The Cryptocurrency Uncertainty Index

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Abstract

We have developed and made available a new Cryptocurrency Uncertainty Index (UCRY) based on news coverage. Our UCRY Index captures two types of uncertainty: that of the price of cryptocurrency (UCRY Price) and uncertainty of cryptocurrency policy (UCRY Policy). We show that the constructed index exhibits distinct movements around major events in cryptocurrency space. We suggest that this index captures uncertainty beyond Bitcoin, and can be used for academic, policy, and practice-driven research.

Keywords: Cryprocurrencies; Policy and price uncertainty; Uncertainty index; Cryptocurrency Uncertainty Index
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1. Introduction

How uncertain are investors about cryptocurrencies, and what drives this? This paper poses a construction and analysis of two indices of policy and price uncertainty for cryptocurrencies in order to address the level of uncertainty that investors experience and the motivating factors of such in regards to cryptocurrencies. Uncertainty is an essential determinant of the volatility of cryptocurrency, in large part due to its association with the future earnings of such. Yet different types of uncertainty may have varying impacts and predictive power on cryptocurrency markets. In addition, it is worth noting the difference between price volatility and price uncertainty. Cryptocurrency price volatility measures the size of variations of cryptocurrency returns, and should be the standard deviation of cryptocurrency logarithmic returns between their daily closing prices. Walther et al. [2019] use 17 different economic and financial indices to predict the volatility of cryptocurrencies. They point out that it is driven by global business and a network of interacting driving factors. The Financial Stress Index and the Chinese Policy Uncertainty Index are useful and impactful predictors for the volatility of cryptocurrencies but are overshadowed by the Global Real Economic Activity Index. Cryptocurrency price uncertainty measures the size of unpredictable disturbances in the price of cryptocurrency. Demir et al. [2018] prove that Economic Policy Uncertainty has a predictive power on Bitcoin returns. Large moves in cryptocurrency uncertainty are less frequent but more persistent than moves in cryptocurrency price volatility.

Akyldirim et al. [2020] showed that during times when investors' fears are elevated, cryptocurrency markets experienced an increase in volatility. The authors used VIX (CBOE-traded) and VSTOXX (DAX-traded) volatility indexes as measures of the United States and European financial market risk respectively. Fang et al. [2020] further analysed the impact of the News-based Implied Volatility index (NVIX) on cryptocurrency returns, providing evidence that NVIX, developed by Manela and Moreira [2017], is a more powerful predictor of the long-term volatility in selected cryptocurrencies than the Global Economic Policy Uncertainty index (GEPU) proposed by Davis [2016]. These results indicate that cryptocurrency market volatility might be more susceptible to price uncertainty and investors' perceptions than to policy uncertainty.

Findings reported by Aysan et al. [2019] demonstrate that the Geopolitical Uncertainty Index (GPR) can predict Bitcoin returns and volatility. Conlon et al. [2020] further compared the impacts of GEPU and GPR indexes on cryptocurrency returns, yet found no substantial safe haven or hedging properties of cryptocurrencies against either uncertainty proxies, apart from a weak ability to hedge against GEPU during a bull market. Their results are consistent with other papers in this area, such as Wu et al. [2019], Al Mamun et al. [2020]. Gozgor et al. [2020] analysed the impact of Trade Policy Uncertainty (TPI) on Bitcoin returns and demonstrated a significant positive correlation between returns and uncertainty variables.

Investment sentiments have been found to be useful for predicting cryptocurrency volatility and returns. Corbet et al. [2020b] constructed a sentiment index based on news stories that followed the announcements of four macroeconomic indicators: GDP, unemployment, Consumer Price Index (CPI) and durable goods. The results showed that Bitcoin returns responded differently to news than to stock market returns. Furthermore, it was found that the price cryptocurrency's reaction to news and announcements may vary depending on the type of digital assets. Thus, according to Corbet et al. [2020a], currency-based digital assets are likely more susceptible to the US monetary policy announcements, while applications or protocol-based digital assets are immune to these shocks. Similar differences are found for mineable and non-mineable currencies, meaning that the response to various types of uncertainty of some digital assets would be distinct from that of Bitcoin. Yarovaya and Zięba [2020] further classified cryptocurrencies with respect to multiple qualitative factors, such as geographical location of headquarters, founder's origin, underlying platform, and the consensus algorithm. They explored the differences in patterns of interconnectedness patterns between trading volume and returns across cryptocurrencies from different categories. Benedetti and Nikbakht [2021] identified that specific heterogeneous characteristics of digital tokens affected the cryptocurrency returns. The speculative nature of cryptocurrency markets has implications for market efficiency, portfolio diversification, the contagion effect and financial stability literature, see Corbet et al. [2018] for a systematic review of past papers in this field.

This paper is motivated by three main theoretical arguments discussed in the aforementioned literature. Firstly, our interest lay in exploring the effect of potential clientele in cryptocurrency markets, that is, different groups of investors who are attracted to particular kinds of cryptocurrencies. Secondly, due to their speculative nature, cryptocurrencies are attractive to amateur investors who have the potential to interpret publicly available information differently from large institutional investors. Thus, the impact of uncertainty on cryptocurrency markets will depend on types of uncertainty and the type of digital assets. Thirdly, we considered the importance of determinants of cryptocurrency market volatility analysis. We did so due to the explosivity of cryptocurrencies, which has created a new type of information asymmetry that affects other markets and poses a significant threat to financial stability (e.g., Akyildirim et al. [2020]). Therefore, it is important to develop a measure that can capture uncertainty in cryptocurrency markets.

In addition to the previously addressed indices, a few papers attempted to design new uncertainty indexes, for example, Huang and Luk [2020] introduced a new China EPU index using 10 mainland Chinese newspapers. Additionally, Trimborn and Härdle [2018] introduced the CRIX index to assess the markets volatility of cryptocurrencies. Moreover, there are further cryptocurrency market indexes available, such as the market capitalisation-weighted Bloomberg Galaxy index. However, there is presently no designed index that captures uncertainty of cryptocurrency markets' price and policy.

We introduce a new Cryptocurrency Uncertainty Index (UCRY) that captures two main types of uncertainty, Cryptocurrency Policy Uncertainty (UCRY Policy) and Cryptocurrency Price Uncertainty (UCRY Price). These indices can be used to assess how policy and regulatory debates affect cryptocurrency returns and volatility, and how this impact differs from reaction to Bitcoin attention in general. It is important to distinguish between two types of cryptocurrency uncertainty, since it may help to better understand the behaviour of different sets of investors in cryptocurrency markets. While informed investors would be sensitive to changes in policy uncertainty, amateurs may react more strongly to general media attention towards cryptocurrencies and their price fluctuations. Increasing institutional interest in digital assets may also make cryptocurrency markets more susceptible to policy uncertainty over time, which further justifies the importance of the indices introduced in this paper.

Thus, in this research note, we gathered 726.9 million news stories from the LexisNexis database spanning January 2014 to January 2021. We designed the UCRY index, which shows the contributions that the UCRY Policy and the UCRY Price indices have made to historical decomposition of the index around key events in cryptocurrency space. This has been compared with other popular uncertainty measures as well as gold and Bitcoin price uncertainties.

The remainder of this paper is organised as follows, section 2 describes the data and methodology used to construct the indices, while section 3 presents the empirical results, and section 4 concludes and discusses the implications of this study.

2. Data and methodology

2.1. Data collection

We build our index on the construct found in Baker et al. [2016], using the material found in the LexisNexis Business Database as our corpus of literature. This covers a very wide variety of newspapers and news-wire feeds. Notably, this is unlike most previous measures, which have relied almost solely on major newspapers (see for example Rice [2020]). The rationale for using a greater range of sources, including but not limited to news-wire feeds and media news transcripts, was to acknowledge the "social" aspect of cryptocurrencies. As new phenomena, these currencies have become subject to extensive discussion via not just traditional media, but alternative and social media. See as examples papers such as Phillips and Gorse [2017], Subramaniam and Chakraborty [2020] for discussion of social and general media.

We therefore ran the following queries on LexisNexis business. *[(uncertain or uncertainty) and price and atl1(Bitcoin or Ethereum or ripple or litecoin or tether or cryptocurrency or cryptocurrencies) and atl1(regulator or regulators or central bank or government)]* was the text search string used to ascertain uncertainty around policy issues, while *[(uncertain or uncertainty) and price and atl1(Bitcoin or Ethereum or ripple or litecoin or tether or cryptocurrency or cryptocurrencies)]* was used to gather results on uncertainty more broadly.

In addition, we set the option for Group Duplicate to MODERATE so as to avoid duplicate results as much as possible. The queries were performed for each month from January 2014 to

January 2021 [1].

2.2. UCRY index construction

The Cryptocurrency Policy Uncertainty Index is calculated as in Equation 1,

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

where $UCRY\ Policy_t$ is the value of the Cryptocurrency Policy Uncertainty Index in the weeks t between December 2013 and February 2021. N_{1t} is the weekly observed value of news articles on LexisNexis business concerning the uncertainty of cryptocurrency policy, μ_1 is the mean of these same articles and σ_1 is the standard deviation of such.

The Cryptocurrency Price Uncertainty Index is calculated as in Equation 2

$$UCRY\ Price_t = (\frac{N_{2t} - \mu_2}{\sigma_2}) + 100, \tag{2}$$

where $UCRY\ Price_t$ is the value of the Cryptocurrency Price Uncertainty Index in the weeks t between December 2013 and February 2021. N_{2t} is the weekly observed value of LexisNexis business news articles concerning the uncertainty of cryptocurrency price news articles, μ_2 is the mean of these and σ_2 is the standard deviation of such.

