addition, IP does not show a significant impact on ICEA in the historical decomposition analysis. This phenomenon maybe because COVID-19 had an extremely strong cumulative shock on the IP, which will cover the shocks from ICEA.

The decomposition also shows that ICEA captures environmental attention that could be more distinctively attributed to the major environment events in cryptocurrencies. Although the price of Bitcoin, the UCRY Policy, the UCRY Price and the ICEA are highly correlated, the ICEA appears to capture environmental attention beyond the Bitcoin price, the UCRY Policy and the UCRY Price as shown by the decomposition.

[INSERT Figure 5 HERE]

4.4. The impact of the ICEA on the cryptocurrency market

ICEA is a new index, so a natural question is whether attention is paid to the environmental aspects of cryptocurrency generation in the cryptocurrency market. Based on this concern, we investigated the relationship between the ICEA and cryptocurrency market by using a panel-pooled OLS model.

The regression model learned from the methodologies of Pastor and Veronesi [2012]; Huynh et al. [2021]; and Foglia and Dai [2021], who examined whether the policy uncertainty can predict the Bitcoin price return, UCRY risk and stock price volatility. The regression model can be defined as Equation 12:

$$Crypto_{it} = \beta_1 ICEA_{i,t} + \beta_2 Crypto_{i,t-1} + CV_{it} + c + \varepsilon_{it}, \tag{12}$$

where Crypto_{it} is the cryptocurrency asset price or index at time t, ICEA_{it} is the cryptocurrency environmental attention index at time t, CV_{it} is the K $\times$ K matrix of control variables, c is a constant, and ε_{it} is an error term. $\text{Crypto}_{i,t-1}$ is designed to remove any serial correlation in $Crypto_{it}$. Equation 12 hypothesises that as the ICEA value increases, the cryptocurrency asset price or index value also increase.

We selected the Bitcoin price and the UCRY indices (UCRY Price and UCRY Policy) as the explained variables. The reasons why we chose these three variables are explained in section 3. 'Ethereum' is also included in the cryptocurrency assets because 'Ethereum' is a key term in our ICEA search string. We also add control variables in Equation 12, selecting them from the left variables in Equation 3 because we have fully demonstrated that these variables may be highly correlated with the ICEA[14]. To eliminate the dimension divergence of the raw data in the regression

[14] When Bitcoin price is the explained variable, ICEA is the explanatory variable, and the control variables are the UCRY indices, GlobalEPU, Vix, BCO, Bitcoin, GTU and IP.

results [Lütkepohl, 2005], we calculated the log change to all the variables in Equation 3, including the additional Ethereum.

Table 7 reports the estimation results of Equation 12. Our regression results are not significantly different whether we add the control variables to our model or not, which indicates the robustness of the findings. All the β_1 coefficient values in model (1) and model (2) are positive and significant, which suggests that the ICEA has a positive impact on the log change of Bitcoin price, Ethereum price and UCRY indices. From the results in model (2), we can see that when we add control variables to Equation 12, all the values of R^2 increase significantly, which indicates that these regressions fit better. At the same time, we can still see that the β_1 values in model (2) do not decrease significantly, which shows that the explanatory power of ICEA for the cryptocurrency market can almost maintain the same level as the condition without control variables. Based on this empirical evidence, we can infer that a single-unit ICEA log change can contribute a 147.67 Bitcoin price log change, a 206.58 Ethereum price log change, a 0.91 UCRY Policy log change and a 1.04 UCRY Price log change. Moreover, these empirical findings are in accordance with the former IRF, FEVD and HD results. These findings perfectly align with the previous literature Liu and Tsyvinski [2021], which finds that cryptocurrency asset returns can be predicted by some factors specific to cryptocurrency markets.

[INSERT Table 7 HERE]

4.5. Robustness test

ICEA is a newly developed index and it is therefore essential to verify its usefulness. In this part, we conduct a test for robustness on an ICEA benchmark.

Two potential issues may exist in the ICEA index. The first and perhaps most obvious is does this index really work? Considering this is such a significant concern, the relationships between the UCRY Policy, UCRY Price, ICEA and Bitcoin price should be definitively proved. The UCRY Policy, UCRY Price, and ICEA are designed to reflect the cryptocurrency market, and the validities of the UCRY Policy and UCRY Price have been proved by Lucey et al. [2021]. For this purpose, a Pearson correlation will be applied to find the relationship between UCRY Policy, UCRY Price, ICEA and Bitcoin price index first.

Secondly, the continuously compounded returns (CCR) of UCRY Policy, UCRY Price, ICEA and Bitcoin price will be calculated by processing the first difference in the logarithmic values of two consecutive prices, which can be expressed as: $CCR_{i,t} = ln(\frac{P_{i,t}}{P_{i,t-1}}) \times 100$, where $CCR_{i,t}$ denotes continuously compounded returns for index i at time t, and P_{it} stands for the price of index i at time t. Then, the Pearson correlation will be applied again to find the relationship between the continuously compounded returns of UCRY Policy, UCRY Price, ICEA and Bitcoin price index. If ICEA, UCRY Policy Index, UCRY Price Index and Bitcoin still show a significant relationship in the continuously compounded returns, we have further evidence to prove the validity of ICEA.

The second issue to consider is whether ICEA can actually impact the financial markets. Based on this potential issue, two further robustness tests were applied. The first test was highly influenced by [Lyu et al., 2021] to re-process stronger Impulse Response Function tests. More specifically, the new Impulse Response Function test increases the confidence interval bootstrapping from 90% to 95% and increase the threshold of runs from 1000 to 2000. By increasing the impulses from the ICEA to the financial markets, the validity of the ICEA's impact on financial markets can be further assessed. We have proved that the log change of ICEA has a significant and positive impact on the log change of Bitcoin price, Ethereum price and UCRY indices. To further examine the robustness of the impacts of ICEA on cryptocurrency markets, we proposed an extra robustness test, which learned from the methodology of Al Mamun et al. [2020], to calculate the CCR for all the variables in Equation 3, including the Ethereum price. We then re-processed the Equation 12 by applying the CCR results.

4.5.1. Robustness test results for indices

From Table 8 panel A, the correlation value of ICEA and UCRY Policy is 0.845 at the 99% significance level. The correlation value of ICEA and UCRY Price is 0.857 at the 99% significance level. The correlation value of ICEA and Bitcoin price is 0.818 at the 99% significance level. These statistical results prove that ICEA has a strong, positive, and significant correlation with the UCRY Policy Index, UCRY Price Index and Bitcoin price. These findings match those in the impulse response analysis and historical decomposition analysis, therefore further validating the usefulness of the ICEA. It is worth noting that the correlation value between the ICEA and the UCRY Price Index is the strongest value among the three correlation relationships. This phenomenon may be because the rise of the UCRY Price Index can awaken an environmental awareness in people, and the high cryptocurrency environmental attention may also stimulate speculations in the cryptocurrency markets. These small yet novel findings can also reflect the accuracies of the UCRY Policy Index, UCRY Price Index and ICEA from the side.

From Table 8 panel B, the correlation value of $\Delta\ln$(ICEA) and $\Delta\ln$(UCRY Policy) is 0.384 at a 99% significance level. The correlation value of $\Delta\ln$(ICEA) and $\Delta\ln$(UCRY Price) is 0.390 at a 99% significance level. The correlation value of $\Delta\ln$(ICEA) and $\Delta\ln$(Bitcoin) is 0.028 at a 99% significance level. These statistical results also can further prove that the $\Delta\ln$(UCRY Policy), $\Delta\ln$(UCRY Price) and $\Delta\ln$(ICEA) have a significantly relationship with $\Delta\ln$(Bitcoin). Therefore, the ICEA can still work from the continuously compounded returns' perspective. Furthermore, the correlation value between $\Delta\ln$(ICEA) and $\Delta\ln$(UCRY Price) is still the strongest among the three ICEA continuously compounded return relationships just mentioned, which means the ICEA is more sensitive to the UCRY Price. These minor yet interesting findings also prove the validity of the UCRY Policy, UCRY Price and ICEA.