The UCRY Policy Index, the Global EPU index, the Vix, the price of Bitcoin, the USFS index of US financial system stress, the USEPU, the gold, and the UCRY Price Index were select as the system variables, as justified in the Introduction section. Each series was identified and recorded in Table 4. We ordered variables as indicated by Equation 3.

$$\mathbf{Y}_t = \begin{bmatrix} UCRY Policy_t \\ Global EPU_t \\ Vix_t \\ Bitcoin_t \\ USFS_t \\ USEPU_t \\ Gold_t \\ UCRY Price_t \end{bmatrix} \tag{3}$$

[1] Weekly values can be downloaded from here https://brianmlucey.wordpress.com/2021/03/16/cryptocurrency-uncertainty-index-dataset/

UCRY Policy Index was ordered first because we believe that GlobalEPU, Vix, Bitcoin, USFS, USEPU and the gold can react contemporaneously to uncertainty shocks. Due to the fact that other indexes are generally react faster than UCRY Price Index, the UCRY Price Index was ordered last.

2.3. Econometric model

The main use of Vector Autoregression (VAR) models are forecasting and structural analysis Lütkepohl [2005]. The standard VAR is a reduced form model and is designed for stationary data forms. If economic theory is used to provide the link between forecast errors and fundamental structural shocks, the Structural Vector Autoregression (SVAR) model will be used. The Vector Error Correction Model (VECM) adds error correction features to the VAR. VECM is designed for the non-stationary but co-integrated forms of variables. It is also possible to apply the SVAR technique to VECM with cointegrated variables, named SVECM.

Firstly, a stationarity test was performed on the data, in this case the Augment Dickey-Fuller (ADF) test was applied. Table 1 shows that the p-value of each variable was more significant than 0.05. These evidences that there are unit roots in all variables and that all variables are nonstationary.

Secondly, if we can further prove the forms of our variables are cointegrated, we can use the SVECM. We therefore applied the Johansen test. The optimal lags calculation results are shown in Table 2. The Akaike information criterion, Hannan - Quinn information criterion, Schwartz information criterion, and prediction error information all suggest four as the optimal lag. From Table 3, $r = 0$, tested for the presence of cointegration. Since the tested statistic exceeded the 1% level significantly ($215.11 > 177.20$), we have strong evidence that our variables forms are cointegrated.

Guided by the above analysis, we applied a SVECM with identification based on a Cholesky recursive assumption to a VECM to trace the effects of different economic shocks in a system of variables. Historical decomposition is a tool used for the SVECM analysis, and allows for the gathering of information on the contribution of structural shocks to a system of variables can get from a historical decomposition. In order to explore the quantitative contribution of UCRY Policy and UCRY Price shocks to the dynamics of the system variables mentioned in Y_t Equation 3, we will performed historical decomposition.

VECM can be expressed as Equation 4

$$\Delta y_t = \alpha\beta^{'} y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \Xi^{+} D_t + u_t, \tag{4}$$

where y_t is a $K \times 1$ dimensional vector of variables observed at time t. The decomposed cointegrated models $\alpha\beta^{'}$ has reduced rank $r = rk(\alpha\beta^{'}) < K$. Additionally, α is a $K \times r$ matrix containing the loading coefficients, β is also a $K \times r$ matrix containing the co-integrated 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. D_t is a vector of deterministic terms, and Ξ^+ is the coefficient matrices corresponded with D_t.

In this way, structural shocks on the system variables y_t based on the VECM can be calculated as Equation 5

$$\bar{A}_0 y_t = \bar{A}_1 y_{t-1} + \cdots + \bar{A}_p y_{t-p} + \bar{\Xi} D_t + \varepsilon_t, \tag{5}$$

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 5 by $\bar{A}_0^{-1}$ can link the reduced form disturbance (forecast errors) u_t to the underlying structural shocks ε_t.

Based on the prior ordering in the SVECM Cholesky decomposition, the relationship between reduced form residuals and structural shocks are show in Equation 6,

$$\begin{bmatrix} u_t^{UCRY\,Policy} \\ u_t^{GlobalEPU} \\ u_t^{Vix} \\ u_t^{Bitcoin} \\ u_t^{USFS} \\ u_t^{USEPU} \\ u_t^{Gold} \\ u_t^{UCRY\,Price} \end{bmatrix} = \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 & 0 & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 & 0 & 0 & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} & 0 & 0 & 0 \\ S_{61} & S_{62} & S_{63} & S_{64} & S_{65} & S_{66} & 0 & 0 \\ S_{71} & S_{72} & S_{73} & S_{74} & S_{75} & S_{76} & S_{77} & 0 \\ S_{81} & S_{82} & S_{83} & S_{84} & S_{85} & S_{86} & S_{87} & S_{88} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{UCRY\,Policy} \\ \varepsilon_t^{GlobalEPU} \\ \varepsilon_t^{Vix} \\ \varepsilon_t^{Bitcoin} \\ \varepsilon_t^{USFS} \\ \varepsilon_t^{USEPU} \\ \varepsilon_t^{Gold} \\ \varepsilon_t^{UCRY\,Price} \end{bmatrix} \tag{6}$$

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

In doing so, we can trace the driving factors of movement in UCRY Policy and UCRY Price. It also enables us to determine UCRY Policy and UCRY Price shocks in our VECM are reflective of uncertainty. The information contained in the historical decomposition could also show the extent to which events are driving shocks to UCRY Policy and UCRY Price.

3. Results

Figure 1 shows the weekly values for the derived Policy and Price uncertainty indices based on 726.9 million total news articles collected for the period spanning 2013-2021, and Figure 2 shows the rolling 26-week correlation. We annotated the weekly policy index in Figure 3, highlighting major changes as they map to events in the crypto and related economic spaces.

The historical decomposition of the UCRY Index is shown in Figure 4. The contribution of UCRY Policy shocks to the historical decomposition of the UCRY Index is given in light blue, while contribution to the UCRY Price is in orange. These shocks match the expectations of the public to a certain extent. For example, the Brexit vote, Donald Trump winning the 2016 United States presidential election, China banning ICOs, the BTC bubble, DeFi take off and other events have been shown to have positively impacted the UCRY Policy and Price uncertainty Indices. Figure 4 also displays some of the largest hacking attacks of cryptocurrency exchanges, such as attacks on Bitfinex, MintPal, Crispy, and Dao exchanges. These occurred from April 2014 to December 2020, and we have shown that the UCRY Price and UCRY Policy Indices reacted to these events. Fiscal policy adjustments contributed to the small shifts in the UCRY Policy, however, the significance of these events may increase in the future. The decomposition also displayed that UCRY Indices captured uncertainty that could be more distinctively attributed to the major events in cryptocurrencies in comparison to VIX, EPU and Global EPU index. While the price of Bitcoin, the UCRY Policy and the UCRY Price are highly correlated, these indices appear to capture uncertainty beyond Bitcoin prices as shown by the decomposition. Finally, the COVID-19 crisis increased both the UCRY Policy and Price uncertainty Indices, therefore this UCRY Index can be used as an effective measure of uncertainty during the pandemic.

4. Conclusions

We have developed a new measure of price and policy uncertainty in cryptocurrency markets. Using 726.9 million news articles from the Lexis Nexis database, we constructed a new Cryptocurrency Uncertainty Index that reflects policy (UCRY Policy) and price uncertainty (UCRY Price) around major cryptocurrencies. This paper provided the historical decomposition of the UCRY Index with major events from 2014 to 2020, such as the COVID-19 crisis, cyberattacks on cryptocurrency exchanges and political elections. Compared to other similar indices it is narrowly range bound, suggesting that while such uncertainty exists, it is not volatile. Nonetheless it does show distinct movements around high profile events in the cryptocurrency space. Our findings suggest that this index can be useful for future research on the uncertainty of cryptocurrency, portfolio diversification, and contagion effect. Additionally, it can have various practical and policy-based implications for measuring the risk stemming from cryptocurrency markets.

Table 1: ADF stationarity test

Variable	Dickey-Fuller	Lag order	p-value
UCRY Policy	-2.101	4	0.5345
GlobalEPU	-2.7013	4	0.2881
Vix	-2.4564	4	0.3886
Bitcoin	-0.43866	4	0.9824
USFS	-3.252	4	0.08493
USEPU	-3.0587	4	0.1414
Gold	-1.1167	4	0.9146
UCRY Price	-1.6002	4	0.74

Table 2: The optimal lags

AIC(n)	HQ(n)	SC(n)	FPE(n)
4	4	4	4

Table 3: Johansen test statistic and critical values

	test	10pct	5pct	1pct
r <= 7	3.83	7.52	9.24	12.97
r <= 6	10.58	17.85	19.96	24.60
r <= 5	22.99	32.00	34.91	41.07
r <= 4	40.32	49.65	53.12	60.16
r <= 3	66.04	71.86	76.07	84.45
r <= 2	97.06	97.18	102.14	111.01
r <= 1	149.28	126.58	131.70	143.09
r = 0	215.11	159.48	165.58	177.20