[INSERT Table 8 HERE]

4.5.2. Robustness test results for empirical analysis

In order to check the validity of the interconnection between the ICEA and financial markets, the new IRF test results concerning ICEA shocks to the variable system Equation 3 are shown in Figure 6. From the new IRF test plots, the responses of the financial markets to the impulses from εICEA still retain the same values, properties and trends as the former IRF test results, although the confidence interval bootstrapping is 95% and the threshold of runs is now at 2000. These robustness test results first prove the reliability and accuracy of the interconnections between the ICEA and financial markets, which have been explained in more detail in the main context, but essentially, the final interconnection results will not be changed by the increasing of the confidence interval bootstrapping and the threshold of runs. These robustness test results also prove that the volume of endogenous shocks and the confidence interval limitation will not impact the potential results. In other words, the responses of the financial market indices, which are described in Equation 3, can only be impacted by the intrinsic characteristics of ICEA. This robustness test can provide enough evidence that the former empirical findings of interconnection relationships between the ICEA and its financial markets are valid and reliable.

[INSERT Figure 6 HERE]

Table 9 displays the Equation 12 estimation results at the CCR level. We find that all the β_1 coefficient values in model (1) and model (2) remain positive and significant, which suggests that the volatility of Bitcoin, Ethereum and UCRY indices increases when there is more attention paid to the environmental aspects of cryptocurrency generation. Based on these statistical results, we can conclude that the impacts of ICEA on cryptocurrency assets remain robust at the CCR level. Finally, we see that ICEA has a positive impact on Bitcoin price, Ethereum price and UCRY indices.

[INSERT Table 9 HERE]

5. Conclusion and implications

We have developed a new measure of attention to sustainability concerns of cryptocurrency markets' growth. An Index of Cryptocurrency Environmental Attention (ICEA) has been constructed using 778.2 million news stories from the LexisNexis News & Business database. The index demonstrates significant increases in attention to cryptocurrency environmental impacts displayed via both traditional and social media channels from 2014 to 2021. Our findings suggest that the public is growing more concerned with energy consumption of these innovative assets. This result should be considered by environmental policy makers and the necessity of regulation of this area should be discussed.

This study further analysed the main drivers of this awareness, and assessed contributions of how ICEA variations can affect various uncertainty measures (UCRY Policy, UCRY Price, GlobalEPU, Vix and GTU) and other factors that might be affected, including the extent of the attention to environmental problems in cryptocurrency markets, traditional energy markets and industrial production (Bitcoin price, BCO and IP). The results from impulse response analysis show that ICEA has a significantly positive impact on the UCRY Policy, the UCRY Price, VIX, BCO, and Bitcoin price, while ICEA has a significantly negative impact on the GlobalEPU and GTU. It is worth nothing that Bitcoin has the strongest reactions from the ICEA variation shocks and ICEA has a significantly positive impact on the IP in the short-term, while having a significantly negative impact in the long-term, and the short-term positive impact is leading.

However, by decomposing the forecast variance into the contributions from exogenous shocks, we demonstrate that at the beginning of our observation period the UCRY Policy was the largest contributor to ICEA variations (19.17%), while Bitcoin and UCRY Price contributed just 4.71% and 0.187% respectively. These findings provide a strong evidence, that environmental concerns originated in policy and regulation domains, and up until recently, were not the main concerns of cryptocurrency investors who have been attracted to this asset class due to the rapid growth of cryptocurrency prices. The historical decomposition of the ICEA displays higher linkages between environmental attention, Bitcoin price, UCRY Policy and UCRY Price around key events that significantly changed prices of digital assets, for example, cyberattacks on cryptocurrency exchanges, the COVID-19 crisis, ICO and DeFi booms, and Bitcoin bubble-like periods. Therefore, we can conclude that overall attention to environmental issues of cryptocurrency will increase cryptocurrency price fluctuations. Thus, growth, expansion and adoption of cryptocurrencies worldwide should not be ignored by regulators and high-level debates around sustainability concerns brought by this disruptive innovation has to be originated. The assessment of the potential negative impacts of this new technology on climate change and potential mitigation strategies have to be included in the global sustainability agendas. Finally, a panel pooled OLS regression model indicates that the ICEA positively impacts Bitcoin price, Ethereum price, and UCRY indices.

Concerning the robustness test, this research applied a Pearson correlation to analyse the relationship between the UCRY Policy, UCRY Price, ICEA and Bitcoin price. We then used the Pearson correlation again to investigate the relationship between the CCR of UCRY Policy, UCRY Price, ICEA and Bitcoin price. These two Pearson correlation analyses successfully proved the usefulness and effectiveness of the ICEA because the index showed a significant relationship with UCRY Policy, UCRY Price and Bitcoin price, as well as with their CCR. Therefore, we have confidence believing the new issuing index is robust. In addition, we raised the confidence interval bootstrapping and threshold of runs in the IRF test to examine the interactions between the ICEA and financial markets. The new IRF tests, with the higher confidence interval bootstrapping and threshold of runs, also show the same results as the outcomes in the main context. These new IRF tests successfully prove the robustness of the findings of the ICEA's impact on the financial markets. In the end, we re-processed the panel pooled OLS regression model at a CCR level. The regression results confirmed the former empirical findings of the ICEA and the cryptocurrency assets we selected.

Although cryptocurrencies are widely considered to be one of the most significant financial innovations in recent times, an investment asset that offers high returns to the inventors, and able to fuel the financial market, especially under the COVID-19, we must assess whether this justifies environmental issues, such as high energy consumption and air pollution from its mining and transactions. While Blockchain technology has a number of useful implications and great potential to transform several industries, high energy consumption and CO_2 pollution issues of cryptocurrency have become one of the main areas of criticism, raising several questions of sustainability of cryptocurrency as a new form of money and investment assets. These results are essential for both policy makers and for academics, since they highlight an urgent need for research addressing key issues such as the growth of carbon produced in the creation of this new digital currency. The results are also important for investors concerned with ethical implications and environmental impacts of their investment choices.

From the perspective that cryptocurrency assets are new speculative assets that gain abnormal returns for a small proportion of the investors and are full of price bubbles[15], (much like sneakers transaction and P2P lending in 2020), cryptocurrency markets cannot bring any real value to society and economies. Based on this, its high energy consumption can be argued to be unnecessary, wasteful and unsustainable. It relies heavily on coal as its main energy source, and thus contributes to the growing climate change problem. This energy could be used more wisely to support more important and critical services in society. Additionally, it increases pressure on power suppliers to produce and distribute more energy. However, if we value cryptocurrency as a novelty method for payment and money transfer, we should not deny the real value of cryptocurrency. Following this line of thinking, we should consider that the negative environmental effect of cryptocurrency is not the problem of the cryptocurrency itself, but the energy sources. Therefore, policy makers should encourage people to use green renewable energy and new low power consumption blockchain technologies, such as solar energy, wind energy and solid oxide fuel cell energy systems to supply the electrical power demand for cryptocurrency mining and transaction processes demand, which can effectively decrease the carbon footprint of cryptocurrency usage and cryptocurrency speculative investments. At the same time, the bull policy regulations may also stimulate the growth of green investment and renewable energy market, which can compensate for cryptocurrency's current carbon footprint.

[15] More details can be obtained from: https://play.acast.com/s/the-irish-economics-podcast/39-what-is-cryptocurrency-prof-brian-lucey-tcd

In the end, the ICEA is important in the analysis of whether cryptocurrency markets are sustainable in terms of their energy consumption requirements and their negative contributions to climate change. A broader impact of the cryptocurrency environmental concern on cryptocurrency market volatility, uncertainty and environmental sustainability should be considered and developed. Moreover, we want to point out future research and policy legislation directions, notably we pose the question of how cryptocurrency can be made more sustainable and environmentally friendly, and how governments' policies on cryptocurrency can address the cryptocurrency markets. Recently, some scholars have already argued that the societal value that Bitcoin provides is worth the resources needed to sustain it[16]. Therefore, discussion papers about cryptocurrency energy consumption issues and the research agenda are urgently needed. In addition, applying sentiment analysis to the corpora used to construct the ICEA also can be considered. It is worth investigating how the different tones about the cryptocurrency environment can impact the cryptocurrency markets.

[16]More details can be found in: https://hbr.org/2021/05/how-much-energy-does-bitcoin-actually-consume.

Declaration of Conflicts of Interest

No conflicts of interest to declare.

CRediT authorship contribution statement

Yizhi Wang: Conceptualisation, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualisation, Project administration, funding acquisition, Writing - Review & Editing. **Brian M. Lucey:** Conceptualisation, Supervision, Project administration, Resources, Writing - Review & Editing. **Samuel A. Vigne:** Conceptualisation, Supervision, Project administration, Resources, Writing - Review & Editing. **Larisa Yarovaya:** Conceptualisation, Supervision, Project administration, Resources, Writing - Review & Editing.

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Table 1: Descriptive statistics

Variable	Count	Mean	Standard deviation	Median	Trimmed mean	Mean absolute deviation	Minimum	Maximum	Range	Skew	Kurtosis	Standard error	J.-B.	Source
ICEA	86	99.88	0.62	99.67	99.76	0.41	99.39	102.61	3.22	1.86	4.03	0.07	114.75^{***}	LexisNexis News & Business
UCRY Policy	86	99.89	0.67	99.72	99.76	0.34	99.22	103.20	3.97	2.78	9.03	0.07	425.59^{***}	LexisNexis News & Business
UCRY Price	86	99.89	0.71	99.69	99.76	0.46	99.19	102.91	3.72	2.15	5.11	0.08	169.28^{***}	LexisNexis News & Business
GlobalEPU	86	193.29	78.62	171.36	186.00	86.14	86.16	429.60	343.45	0.73	-0.27	8.48	7.969^{**}	policyuncertainty.com
VIX	86	17.58	7.49	15.18	16.31	4.53	9.51	53.54	44.03	2.13	5.74	0.81	194.19^{***}	Yahoo Finance
BCO	86	61.57	19.46	57.54	59.33	13.64	25.27	111.96	86.69	1.01	0.64	2.10	16.972^{***}	Yahoo Finance
Bitcoin	86	5464.53	7454.22	3151.87	4114.64	4226.66	229.67	45137.77	44908.10	2.84	10.52	803.81	540.74^{***}	Yahoo Finance
GTU	86	0.08	0.02	0.08	0.08	0.02	0.05	0.12	0.08	0.38	-0.40	0.00	2.5095^{**}	Berkeley Earth
IP	86	101.92	3.67	101.56	102.21	3.18	84.53	106.47	21.94	-1.75	6.05	0.40	185.79^{***}	OECD

Table 2: ICEA variable system Pearson correlation

	ICEA	UCRY Policy	UCRY Price	GlobalEPU	VIX	BCO	Bitcoin	GTU	IP
ICEA	1.0000								
UCRY Policy	0.8699^{***}	1.0000							
UCRY Price	0.9046^{***}	0.9785^{***}	1.0000						
GlobalEPU	-0.2901^{**}	0.2942^{**}	0.3505^{***}	1.0000					
VIX	0.2256^{*}	0.2898^{**}	0.3272^{**}	0.5241^{***}	1.0000				
BCO	0.0464^{*}	-0.1080^{*}	-0.1110^{*}	-0.4811^{***}	-0.3841^{***}	1.0000			
Bitcoin	0.8190^{***}	0.7893^{***}	0.7988^{***}	0.4973^{***}	0.3999^{***}	-0.1232^{*}	1.0000		
GTU	-0.1272^{*}	0.0825^{*}	0.0730^{*}	0.1745^{*}	-0.0792^{*}	0.1085^{*}	0.1970^{*}	1.0000	
IP	0.4626^{***}	0.2303^{*}	0.2693^{*}	-0.0436^{*}	-0.2686^{*}	0.1911^{*}	0.2497^{*}	0.2301^{*}	1.0000

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 3: Unit root test

Variable	ADF				KPSS			
	DF	Lag order	p-value	Stationarity	Level	Truncation lag	p-value	Stationarity
UCRY Policy	-2.2541	4	$0.4716 > 0.05$	Nonstationarity	0.86334	3	$< 0.01 < 0.05$	Nonstationarity
GlobalEPU	-2.6359	4	$0.3148 > 0.05$	Nonstationarity	1.7739	3	$< 0.01 < 0.05$	Nonstationarity
Vix	-2.5373	4	$0.3553 > 0.05$	Nonstationarity	0.80942	3	$< 0.01 < 0.05$	Nonstationarity
BCO	-2.7211	4	$0.2798 > 0.05$	Nonstationarity	0.50869	3	$0.03971 < 0.05$	Nonstationarity
Bitcoin	0.36577	4	$0.99 > 0.05$	Nonstationarity	1.4532	3	$< 0.01 < 0.05$	Nonstationarity
GTU	-3.4224	4	$0.05695 > 0.05$	Nonstationarity	0.39812	3	$0.04779 < 0.05$	Nonstationarity
UCRY Price	-2.4411	4	$0.3948 > 0.05$	Nonstationarity	1.0292	3	$< 0.01 < 0.05$	Nonstationarity
IP	-2.5847	4	$0.3359 > 0.05$	Nonstationarity	0.49935	3	$0.04181 < 0.05$	Nonstationarity
ICEA	-1.3315	4	$0.8505 > 0.05$	Nonstationarity	1.1206	3	$< 0.01 < 0.05$	Nonstationarity

Notes: 5% Critical Values are given in parentheses.

Table 4: Johansen cointegration test

	Johansen trace test				Johansen maximum eigenvalue			
	test	10pct	5pct	1pct	test	10pct	5pct	1pct
$r \leq 8$	4.88	7.52	9.24	12.97	4.88	7.52	9.24	12.97
$r \leq 7$	14.18	17.85	19.96	24.60	9.30	13.75	15.67	20.20
$r \leq 6$	27.56	32.00	34.91	41.07	13.37	19.77	22.00	26.81
$r \leq 5$	49.58	49.65	53.12	60.16	22.02	25.56	28.14	33.24
$r \leq 4$	79.90	71.86	76.07	84.45	30.33	31.66	34.40	39.79
$r \leq 3$	112.58	97.18	102.14	111.01	32.68	37.45	40.30	46.82
$r \leq 2$	158.53	126.58	131.70	143.09	45.95	43.25	46.45	51.91
$r \leq 1$	217.26	159.48	165.58	177.20	58.74	48.91	52.00	57.95
$r = 0$	285.27	196.37	202.92	215.74	68.01	54.35	57.42	63.71

Notes: 5% Critical Values are given in parentheses.