Notes: Johansen trace statistic, lags = 4

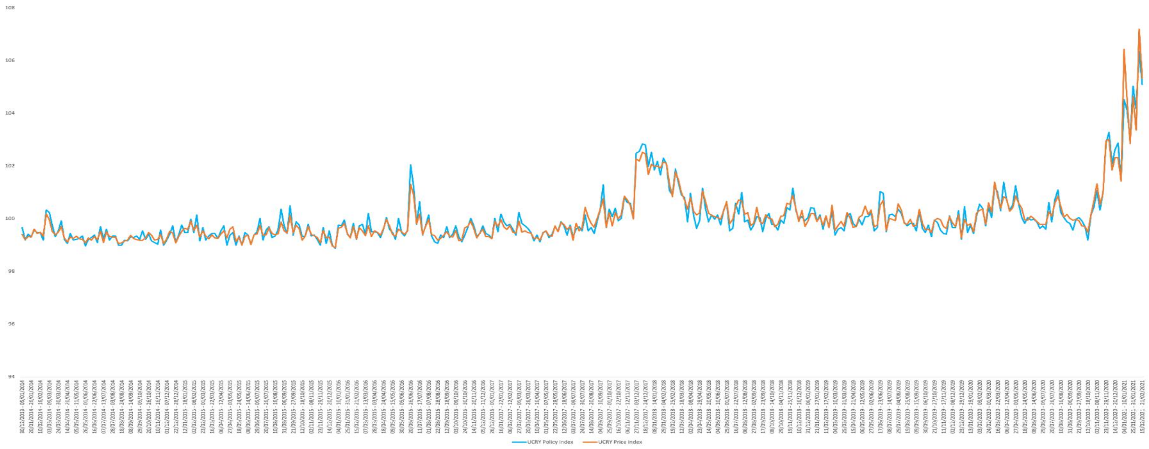

Figure 1: Price and policy uncertainty indices

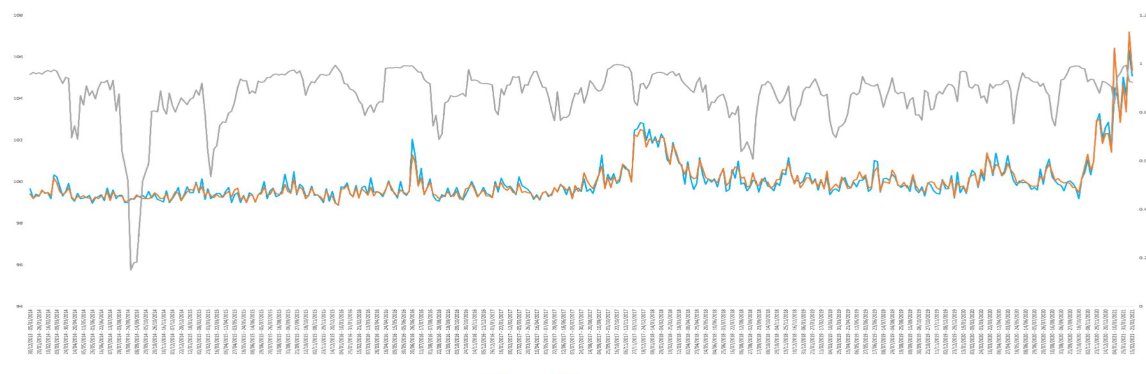

Figure 2: Indices and correlation

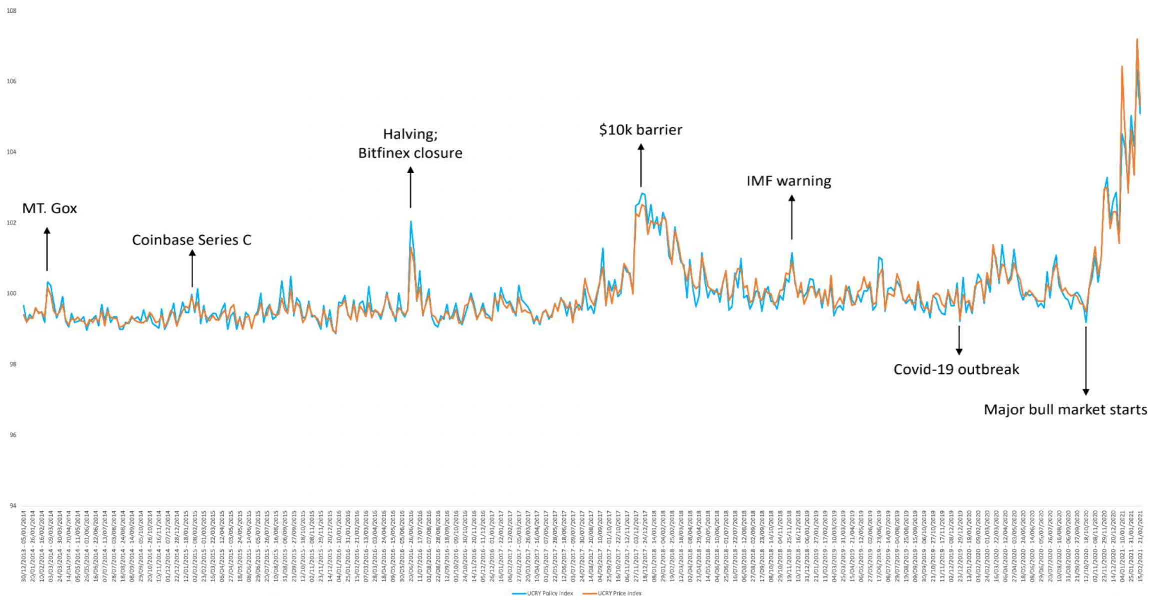

Figure 3: Annotated indices

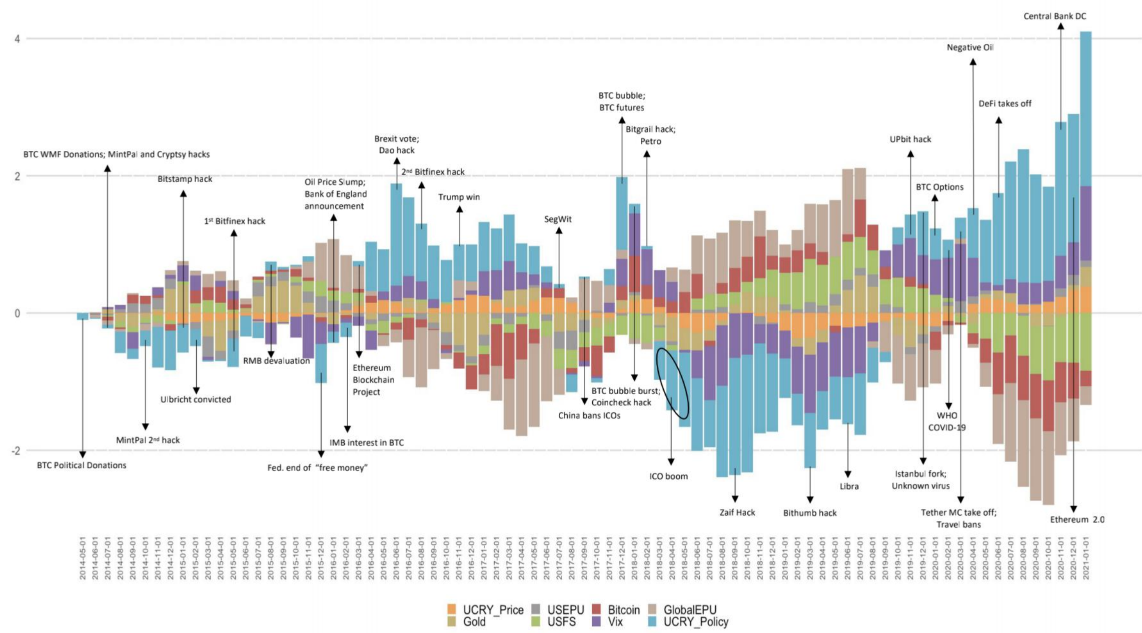

Figure 4: UCRY index historical decomposition with major events

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Appendix

Appendix A - Figure

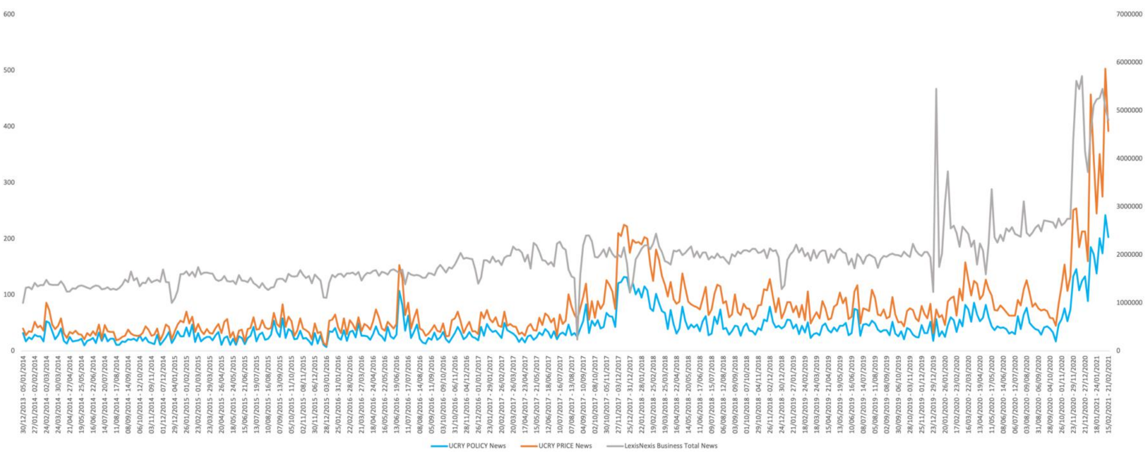

Figure 5: News trend

Appendix B - Tables

Table 4: Descriptive statistics

Variables	**Count**	**Minimum**	**Maximum**	**Mean**	**Median**	**Variance**	**Stdev**	**Skewness**	**Kurtosis**
UCRY Policy	85	99.1009	104.3415	99.9755	99.759	0.714393	0.8452	2.5765	8.4451
GlobalEPU	85	86.17	429.43	192.9751	168.95	6261.7856	79.1314	0.7316	-0.2937
Vix	85	9.5100	53.54	17.4523	15.08	55.420802	7.4445	2.2090	6.1422
Bitcoin	85	2.296700e+02	3.464109e+04	4.997788e+03	2.886710e+03	3.726869e+07	6.104809e+03	2.225124e+00	7.073033e+00
USFS	85	100.05	102.13	100.5342	100.52	0.1025	0.320221	1.7517	6.5731
USEPU	85	29.32.	557.19	119.4641	94.57	9742.6910	98.7050	2.4928	6.9873
Gold	85	1061.10	1975.86	1344.3094	1283.53	45934.2393	214.3228	1.48994	1.4250
UCRY Price	85	99.091	104.8057	99.9766	99.7759	0.737670	0.8589	2.7865	10.8790