Table 5: IRF results: ICEA to other factors

Period	**εUCRY Policy**	**εUCRY Price**	**εGlobalEPU**	**εVix**	**εBCO**	**εBitcoin**	**εGTU**	**εIP**
Coefficient								
1	1.967227e-01	1.573877e-01	-3.6054517648	0.564613645	2.431872e+00	4.532492050	-2.263866353	0.2070491361
2	9.341305e-02	1.161612e-01	-2.2286375015	3.247607047	1.372654e+00	0.600119949	-2.015212309	0.1449969521
3	5.389113e-02	4.060097e-02	0.0789649023	0.486476717	1.290752e-01	0.906651708	0.044657879	-0.0690251379
4	1.500594e-02	2.165431e-02	-0.4326260907	0.410123320	2.976474e-01	-0.046155858	-0.653205380	-0.0122017362
5	7.728590e-03	3.496902e-03	-0.0528110136	0.031277900	1.162584e-01	0.265830932	0.116642558	-0.0132848803
6	2.528420e-03	4.767345e-03	-0.0827874951	0.096946522	1.081316e-01	-0.015186549	-0.207127224	0.0139845174
7	2.315880e-03	9.501722e-04	-0.0406714504	-0.010919173	1.773529e-02	0.090336949	0.039689807	-0.0007224514
8	8.731235e-04	1.662775e-03	-0.0146625118	0.049370468	1.778323e-02	-0.013292748	-0.044079287	0.0032294855
9	6.254303e-04	1.542177e-04	-0.0008523798	-0.007404554	-1.879768e-03	0.020868499	0.012914503	-0.0019150588
10	9.428352e-05	3.596596e-04	-0.0053248613	0.011152507	5.279797e-03	-0.007008390	-0.013534873	0.0005060190
Lower Band, CI= 0.90								
1	0.1112917081	0.0827074277	-6.0730578	-4.10278190	0.85762736	0.669928727	-5.54589351	-0.045004094
2	0.0320516493	0.0546557018	-4.6870304	-1.47929927	-0.56636702	-2.813431675	-5.04883455	-0.144093421
3	0.0015471222	-0.0097556622	-1.7807244	-1.82177607	-1.23538621	-1.077125025	-2.16587653	-0.309136493
4	-0.0154264267	-0.0096015665	-1.7904876	-0.72037657	-0.55879766	-1.226770701	-2.40944142	-0.158824653
5	-0.0093799568	-0.0125498385	-0.6823626	-0.79669168	-0.33831834	-0.391982498	-0.56079341	-0.083617159
6	-0.0071106876	-0.0036926814	-0.6144655	-0.33732328	-0.10351854	-0.451769558	-0.80151882	-0.030424609
7	-0.0032263080	-0.0060956529	-0.3426064	-0.37759386	-0.09290785	-0.055275309	-0.19267036	-0.021987691
8	-0.0032541741	-0.0010427703	-0.2673422	-0.12583288	-0.03518261	-0.105085098	-0.35061714	-0.009040284
9	-0.0007344432	-0.0021091802	-0.1379752	-0.14473565	-0.04793141	-0.019247300	-0.10031658	-0.010821758
10	-0.0011331546	-0.0004306747	-0.1089770	-0.05395104	-0.01048233	-0.047351654	-0.13961812	-0.003301702
Upper Band, CI= 0.90								
1	0.264827892	0.213127489	-1.09492012	3.75429238	4.08608082	8.8272914	1.09871793	0.470445632
2	0.136926629	0.161255150	0.37069148	6.37146245	3.19813943	3.7612103	1.20450537	0.478372534
3	0.103442486	0.087842423	1.95377602	2.38625480	1.52743450	3.4933862	2.41941541	0.210212243
4	0.046738243	0.055442642	0.53710708	1.74401149	1.42720700	1.7523379	0.45381529	0.144902969
5	0.036156102	0.031841978	0.71470115	0.80431079	0.70653907	1.4925940	0.93859147	0.076735037
6	0.022300459	0.022847091	0.32855129	0.61025248	0.55979072	0.8256394	0.17511838	0.069120356
7	0.017412213	0.017089298	0.17415472	0.21969593	0.31687888	0.7024221	0.47098785	0.025427726
8	0.010673702	0.011019437	0.10424717	0.31919301	0.26864251	0.4525078	0.08319119	0.029870606
9	0.008034058	0.007633812	0.06713752	0.08366046	0.15845819	0.3183578	0.16385723	0.010965419
10	0.005095490	0.005234231	0.04271068	0.13759478	0.12416192	0.2255538	0.05167892	0.010712580

Table 6: FEVD of ICEA

Period	ε**UCRY Policy**	ε**GlobalEPU**	ε**Vix**	ε**BCO**	ε**Bitcoin**	ε**GTU**	ε**UCRY Price**	ε**IP**	ε**ICEA**
1	0.191701	0.108649	0.000408	0.001206	0.047191	0.001110	0.000187	0.045025	0.604523
2	0.124666	0.088249	0.002336	0.018531	0.403542	0.015790	0.027308	0.023193	0.296386
3	0.122300	0.076120	0.009836	0.028623	0.453629	0.015337	0.025404	0.022485	0.246266
4	0.114578	0.071397	0.012185	0.035249	0.480270	0.015305	0.027854	0.020407	0.222755
5	0.112714	0.069255	0.013849	0.038611	0.489422	0.015386	0.027838	0.019558	0.213368
6	0.111570	0.068155	0.014222	0.040232	0.494268	0.015459	0.028257	0.019125	0.208712
7	0.111181	0.067706	0.014363	0.040934	0.496555	0.015486	0.028302	0.018923	0.206549
8	0.110952	0.067456	0.014450	0.041267	0.497727	0.015502	0.028377	0.018821	0.205448
9	0.110844	0.067341	0.014487	0.041437	0.498315	0.015508	0.028394	0.018770	0.204904
10	0.110785	0.067279	0.014513	0.041523	0.498608	0.015511	0.028410	0.018745	0.204626

Table 7: The impact of the ICEA on cryptocurrency market

	Δ*ICEA impact*	
	Model	Model
	(1)	(2)
ΔBitcoin	176.2954***	147.6654***
	(0.9071)	(0.5291)
Control variables	No	Yes
R^2	64.90%	88.06%
Observations	86	86
ΔEthereum	211.9687***	206.57732***
	(1.347)	(0.6358)
Control variables	No	Yes
R^2	49.66%	88.78%
Observations	66	66
ΔUCRY Policy	0.9376***	0.9097*
	(0.00332)	(0.00125)
Control variables	No	Yes
R^2	75.16%	96.46%
Observations	86	86
ΔUCRY Price	1.04144***	1.03549*
	(0.003049)	(0.001173)
Control variables	No	Yes
R^2	81.63%	97.28%
Observations	86	86

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: UCRY, ICEA, Bitcoin indices Pearson correlation

Panel A: UCRY, ICEA, Bitcoin indices Pearson correlation				
	UCRY Policy	UCRY Price	ICEA	Bitcoin
UCRY Policy	1***	0.985***	0.845***	0.847***
UCRY Price	0.985***	1***	0.857***	0.852***
ICEA	0.845***	0.857***	1***	0.818***
Bitcoin	0.847***	0.852***	0.818***	1***
Panel B: UCRY, ICEA, Bitcoin indices volatility Pearson correlation				
	Δln(UCRY Policy)	Δln(UCRY Price)	Δln(ICEA)	Δln(Bitcoin)
Δln(UCRY Policy)	1***	0.903***	0.384***	0.056***
Δln(UCRY Price)	0.903***	1***	0.390***	0.048***
Δln(ICEA)	0.384***	0.390***	1***	0.028***
Δln(Bitcoin)	0.056***	0.048***	0.028***	1***

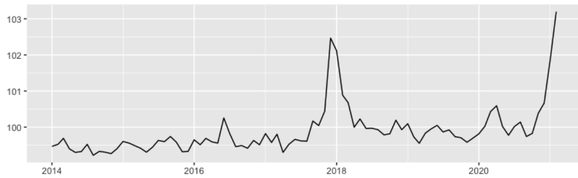
Note: *p<0.1; **p<0.05; ***p<0.01.