Table 5: Pearson correlation

	UCRY Policy	**GlobalEPU**	**Vix**	**Bitcoin**	**USFS**	**USEPU**	**Gold**	**UCRY Price**
UCRY Policy	1.0000							
GlobalEPU	0.3886	1.0000						
Vix	0.3107	0.5257	1.0000					
Bitcoin	0.8299	0.5910	0.3879	1.0000				
USFS	0.0203	-0.0464	0.1167	-0.0564	1.0000			
USEPU	0.3287	0.7398	0.6682	0.4282	0.3192	1.0000		
Gold	0.4691	0.7417	0.5717	0.7441	-0.0237	0.6387	1.0000	
UCRY Price	0.9894	0.3994	0.3230	0.8589	0.0156	0.3198	0.4902	1.0000

Table 6: Historical decomposition of UCRY index results 1 (2014-01-01 To 2015-12-01)

	UCRY Policy	**GlobalEPU**	**Vix**	**Bitcoin**	**USFS**	**USEPU**	**Gold**	**UCRY Price**
2014-01-01	NA	NA	NA	NA	NA	NA	NA	NA
2014-02-01	NA	NA	NA	NA	NA	NA	NA	NA
2014-03-01	NA	NA	NA	NA	NA	NA	NA	NA
2014-04-01	NA	NA	NA	NA	NA	NA	NA	NA
2014-05-01	-0.10402476	0.000000000	0.0000000000	0.000000000	0.000000000	0.0000000000	0.000000000	0.0000000000
2014-06-01	-0.01999937	-0.041680891	-0.0087783093	0.006873933	0.003777310	-0.0146713300	-0.001564298	-0.0009801533
2014-07-01	-0.04982174	-0.068101891	0.0323098243	-0.049009508	-0.027061577	-0.0226335059	0.053081055	-0.0071868416
2014-08-01	-0.31771865	-0.036741479	0.0599924512	-0.019954724	-0.086694660	0.0562439747	-0.110892636	-0.0138661835
2014-09-01	-0.14465418	0.021133618	-0.2427652316	0.127245706	-0.077533863	0.1387246526	-0.197081203	-0.0045186074
2014-10-01	-0.22834335	-0.105431110	-0.0060768447	0.117491588	-0.069744896	0.1305078656	-0.071581531	-0.0040496262
2014-11-01	-0.59551227	-0.073670261	0.1159334471	0.039751049	-0.095409561	0.1611467785	0.055779547	-0.0328919163
2014-12-01	-0.57804392	0.073201542	0.0501642318	-0.098723764	-0.048456466	0.1505338084	0.353261289	-0.1110214840
2015-01-01	-0.40675110	0.061943456	0.2311611091	-0.005557091	0.042881299	-0.0210240801	0.417691896	-0.1432414543
2015-02-01	-0.25134052	0.070997466	0.2185223677	0.186359708	0.050466252	-0.0947933462	0.089792782	-0.1351846689
2015-03-01	-0.02599374	0.195238014	-0.0490178679	0.187473154	0.188712450	-0.2924616641	-0.228762154	-0.1154327195
2015-04-01	-0.02365878	0.139982086	0.0874302172	0.233070853	0.146309129	-0.1260693114	-0.441218119	-0.1103498853
2015-05-01	-0.41229032	0.156753978	0.1243731546	0.145468381	0.049935032	-0.1156198339	-0.170720798	-0.0838525175
2015-06-01	-0.30374573	0.083475433	0.0002910551	0.057866233	0.016365204	-0.0011528234	0.053478161	-0.0408072534
2015-07-01	-0.22361433	-0.021938747	-0.0256910325	0.053123666	0.039099182	0.2013721443	0.241150306	-0.0919366520
2015-08-01	0.13322273	-0.007478883	-0.3185457513	0.051033667	0.037410502	0.1355757977	0.394024902	-0.1358569900
2015-09-01	0.03880447	-0.019261504	-0.0123505154	0.032851183	-0.008198933	0.1297719625	0.469859977	-0.1235243286
2015-10-01	0.01975367	0.040429230	-0.3035398833	0.111663183	0.085791225	0.0467972840	0.394812514	-0.0540718706
2015-11-01	0.07486613	0.230198759	-0.6449739800	0.047487459	0.154931979	0.1662118351	0.149961139	-0.0184365599
2015-12-01	-0.56921032	0.557919682	-0.3210335362	-0.074327954	0.219522421	0.2462712305	-0.045532591	-0.0129938249

Notes: Lags = 4

Table 7: Historical decomposition of UCRY index results 2 (2016-01-01 To 2017-12-01)

	UCRY Policy	**GlobalEPU**	**Vix**	**Bitcoin**	**USFS**	**USEPU**	**Gold**	**UCRY Price**
2016-01-01	-0.16731316	0.703779838	-0.1046028683	0.038956699	0.152846624	0.1715096632	-0.164851036	0.0073626427
2016-02-01	-0.21287727	0.539625857	-0.0564546110	-0.049223474	0.154330717	0.1053194751	-0.029764901	0.0397691454
2016-03-01	0.08203874	0.327042221	-0.1307217575	0.051985123	0.115257099	-0.0544491208	0.078495848	0.1033591367
2016-04-01	0.71579845	0.073830209	-0.2813151003	0.100001500	-0.088058928	-0.0744901352	-0.091826217	0.1480155619
2016-05-01	0.61538202	-0.160952779	0.1202778470	-0.020142397	-0.180461651	-0.1100733452	-0.007287772	0.1899703880
2016-06-01	1.48837545	-0.182440138	0.2278906526	-0.101996489	-0.089476906	-0.0510833418	0.024715291	0.1489620054
2016-07-01	1.14629962	-0.542785788	0.3250959845	-0.321875517	-0.057355610	-0.0127916739	0.143364903	0.0725526159
2016-08-01	0.84104897	-0.876112562	0.2699274654	-0.115144868	0.034165767	-0.0924197896	0.138446381	0.0200144310
2016-09-01	0.78405704	-0.571612987	0.1285538608	-0.014085888	0.011033903	-0.0925376469	-0.142013435	0.0614034354
2016-10-01	0.61667297	-0.088898749	-0.0526093270	-0.062985898	0.032573006	-0.1851189592	-0.281347487	0.1262794590
2016-11-01	0.51553373	0.263767292	0.0243161356	-0.235167790	-0.020129262	-0.0847661423	-0.469564278	0.1919534562
2016-12-01	0.54226072	0.130012143	0.0623411836	-0.349708339	-0.028673937	-0.1068270040	-0.628559580	0.2667941502
2017-01-01	0.71415146	-0.244016739	0.3613254732	-0.291688440	-0.125742514	-0.1593112958	-0.315141120	0.2484425944
2017-02-01	0.60057857	-0.505602577	0.4317196874	-0.613245754	-0.078862221	-0.0798516001	0.044469925	0.1521580442
2017-03-01	0.68023485	-0.743978668	0.4256111703	-0.664899879	-0.127474675	-0.1628635832	0.245147751	0.0864609781
2017-04-01	0.42075152	-1.116317501	0.2444848378	-0.514504175	-0.105676629	-0.0542157117	0.248898840	0.0988890691
2017-05-01	0.41642663	-1.217573515	0.1547559947	-0.206291341	-0.236403689	0.0344090316	0.192088160	0.1787672619
2017-06-01	0.23335718	-0.946593444	0.0820251599	0.136814988	-0.219573643	-0.0964231013	-0.022478936	0.2236224196
2017-07-01	0.05673811	-0.376003020	0.0037297722	0.138121964	-0.296063660	-0.2498564315	-0.269882388	0.2212449683
2017-08-01	-0.25192552	0.081291641	-0.0264136871	-0.068502326	-0.267013967	-0.2789791350	-0.257509363	0.1461065374
2017-09-01	0.03033868	0.458020625	-0.0803250680	-0.200272183	-0.220358286	-0.1766794478	-0.102680956	0.0391875696
2017-10-01	-0.06621620	0.441034527	-0.0308330741	-0.446208786	-0.259189903	0.0294886050	-0.142184888	-0.0701464151
2017-11-01	0.23719023	0.257060497	0.1392316058	-0.238241300	-0.198926833	0.0083509033	-0.070843734	-0.0700648379
2017-12-01	1.05967138	0.131626295	0.3960657398	0.204166290	-0.279742279	-0.0373189687	0.131823459	0.0543724535

Notes: Lags = 4

Table 8: Historical decomposition of UCRY index results 3 (2018-01-01 To 2019-12-01)