Table 9: Robustness test

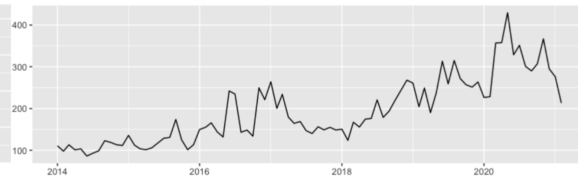
	$\Delta ln ICEA$ *impact*	
	Model (1)	Model (2)
Δln**Bitcoin**	140.311***	107.3383***
	(0.285)	(0.242)
Control variables	No	Yes
R^2	51.84%	79.49%
Observations	85	85
Δln**Ethereum**	19.1874*	17.1546***
	(1.690)	(1.673)
Control variables	No	Yes
R^2	29.99%	44.01%
Observations	65	65
Δln**UCRY Policy**	0.9476***	0.9410*
	(0.9746)	(0.1581)
Control variables	No	Yes
R^2	80.84%	97.24%
Observations	85	85
Δln**UCRY Price**	1.0459***	1.02432*
	(0.4012)	(0.1488)
Control variables	No	Yes
R^2	84.51%	97.87%
Observations	85	85

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

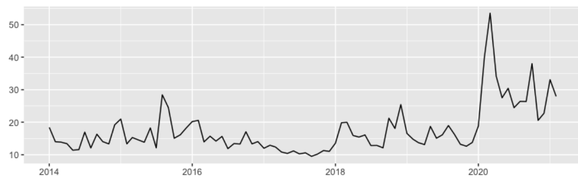
Figure 1: Time series of the factors



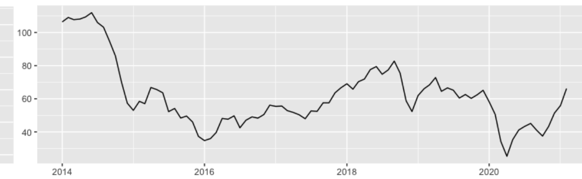
(a) UCRY Policy time series



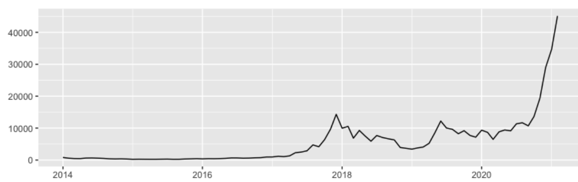
(b) GlobalEPU time series



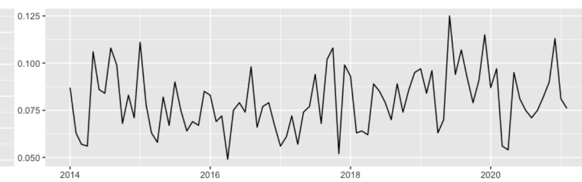
(c) Vix time series



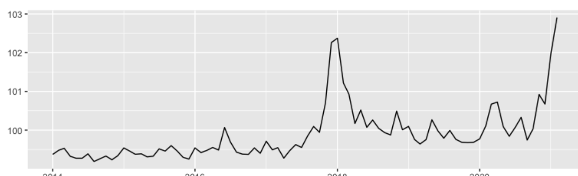
(d) BCO time series



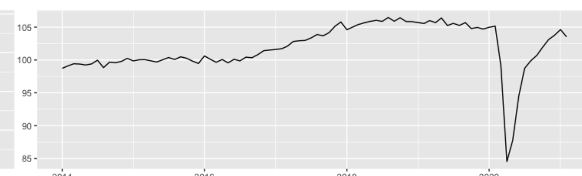
(e) Bitcoin time series



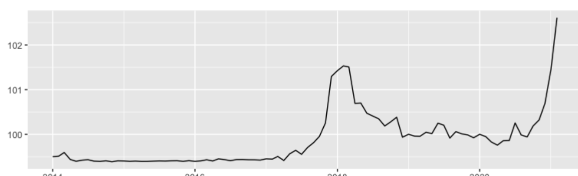
(f) GTU time series



(g) UCRY Price time series



(h) IP time series



(i) ICEA time series

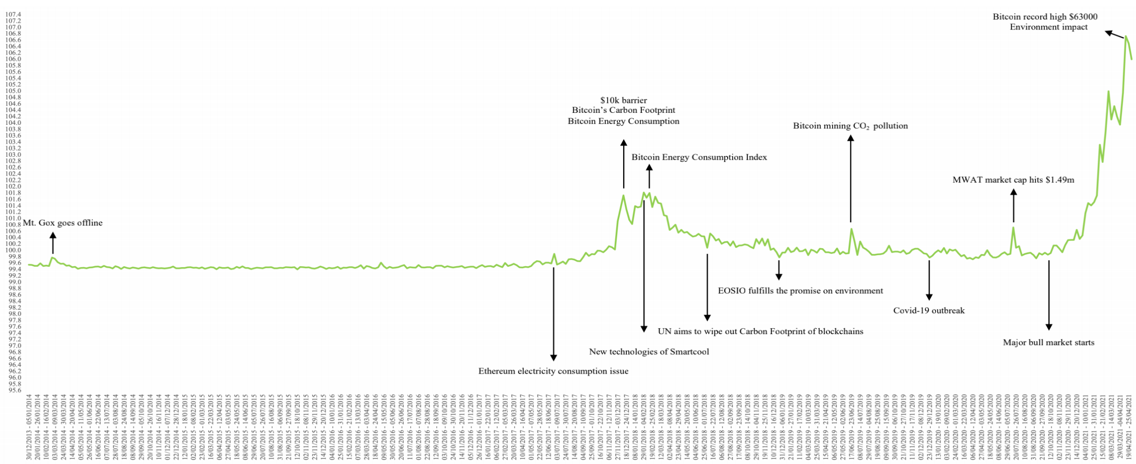
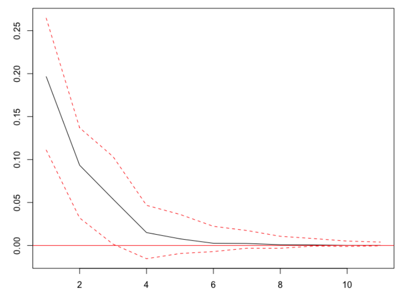
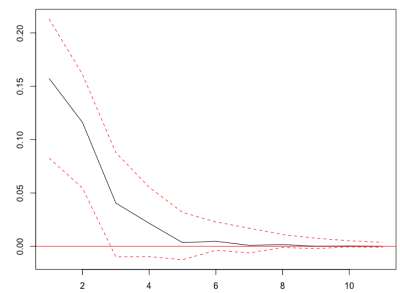


Figure 2: Annotated ICEA Index

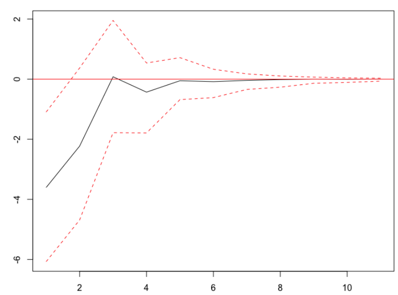
Figure 3: Impulse from ICEA to variable system



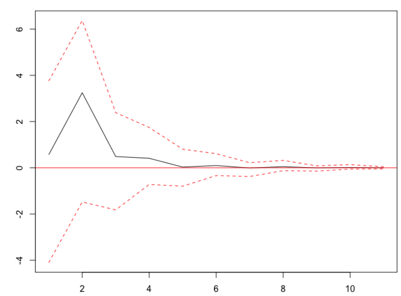
(a) εICEA impulse to UCRY Policy



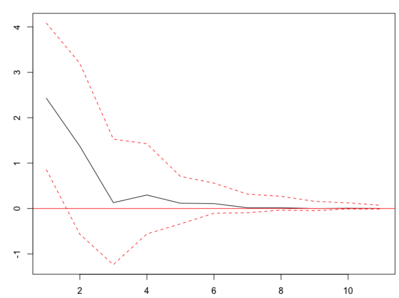
(b) εICEA impulse to UCRY Price



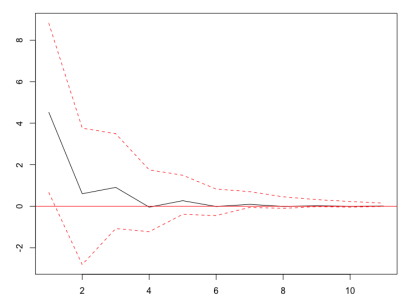
(c) εICEA impulse to GlobalEPU



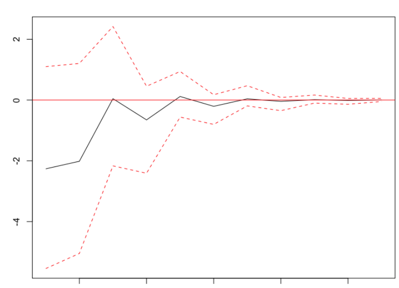
(d) εICEA impulse to Vix



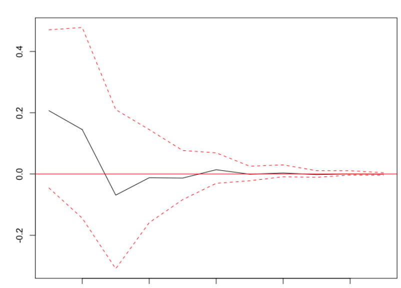
(e) εICEA impulse to BCO



(f) εICEA impulse to Bitcoin



(g) εICEA impulse to GTU



(h) εICEA impulse to IP

Notes: 90% confidence interval bootstrapping, 1000 runs

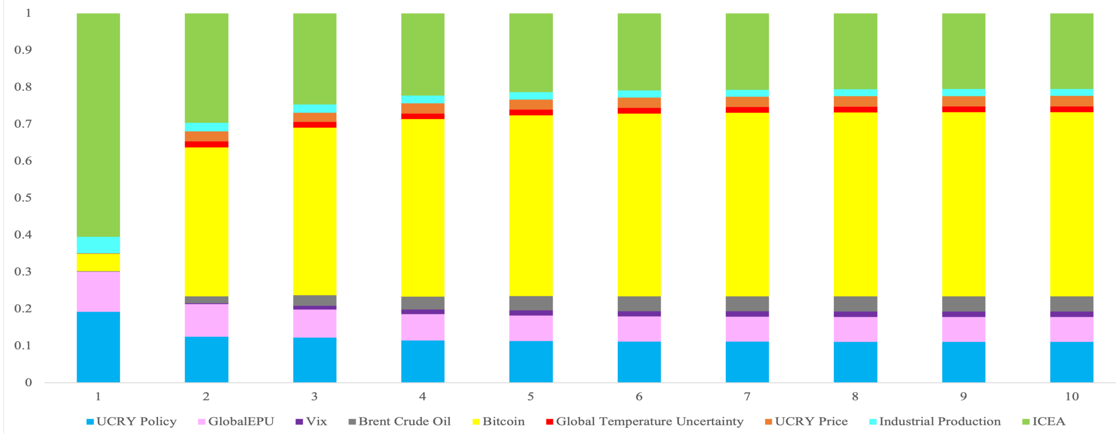


Figure 4: FEVD of ICEA

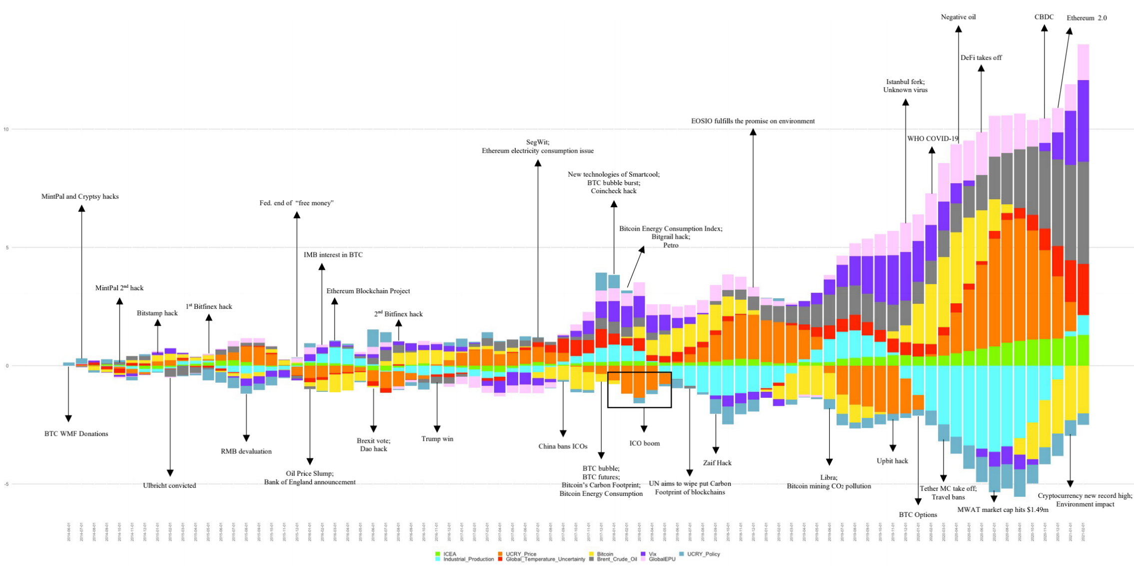
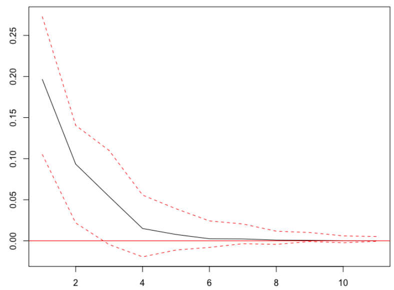
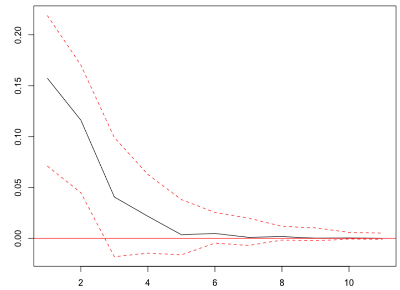


Figure 5: ICEA index historical decomposition with major events

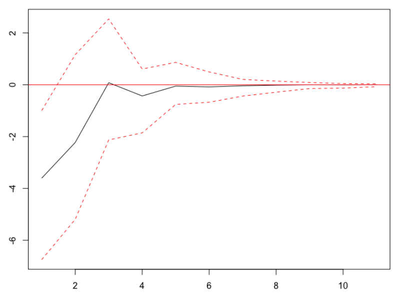
Figure 6: Impulse from ICEA to other factors robustness test



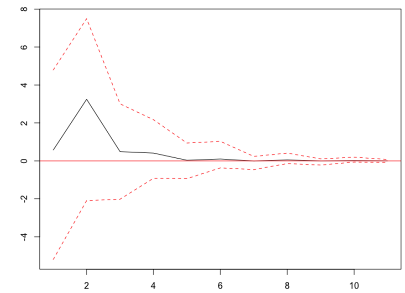
(a) εICEA impulse to UCRY Policy robustness test