	UCRY Policy	**GlobalEPU**	**Vix**	**Bitcoin**	**USFS**	**USEPU**	**Gold**	**UCRY Price**
2018-01-01	0.13936295	-0.073609720	0.6118938725	0.529814788	-0.376837374	0.0514498952	0.075609001	0.1815271834
2018-02-01	0.04560749	-0.093633503	0.5256242599	0.205748501	-0.391840243	-0.0358607436	-0.004039436	0.2007949021
2018-03-01	-0.56169722	-0.022592864	0.4016892081	0.137311270	-0.186782466	-0.0247762379	-0.180752014	0.0891074380
2018-04-01	-0.87314171	0.211082372	0.2873395010	0.169078979	-0.075242339	-0.0541678085	-0.347400206	-0.0646530707
2018-05-01	-1.08283671	0.328701367	-0.0399622790	0.307000737	-0.006753596	0.0004119471	-0.302175329	-0.2281089486
2018-06-01	-1.05818835	0.558351933	-0.4099032444	0.360687233	0.159277170	0.0509188495	-0.254158172	-0.2871663705
2018-07-01	-0.68728574	0.812158253	-0.7887009771	-0.081237887	0.225210982	0.0510216942	-0.160061993	-0.2404416566
2018-08-01	-1.32905043	0.733440627	-0.8837649563	0.154768538	0.195878137	0.0885015943	-0.072298158	-0.1057205845
2018-09-01	-1.71061988	0.694090654	-0.6485506606	0.345742009	0.183310788	-0.0045073372	0.117711970	0.0072733586
2018-10-01	-1.71261249	0.520064250	-0.6052597645	0.365976383	0.150955430	-0.0005864871	0.274747577	0.0310535301
2018-11-01	-1.31038872	0.373243007	-0.2798708583	0.609594113	0.274527655	-0.1143200462	0.231438056	-0.0470319541
2018-12-01	-1.13935360	0.369345628	-0.4256966908	0.200981582	0.403621259	-0.0257921246	0.231501193	-0.1381926349
2019-01-01	-0.57374726	0.193288751	-0.4048898804	0.221221480	0.464342154	0.0807709055	0.041580253	-0.2563049224
2019-02-01	-0.45820001	0.300372134	-0.6828313616	0.315494454	0.536964134	0.0574205312	-0.130339604	-0.3622369265
2019-03-01	-0.80010244	0.571241700	-0.8487418776	0.227720814	0.629501750	0.1596836206	-0.254763247	-0.3555311080
2019-04-01	-0.56385539	0.692935294	-0.7052985839	0.191388213	0.590387547	0.1091373155	-0.190090609	-0.2406442657
2019-05-01	-0.62594377	0.827521524	-0.6440571321	-0.094344508	0.547109969	0.1588929440	0.111662573	-0.1884866928
2019-06-01	-0.68441447	0.951097315	-0.7262511028	0.111038412	0.555784336	0.1464929659	0.335340909	-0.2071609444
2019-07-01	-0.90061599	0.457697190	-0.6828360430	0.544230858	0.451397319	0.1153358244	0.543652624	-0.1953233721
2019-08-01	-0.50355018	-0.090946132	-0.2727345192	0.369117017	0.352184256	0.1809337546	0.381698000	-0.1430495862
2019-09-01	-0.14691349	-0.434362628	0.2417491204	0.178494201	0.361528773	0.1291989687	-0.020551518	-0.1130201185
2019-10-01	0.24492768	-0.700673284	0.4808364848	0.006213433	0.425854241	0.0871479677	-0.256029892	-0.0712271106
2019-11-01	0.34328635	-0.677520408	0.5681644953	0.140757280	0.381538334	-0.0973435699	-0.398692703	-0.1026940439
2019-12-01	0.63872333	-0.640504921	0.4182092695	0.065933039	0.358637833	-0.1296625730	-0.133263680	-0.1791012831

Notes: Lags = 4

Table 9: Historical decomposition of UCRY index results 4 (2020-01-01 To 2021-01-01)

	UCRY Policy	**GlobalEPU**	**Vix**	**Bitcoin**	**USFS**	**USEPU**	**Gold**	**UCRY Price**
2020-01-01	0.44580473	-0.487289259	0.5143564145	-0.268997848	0.201415867	-0.0776259519	0.068380230	-0.1910786127
2020-02-01	0.26116095	-0.136234915	0.5886335179	-0.058774238	0.057110243	0.0594877770	0.101566814	-0.1174770262
2020-03-01	0.29780442	0.081187007	0.8348785647	-0.030158111	-0.096135083	0.1708107756	-0.042108151	0.0003150036
2020-04-01	0.72532173	-0.059076939	0.5564711992	-0.149904357	-0.145899526	0.1103487205	-0.152212471	0.1344524045
2020-05-01	0.90554992	-0.349222977	0.1184707181	-0.350795694	-0.372763613	0.0599033111	0.058582812	0.2119281283
2020-06-01	1.34415629	-0.729153084	0.0766115501	-0.607456902	-0.573436933	-0.0010123107	0.127151715	0.1995155918
2020-07-01	1.71164162	-1.145845071	0.1990492548	-0.686832339	-0.328320104	-0.0017097290	0.145816619	0.1466861724
2020-08-01	1.93457320	-1.257690455	0.3221010633	-0.649845207	-0.582691857	-0.0390430239	0.014735636	0.1121150073
2020-09-01	1.58359491	-1.199749141	0.3016195610	-0.651897772	-0.691887256	0.0179793176	-0.193325222	0.1194738306
2020-10-01	1.37291957	-1.081506567	0.3099407974	-0.734709162	-0.791624760	-0.0074050405	-0.184423733	0.1614596802
2020-11-01	1.94359573	-0.775991091	0.4754849735	-0.583113168	-0.663836983	0.1241973614	-0.051257187	0.2378443049
2020-12-01	1.86924221	-0.625354105	0.4797052707	-0.519267098	-0.725707678	0.1405270696	0.071385141	0.3389432918
2021-01-01	2.25698664	-0.270919716	1.0764566164	-0.230167768	-0.837561024	0.1001535373	0.285592318	0.3828365149

Notes: Lags = 4

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.

Keywords: Cryprocurrencies; Environmental impact; Energy consumption; Climate change
JEL Code: C43, C52, C54, D80, F18, F64

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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:

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

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. $Crypto_{i,t-1}$ 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 Δln(ICEA) and Δln(UCRY Policy) is 0.384 at a 99% significance level. The correlation value of Δln(ICEA) and Δln(UCRY Price) is 0.390 at a 99% significance level. The correlation value of Δln(ICEA) and Δln(Bitcoin) is 0.028 at a 99% significance level. These statistical results also can further prove that the Δln(UCRY Policy), Δln(UCRY Price) and Δln(ICEA) have a significantly relationship with Δln(Bitcoin). Therefore, the ICEA can still work from the continuously compounded returns' perspective. Furthermore, the correlation value between Δln(ICEA) and Δln(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 (1)	Model (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***

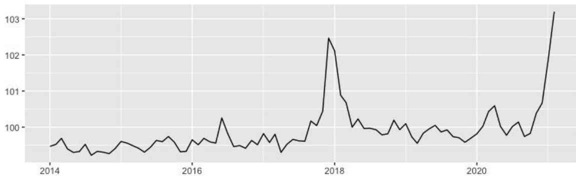
Note: *p<0.1; **p<0.05; ***p<0.01.

Table 9: Robustness test

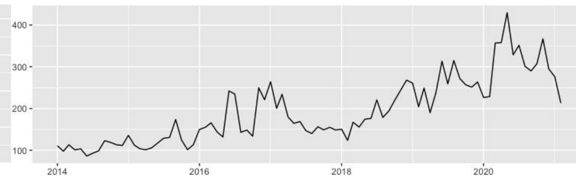
	$\Delta lnICEA$ *impact*	
	Model (1)	Model (2)
Δln**Bitcoin**	140.311***	107.3383***
	(0.285)	(0.242)
Control variables	No	Yes
R^2	51.84%	79.49%
Observations	85	85
Δln**Ethereum**	19.1874*	17.1546***
	(1.690)	(1.673)
Control variables	No	Yes
R^2	29.99%	44.01%
Observations	65	65
Δln**UCRY Policy**	0.9476***	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: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