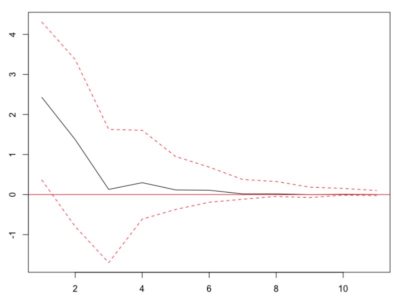
(b) εICEA impulse to UCRY Price robustness test



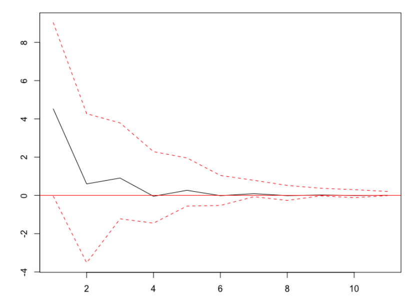
(c) εICEA impulse to GlobalEPU robustness test



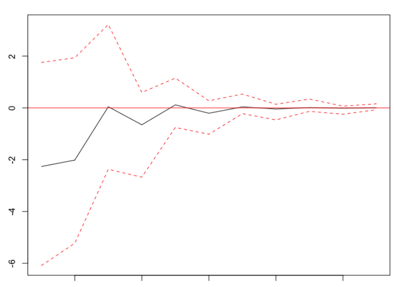
(d) εICEA impulse to VIX robustness test



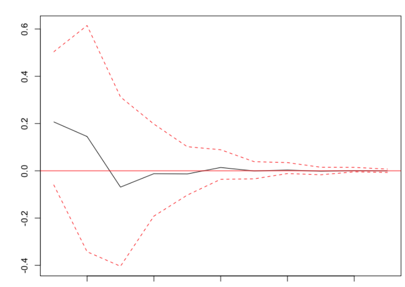
(e) εICEA impulse to BCO robustness test



(f) εICEA impulse to Bitcoin robustness test



(g) εICEA impulse to GTU robustness test



(h) εICEA impulse to IP robustness test

Notes: 95% confidence interval bootstrapping, 2000 runs

References

Adrian, T. and H. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation 19*(3), 418–437.

Ahmed, Z., M. Cary, M. Shahbaz, and X. Vo (2021). Asymmetric nexus between economic policy uncertainty, renewable energy technology budgets, and environmental sustainability: Evidence from the united states. *Journal of Cleaner Production 313*.

Al Mamun, M., G. Uddin, M. Suleman, and S. Kang (2020). Geopolitical risk, uncertainty and bitcoin investment. *Physica A: Statistical Mechanics and its Applications 540*.

Arslan-Ayaydin, and J. Thewissen (2016). The financial reward for environmental performance in the energy sector. *Energy and Environment 27*(3-4), 389–413.

Badea, L. and M. Mungiu-Pupazan (2021). The economic and environmental impact of bitcoin. *IEEE Access 9*, 48091–48104.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The quarterly journal of economics 131*(4), 1593–1636.

Bouri, E., C. Lau, B. Lucey, and D. Roubaud (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. *Finance Research Letters 29*, 340–346.

Bozkus, S., H. Kahyaoglu, and A. Mahamane Lawali (2020). Multifractal analysis of atmospheric carbon emissions and oecd industrial production index. *International Journal of Climate Change Strategies and Management 12*(4), 411–430.

Brulle, R. J., J. Carmichael, and J. C. Jenkins (2012). Shifting public opinion on climate change: an empirical assessment of factors influencing concern over climate change in the us, 2002-2010. *Climatic change 114*(2), 169–188.

Capstick, S., L. Whitmarsh, W. Poortinga, N. Pidgeon, and P. Upham (2015). International trends in public perceptions of climate change over the past quarter century. *Wiley Interdisciplinary Reviews: Climate Change 6*(1), 35–61.

Chudinovskikh, M. and V. Sevryugin (2019). Cryptocurrency regulation in the brics countries and the eurasian economic union. *BRICS Law Journal 6*(1), 63–81.

Conlon, T., S. Corbet, and R. McGee (2020). Are cryptocurrencies a safe haven for equity markets? an international perspective from the covid-19 pandemic. *Research in International Business and Finance 54*.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya (2020). The impact of macroeconomic news on bitcoin returns. *European Journal of Finance*.

Corbet, S., B. Lucey, and L. Yarovaya (2018). Datestamping the bitcoin and ethereum bubbles. *Finance Research Letters 26*, 81–88.

Corbet, S., B. Lucey, and L. Yarovaya (2021). Bitcoin-energy markets interrelationships-new evidence. *Resources Policy 70*, 101916.

Corbet, S. and L. Yarovaya (2020). The environmental effects of cryptocurrencies. In *Cryptocurrency and Blockchain Technology*, pp. 149–184. De Gruyter.

Davis, D. and D. Weinstein (1999). Economic geography and regional production structure: An empirical investigation. *European Economic Review 43*(2), 379–407.

de Vries, A. (2020). Bitcoin's energy consumption is underestimated: A market dynamics approach. *Energy Research and Social Science 70*.

Dongyang, Z. (2021). Does a green-designed fiscal policy optimal firm innovation scheme on volatility? a firm level evidence in the post-covid-19 era. *Resources Policy 74*.

Duijndam, S. and P. van Beukering (2020). Understanding public concern about climate change in europe, 2008-2017: the influence of economic factors and right-wing populism. *Climate Policy*, 1–15.

Durlauf, S. and L. Blume (2016). *Macroeconometrics and time series analysis*. Springer.

Feng, G., K. R. McLaren, O. Yang, X. Zhang, and X. Zhao (2021). The impact of environmental policy stringency on industrial productivity growth: A semi-parametric study of oecd countries. *Energy Economics 100*, 105320.

Fernandez, V. (2016). Futures markets and fundamentals of base metals. *International Review of Financial Analysis 45*, 215–229.

Foglia, M. and P.-F. Dai (2021). "ubiquitous uncertainties": spillovers across economic policy uncertainty and cryptocurrency uncertainty indices. *Journal of Asian Business and Economic Studies*.

Gallersdörfer, U., L. Klaaßen, and C. Stoll (2020). Energy consumption of cryptocurrencies beyond bitcoin. *Joule 4*(9), 1843–1846.

Ghosh, T. and S. Kumar (2021). The effectiveness of macro-prudential policies in the face of global uncertainty –the role of exchange-rate regimes. *Finance Research Letters*.

Hu, D. (2014). Environment protection and energy saving in public private partnerships governance in the distributed energy generation. *Applied Mechanics and Materials 508*, 236–242.

Huang, Y. and P. Luk (2020). Measuring economic policy uncertainty in china. *China Economic Review 59*.

Hudson, R. and A. Urquhart (2021). Technical trading and cryptocurrencies. *Annals of Operations Research 297*(1-2), 191–220.

Huynh, T. L. D., M. Wang, and V. X. Vo (2021). Economic policy uncertainty and the bitcoin market: An investigation in the covid-19 pandemic with transfer entropy. *The Singapore Economic Review*, 1–27.

Ji, Q., E. Bouri, C. Lau, and D. Roubaud (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis 63*, 257–272.

Jiang, S., Y. Li, Q. Lu, Y. Hong, D. Guan, Y. Xiong, and S. Wang (2020). Policy assessments for the carbon emission flows and sustainability of bitcoin blockchain operation in china.

Kanamura, T. (2020). Are green bonds environmentally friendly and good performing assets? *Energy Economics 88*.

Khan, M., M. Khan, and M. Rehan (2020). The relationship between energy consumption, economic growth and carbon dioxide emissions in pakistan. *Financial Innovation 6*(1).

Klein, A., L. Kirilov, and M. Riekert (2019). Cryptocurrency crashes: A dataset for measuring the effect of regulatory news in online media. Volume 2397, pp. 85–88.