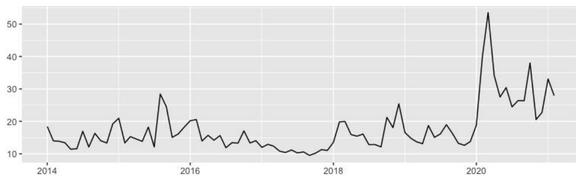
Figure 1: Time series of the factors



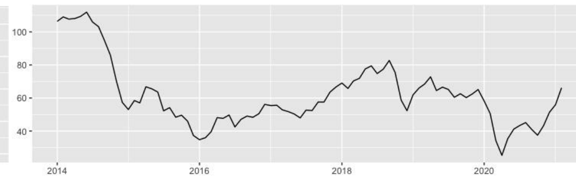
(a) UCRY Policy time series



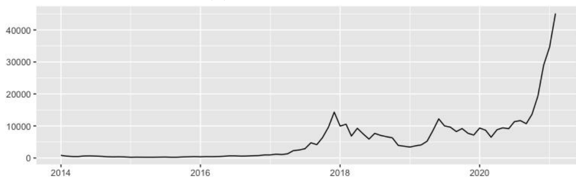
(b) GlobalEPU time series



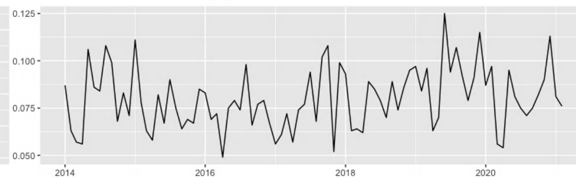
(c) Vix time series



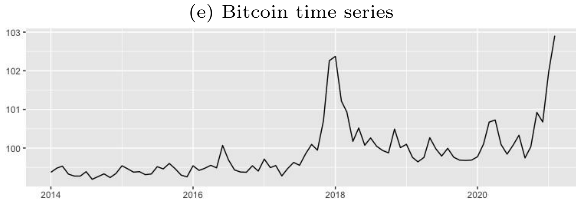
(d) BCO time series



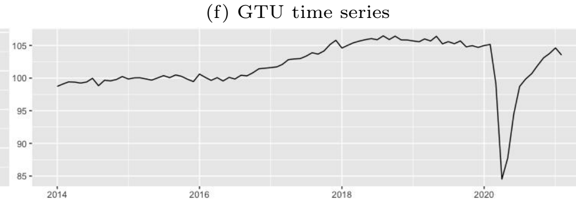
(e) Bitcoin time series



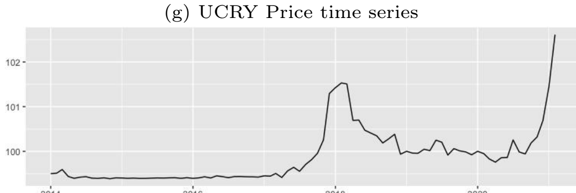
(f) GTU time series



(g) UCRY Price time series



(h) IP time series



(i) ICEA time series

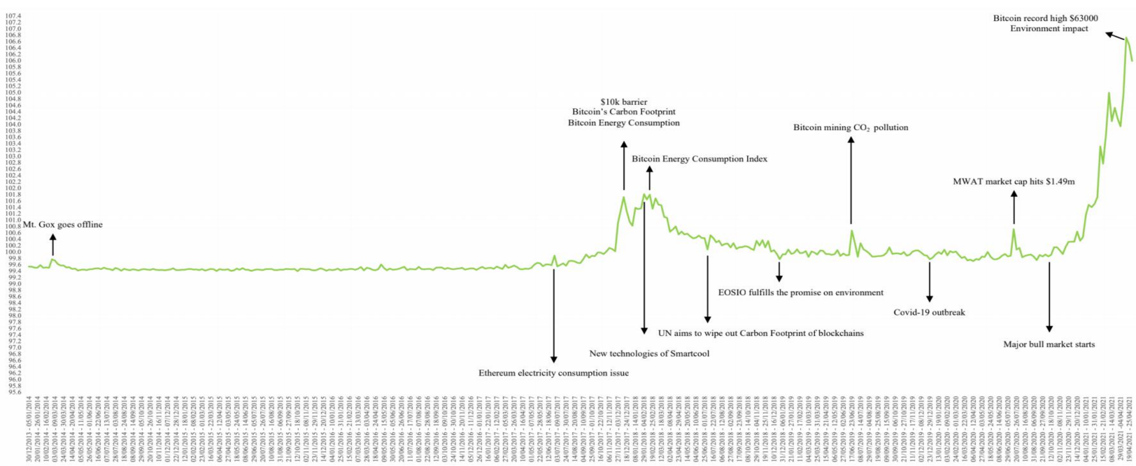
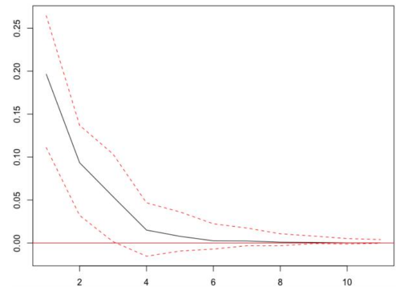
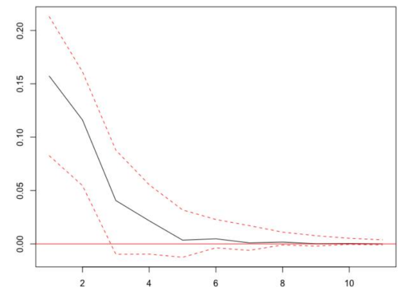
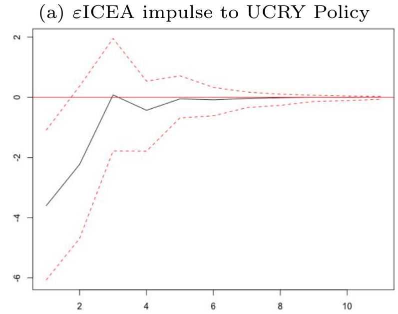


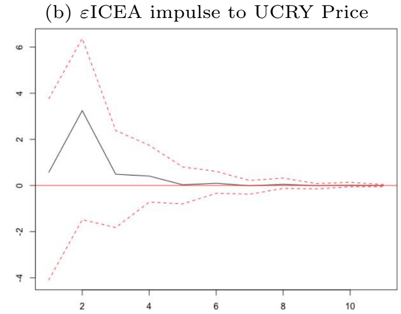
Figure 2: Annotated ICEA Index

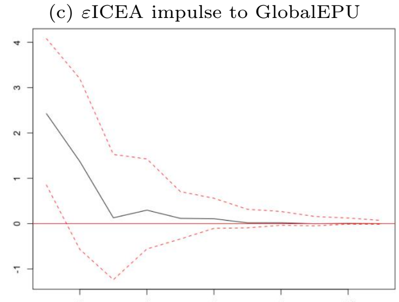
Figure 3: Impulse from ICEA to variable system