Klein, T., H. Pham Thu, and T. Walther (2018). Bitcoin is not the new gold – a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis 59*, 105–116.

Kočenda, E. and A. Černý (2015). *Elements of time series econometrics: An applied approach.* Charles University in Prague, Karolinum Press.

Krause, M. J. and T. Tolaymat (2018). Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability 1*(11), 711–718.

Lee, T. M., E. M. Markowitz, P. D. Howe, C.-Y. Ko, and A. A. Leiserowitz (2015). Predictors of public climate change awareness and risk perception around the world. *Nature climate change 5*(11), 1014–1020.

Leung, M., Y. Li, A. A. Pantelous, and S. A. Vigne (2021). Bayesian value-at-risk backtesting: The case of annuity pricing. *European Journal of Operational Research 293*(2), 786–801.

Liao, G., P. Hou, X. Shen, and K. Albitar (2021). The impact of economic policy uncertainty on stock returns: The role of corporate environmental responsibility engagement. *International Journal of Finance and Economics 26*(3), 4386–4392.

Liu, Y. and A. Tsyvinski (2021). Risks and returns of cryptocurrency. *Review of Financial Studies 34*(6), 2689–2727.

Long, S., H. Pei, H. Tian, and K. Lang (2021). Can both bitcoin and gold serve as safe-haven assets? — a comparative analysis based on the nardl model. *International Review of Financial Analysis 78*.

Lucey, B. M., S. A. Vigne, L. Yarovaya, and Y. Wang (2021). The cryptocurrency uncertainty index. *Finance Research Letters*, 102147.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis.* Springer Science & Business Media.

Lyu, Y., S. Tuo, Y. Wei, and M. Yang (2021). Time-varying effects of global economic policy uncertainty shocks on crude oil price volatility: New evidence. *Resources Policy 70*, 101943.

Malfuzi, A., A. Mehr, M. Rosen, M. Alharthi, and A. Kurilova (2020). Economic viability of bitcoin mining using a renewable-based sofc power system to supply the electrical power demand. *Energy 203*.

Maronna, R. A., R. D. Martin, V. J. Yohai, and M. Salibián-Barrera (2019). *Robust statistics: theory and methods (with R).* John Wiley & Sons.

Marques, A., J. Fuinhas, and C. Tomás (2019). Energy efficiency and sustainable growth in industrial sectors in european union countries: A nonlinear ardl approach. *Journal of Cleaner Production 239*.

Mensi, W., S. Hammoudeh, J. Reboredo, and D. Nguyen (2014). Do global factors impact brics stock markets? a quantile regression approach. *Emerging Markets Review 19*, 1–17.

Mnif, E., A. Jarboui, and K. Mouakhar (2020). How the cryptocurrency market has performed during covid 19? a multifractal analysis. *Finance Research Letters 36*.

Naeem, M. and S. Karim (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters 208*.

Nasekin, S. and C. Y.-H. Chen (2020). Deep learning-based cryptocurrency sentiment construction. *Digital Finance*, 1–29.

O'Dwyer, K. J. and D. Malone (2014). Bitcoin mining and its energy footprint. In *25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communications Technologies (ISSC 2014/CIICT 2014)*, pp. 280–285. IET.

Pastor, L. and P. Veronesi (2012). Uncertainty about government policy and stock prices. *The journal of Finance 67*(4), 1219–1264.

Phillips, R. C. and D. Gorse (2017). Predicting cryptocurrency price bubbles using social media data and epidemic modelling. In *2017 IEEE symposium series on computational intelligence (SSCI)*, pp. 1–7. IEEE.

Pianta, S. and M. R. Sisco (2020). A hot topic in hot times: how media coverage of climate change is affected by temperature abnormalities. *Environmental Research Letters 15*(11), 114038.

Pidgeon, N. (2012). Public understanding of, and attitudes to, climate change: Uk and international perspectives and policy. *Climate Policy 12*(sup01), S85–S106.

Platt, M., J. Sedlmeir, D. Platt, P. Tasca, J. Xu, N. Vadgama, and J. I. Ibañez (2021). Energy footprint of blockchain consensus mechanisms beyond proof-of-work. *arXiv preprint arXiv:2109.03667*.

Poizot, P. and F. Dolhem (2011). Clean energy new deal for a sustainable world: From non-co2 generating energy sources to greener electrochemical storage devices. *Energy and Environmental Science 4*(6), 2003–2019.

Reboredo, J. and G. Uddin (2016). Do financial stress and policy uncertainty have an impact on the energy and metals markets? a quantile regression approach. *International Review of Economics and Finance 43*, 284–298.

Rice, J. et al. (2020). Economic policy uncertainty in small open economies: a case study in ireland. Technical report, Central Bank of Ireland.

Riley, J. (2021). The current status of cryptocurrency regulation in china and its effect around the world. *China and WTO Review 7*(1), 135–152.

Shanaev, S., S. Sharma, B. Ghimire, and A. Shuraeva (2020). Taming the blockchain beast? regulatory implications for the cryptocurrency market. *Research in International Business and Finance 51*.

Shehadeh, A., Y. Li, S. Vigne, M. Almaharmeh, and Y. Wang (2021). The existence and severity of the forward premium puzzle during tranquil and turbulent periods: Developed versus developing country currencies. *International Review of Financial Analysis 78*.

Soliman, A. and M. Nasir (2019). Association between the energy and emission prices: An analysis of eu emission trading system. *Resources Policy 61*, 369–374.

Stoll, C., L. Klaaßen, and U. Gallersdörfer (2019). The carbon footprint of bitcoin. *Joule 3*(7), 1647–1661.

Subramaniam, S. and M. Chakraborty (2020). Investor attention and cryptocurrency returns: Evidence from quantile causality approach. *Journal of Behavioral Finance 21*(1), 103–115.

Umar, Z. and M. Gubareva (2020). A time–frequency analysis of the impact of the covid-19 induced panic on the volatility of currency and cryptocurrency markets. *Journal of Behavioral and Experimental Finance 28*.

Vu, T. and W. Dang (2021). Environmental commitment and firm financial performance: a moderated mediation study of environmental collaboration with suppliers and ceo gender. *International Journal of Ethics and Systems 37*(1), 53–69.

Wang, G.-J., C. Xie, D. Wen, and L. Zhao (2019). When bitcoin meets economic policy uncertainty (epu): Measuring risk spillover effect from epu to bitcoin. *Finance Research Letters 31*, 489–497.

Whaley, R. (2000). The investor fear gauge: Explication of the cboe vix. *Journal of Portfolio Management 26*(3), 12–17.

Whaley, R. (2009). Understanding the vix. *Journal of Portfolio Management 35*(3), 98–105+10.

Wimbush, S. (2018). Cryptocurrency mining is neither wasteful nor uneconomic. *Nature 555*(7697).

Yu, J., X. Shi, D. Guo, and L. Yang (2021). Economic policy uncertainty (epu) and firm carbon emissions: Evidence using a china provincial epu index. *Energy Economics 94*.

Yu, L., J. Li, and L. Tang (2015). Dynamic volatility spillover effect analysis between carbon market and crude oil market: A dcc-icss approach. *International Journal of Global Energy Issues 38*(4-6), 242–256.

Zade, M., J. Myklebost, P. Tzscheutschler, and U. Wagner (2019). Is bitcoin the only problem? a scenario model for the power demand of blockchains. *Frontiers in Energy Research 7*(MAR).

Zhang, D. and Q. Kong (2021). How does energy policy affect firms' outward foreign direct investment: An explanation based on investment motivation and firms' performance. *Energy Policy 158*.

Zhang, X., J. Tan, and K. Chan (2021). Air pollution and initial public offering underpricing. *Applied Economics 53*(39), 4582–4595.