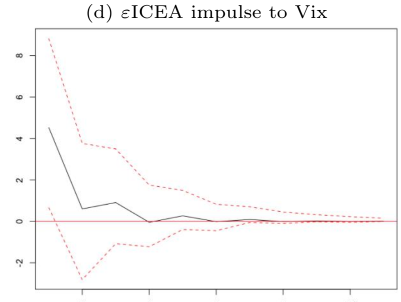

(a) εICEA impulse to UCRY Policy

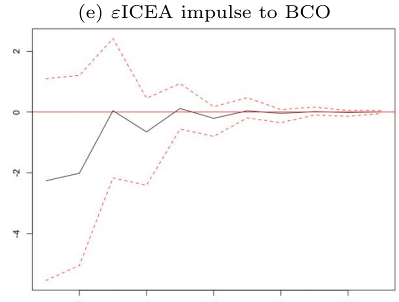

(b) εICEA impulse to UCRY Price

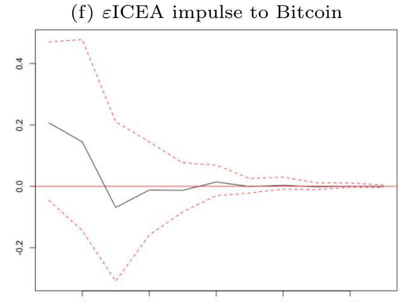

(c) εICEA impulse to GlobalEPU


(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

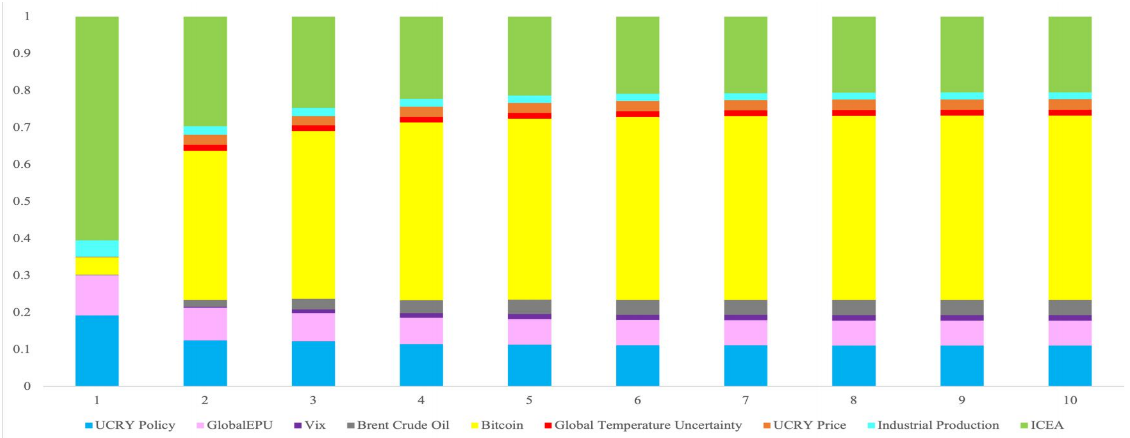


Figure 4: FEVD of ICEA

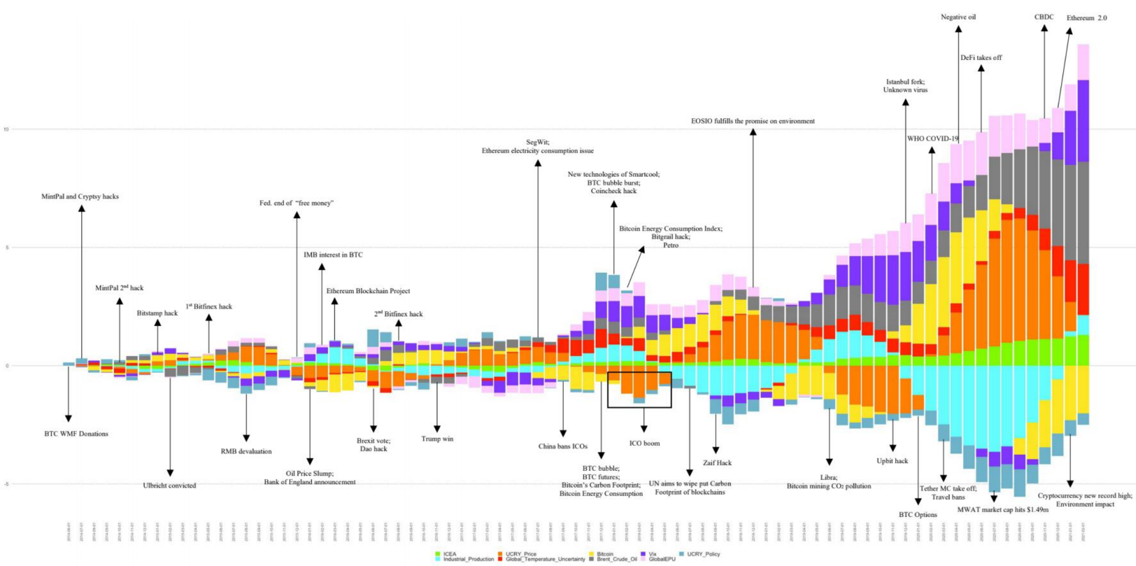
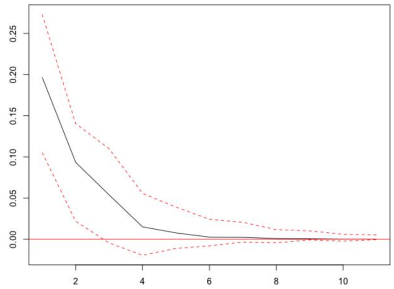
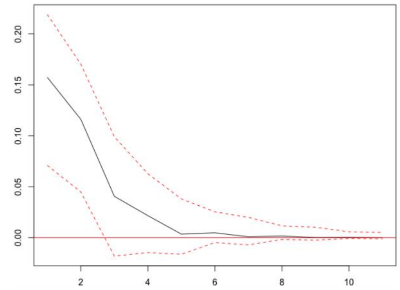


Figure 5: ICEA index historical decomposition with major events

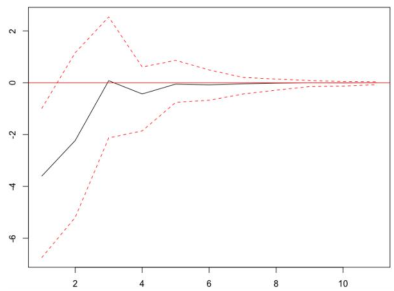
Figure 6: Impulse from ICEA to other factors robustness test



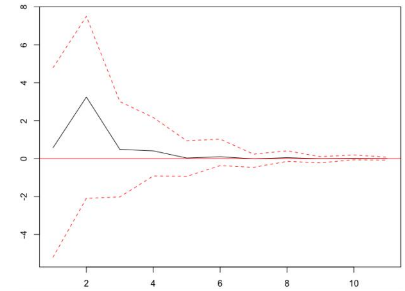
(a) εICEA impulse to UCRY Policy robustness test



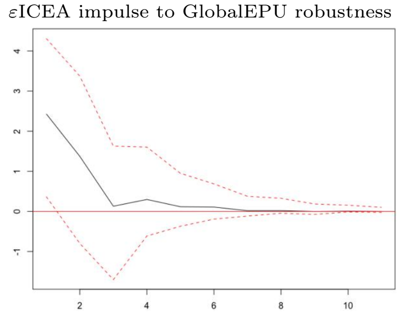
(b) εICEA impulse to UCRY Price robustness test



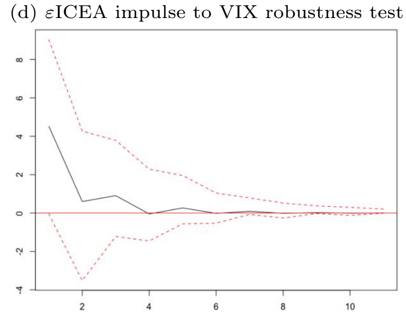
(c) εICEA impulse to GlobalEPU robustness test



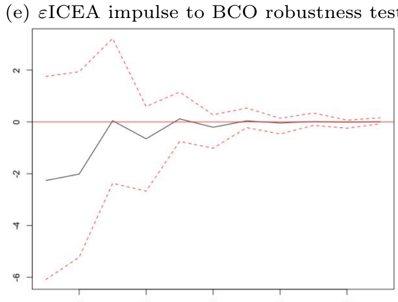
(d) εICEA impulse to VIX robustness test



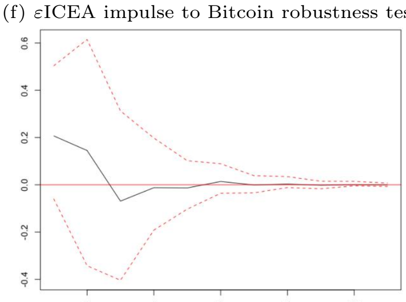
(e) εICEA impulse to BCO robustness test



(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

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The Effects of Central Bank Digital Currencies News on Financial Markets

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Abstract

Based on coverage of over 660m news stories from LexisNexis News & Business between 2015–2021, we provide two new indices around the growing area of Central Bank Digital Currencies (CBDC): the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI). We show that both indices spiked during news related to new developments in CBDC and in relation to digital currency news items. We demonstrate that CBDC indices have a significant negative relationship with the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index, and positive with the volatilities of cryptocurrency markets, foreign exchange markets, VIX, and gold. Our results suggest that financial markets are more sensitive to CBDC Uncertainty than CBDC Attention as proxy by these indices. These findings contain useful insights to individual and institutional investors, and can guide policymakers, regulators, and the media on how CBDC evolved as a barometer in the new digital-currency era.

Keywords: CBDC; Uncertainty and attention index; Market effect; SVAR; DCC-GJR-GARCH
JEL Code: C43, C58, D80, E42, E58, F31, G15, G21

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1. Introduction

While our times are certainly changing, let us hope money remains with us. As a medium of exchange, money has evolved from shells, dogs teeth, knotted fabric, precious metals, banker's notes, cash to cryptocurrency [Davies, 2010]. While cryptocurrency is still a largely unregulated area, the introduction of the Central Bank Digital Currencies (CBDC) will manifest the beginning of a new monetary era [Laboure et al., 2021]. Now, the Bahamas has already implemented CBDC in its territory, and China has recently completed two CBDC tests. The CBDC wallet app is now available in Suzhou, Xiongan, Shenzhen, and Chengdu, and the People's Bank of China and the Hong Kong Monetary Authority has begun 'technical testing' for cross-border use of e-CNY. Uruguay has also completed a CBDC pilot test. CBDC is a virtual form of a country's fiat currency issued by the central bank [Yao, 2018b]. CBDC was initially called a Digital Fiat Currency (DFC) [Krylov et al., 2018], which draws inspiration from famous crypto assets such as Bitcoin, Ethereum, Binance Coin, among others. In 2013, Shoaib et al. [2013] introduced the alternative terms of Official Digital Currency (ODC) and the Official Digital Currency System (ODCS).

CBDC is of great importance over conventional cryptocurrencies and fiat currencies when studying. First, from the perspective of payment, it saves costs, prevents counterfeiting, and strengthens the authority of legal tender while enhancing the inclusive character of the payment system [Sun et al., 2018]. It also optimises the payment function of legal tender, reducing the reliance on payment services on business banks and private sectors, thereby decreasing the burden and pressure of supervision on the central bank [Qian, 2019]. Second, CBDC can benefit to the monetary supervision and regulation. The structured currency circulation data allows total amount of money supply to be regulated precisely [Agarwal et al., 2020 and Fernández-Villaverde et al., 2021]. This ameliorates the dilemmas facing modern monetary policies, such as inefficient policy transmissions, difficult regulation of conversion periods, the flow of money from the real economy to the virtual one, and the failed realisation of expected requirements by monetary policies [Karamollaoglu and Tuncay, 2019]. Moreover, capital flow information can be fully and quickly investigated, thereby aiding anti-corruption, anti-money laundering, anti-terrorist financing, and anti-tax evasion efforts [Tronnier, 2021 and Dupuis et al., 2021]. Third, CBDC has the potential to promote financial market stability by adjusting monetary, mitigating financial systemic risk, reducing shadow banking, among others [Larina and Akimov, 2020; Copeland, 2020 and Zams et al., 2020]. CBDC's encouraging progress has generated extensive attention and discussions among academics and economists.

The majority of available studies still concentrate on the fundamental qualitative analysis of CBDC and its technological innovations. The latest CBDC studies can be classified into five subgroups. The first discusses (among other aspects) the definition, characteristics, classification, main models, and implications of the CBDC variants, as well as the potential advantages and risks of its introduction [Cunha et al., 2021 and Kochergin, 2021]. The second focuses on the design theory, technology innovation, and model optimisation of CBDC [Qian, 2019 and Lee et al., 2021].

The third examines its security and privacy [Borgonovo et al., 2021 and Lee et al., 2021]. The fourth analyses CBDC's impacts on the monetary system and monetary policy [Davoodalhosseini, 2021 and Meaning et al., 2021]. The fifth group investigates the relationships between CBDC and banking, including commercial and central banking [Fernández-Villaverde et al., 2021 and Williamson, 2021]. Whereas only few studies investigate how current CBDC's discussion among regulators and in the media affect behaviour of financial markets. Considering the CBDC is at the early stages of development and adoption there is the lack of data or proxies which can reflect and stand for the CBDC, thus hindering quantitative analyses of CBDC's effects on financial markets.

To fill this research gap and conduct a quantitative analysis of CBDC with financial markets, we developed and made available two CBDC indices – the CBDC Uncertainty (CBDCUI) and the CBDC Attention (CBDCAI), that can be used to track CBDC's trends and variations. Our data covers the main period of CBDC development and the period of the most active discussion of this new asset in the media, i.e. from January 2015 to June 2021. Thus, we construct our indices use 663,881,640 news items collected from Lexis-Nexis News & Business. In this paper, we first to empirically examine the impact of CBDC news on the financial markets. Our sample includes the main cryptocurrency uncertainty indices, which are Cryptocurrency Policy Uncertainty Index (UCRY Policy), Cryptocurrency Price Uncertainty Index (UCRY Price), Cryptocurrency Environmental Attention Index (ICEA); Bitcoin as a proxy of cryptocurrency markets; the MSCI World Banks Index to represent the commercial banking sector. Furthermore, we selected EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD to represent the foreign exchange market. To account for economic price and policy uncertainty we also included the VIX (The Cboe Volatility Index) and US EPU (The United States Economic Policy Uncertainty Index) in our sample. Finally, we chose the FTSE All-World Index to represent the stock markets and gold as a safe-haven assets that often has been compared with Bitcoin.

We begin our empirical analysis with a vector autoregression (VAR) as the most suitable model for testing the effectiveness and validity of the newly issued indices. Then, we apply a structural vector autoregression (SVAR) model to process a structural shock analysis of the effects of CBDCUI and CBDCAI on indices, as well as macro- or microeconomic variables using IRF (Impulse response function), FEVD (Forecast errors variance decomposition), and HD (Historical decomposition) tests. We further employ the dynamic conditional correlation (DCC-GJR-GARCH) model to investigate interconnections between indices and financial variables. Applications of VAR and DCC-GARCH models to our set of variables, helps us to uncover how CBDC indices interact with these financial indicators providing novel empirical evidence on the CBDC news on financial markets.

This paper contributes to the existing literature in three main ways. First, based on news coverage from LexisNexis News & Business, we developed two new indices for CBDC between 2015–2021: the CBDCUI and CBDCAI, that can be used by investors, policy makers and financial regulators to monitor the impact of CBDC-related discussions on volatility of financial markets. Our indices capture CBDC trends and uncertainties as they are able to react to major relevant events. For example, our indices spiked near new CBDC announcements, digital currency flash-news, and main policy debates. Second, the paper reports that CBDCUI and CBDCAI indices had a significantly negative effect on the volatilities of the MSCI World Banks Index, USEPU, and FTSE All-World Index, where the volatilities of the financial variables reacted more strongly to shocks transmitted from the CBDCUI. Third, the paper presents the historical decomposition results, that show that the cumulative positive and negative effects of CBDCUI disturbances tend to be larger than those of the CBDCAI on the financial variables. Positive news items and government policy announcements can have a significant negative affect on the CBDCUI historical decomposition results, i.e. decreasing the uncertainty around CBDC introduction. Besides, we show that both CBDCUI and CBDCAI historical decomposition results significantly spiked near key CBDC progress news and significant events regarding digital currency.

Our paper offers useful proxies of CBDC Uncertainty and Attention and a novel evidence for future quantitative studies into CBDC. Moreover, this paper successfully links CBDC to the financial markets and other volatility and uncertainty measures, that can originate another strand of CBDC literature. The results provide novel useful insights for investors, policymakers, regulators, and media on how CBDC evolved as a barometer in the new digital-currency era. For example, policymakers and regulators can adjust fiscal policy by referencing our CBDC indices. And the CBDC indices can guide investors to increase or reduce their financial assets' net long positions.

The remainder of this paper is structured as follows. section 2 outlines previous CBDC literature and the existing methodologies used to analyse the relationships between financial variables. section 3 describes the construction of the indices and the data for the empirical analysis, while section 4 describes the econometric methods used. section 5 presents the empirical results and robustness tests. Finally, section 6 discussed the main findings of this research and its implications.

2. Literature review

CBDC is a government credit-based digital currency, thereby reducing their risks. Therefore, some economic agents and individuals might prefer to transfer money from commercial banks to CBDCs during financial crises [Sinelnikova-Muryleva, 2020]. Many regulators and researchers regard CBDC as a nationally issued 'stablecoin', and believe it can balance the banking system [Sissoko, 2020] and positively impacts financial stability [Larina and Akimov, 2020; Copeland, 2020; McLaughlin, 2021; Buckley et al., 2021]. Indeed, Zams et al. [2020], using an analytic network process and the Delphi method, demonstrated that the cash-like CBDC model is the most suitable CBDC design for Indonesia because it can improve financial inclusion and reduce shadow banking. Tong and Jiayou [2021] investigated the effects of the issuance of digital currency/electronic payment on economics based on a four-sector DSGE model, and conclude that CBDC can mitigate the leverage ratio and the systemic financial risk. Barrdear and Kumhof [2021] examined the macroeconomic consequences of launching CBDC by a DSGE model, and found that CBDC issuance 30%'s GDP, against government bonds, could be permanently raised by 3%. Additionally, Fantacci and Gobbi [2021] focused on the geopolitical, strategic, and military impacts of CBDC.

However, CBDC is a new research field within digital currency and fintech domain, and a few paper available to date can be roughly allocated into five main sub-groups.

The first group discusses, among other aspects, the definition, characteristics, classification, main models, and implications of the CBDC variants, and the potential advantages and risks of its introduction [Yao, 2018b; Masciandaro, 2018; Cunha et al., 2021; Kochergin, 2021; Li and Huang, 2021]. While the above mentioned researchers hold positive attitudes towards CBDCs, Kirkby [2018] criticised CBDC as it would increase the central bank's costs for the whole money supply system.

The second group of studies focuses on the CBDC's design theory, technological innovation, and model optimisation. Sun et al. [2018] proposed a multi-blockchain data centre model for CBDCs in order to help central banks manage the issuance of currency, prevent double-spending issues, and protect user privacy. Yao [2018a] conducted an experimental study on a Chinese prototype of a CBDC system. Qian [2019] introduced a CBDC issuance framework designed for forward contingencies in order to prevent the currency from circulating beyond the real economy. Wagner et al. [2021] discussed and proposed a potential blueprint for a digital euro and proved its possibility. Lee et al. [2021] proposed a blockchain-based settlement system using cross-chain atomic swaps that could be implemented for the CBDC to manage settlement risks.

The third group illustrates CBDC's security and privacy. Fu et al. [2019], Tronnier [2021] and Borgonovo et al. [2021] demonstrated the significance of anonymity for increasing the overall attraction of CBDC's social medium payment. Lee et al. [2021] conducted a survey on security and privacy in blockchain-based CBDCs to address the remaining security and privacy research gaps, and a techno-legal taxonomy of methodologies was further proposed to balance CBDC privacy and transparency without impeding accountability [Pocher and Veneris, 2021].

The fourth group analyses the impacts of CBDCs on monetary systems and policy. For instance, using a literature review, Tronnier et al. [2020] systematically revised CBDC and further discussed its implications on economics, monetary policy, and legal issues. Meaning et al. [2021] discussed CBDC's potential impact on monetary transmission mechanisms, and found that monetary policy can operate as it does now by adjusting the price or quantity of CBDC. Shen and Hou [2021] applied a qualitative analysis of China's CBDC and its impacts on monetary policy and payment competition, and argued that it has potential to transform the field completely rather than be a mere regulatory toolkit, especially when CBDC will be adopted at a large-scale. To put it simply, some scholars hold positive views towards CBDC on monetary policy. They have argued that CBDC is a useful complement to monetary and reserve policy [Davoodalhosseini, 2021], and that it has the potential power to strengthen the monetary transmission mechanism and bear interest [Stevens, 2021]. However, other studies have discussed CBDC's monetary risks, for example, Viñuela et al. [2020] listed the sources of these risks, and presented both solutions and suggestions for further CBDC research.

The fifth group investigates the relationships between CBDC and banking, including commercial and central banking. Cukierman [2020] provided two proposals CBDC's implementation, i.e the moderate and radical. The former suggests that only the banking sector can have access to deposits at central banks, while the latter suggests that the whole private sector could hold digital currency deposits at central banks. Cukierman supported the radical proposal due to its ability to condense the banking system and reduce the need for deposit insurance. Furthermore, some discussions have centred around the new role of central banks in the digital currency era. Some scholars believe that CBDC can upset commercial banking because central banks are more stable and can play an essential role in reducing risks in economic transactions [Yamaoka, 2019; Zams et al., 2020; Sinelnikova-Muryleva, 2020]. This could possibly even lead to commercial banking panic [Williamson, 2021] or allow central banks to become deposit monopolists [Fernández-Villaverde et al., 2021].

All of these studies have not explained how the CBDC as a 'stablecoin' can enhance the stability of financial markets. Can CBDC really help to achieve financial stability? What are the potential impacts of CBDC on financial markets? Motivated by these questions, we seek to uncover CBDC's effects on financial markets. As mentioned earlier, an existing issue in the field of CBDC research is the lack of a proxy to represent the CBDC. Therefore, we introduce new CBDC indices to capture the existing trends and reflect the variations of CBDC uncertainty and attention through gathering a large amount of news items around CBDC, i.e. >663 million news items which can be considered as a Big Data, and analysing this rich dataset using variety of quantitative techniques. We built the CBDCUI and CBDCAI based on constructs found in [Baker et al., 2016, Huang and Luk, 2020, Lucey et al., 2021, and Lucey et al., 2021]. CBDCUI is designed to capture CBDC's uncertainty, while CBDCAI to be used a proxy for the attention to the CBDC. Our methods, however, differ from Baker et al. [2016] and Huang and Luk [2020], who collected data only from newspapers for constructing their indices. In contrast, we choose LexisNexis News & Business as our database because its provides access to much larger volume of articles across various publication sources.

This paper adds to the CBDC literature in two main ways. First, it introduces new CBDCUI and the CBDCAI indices that can capture the uncertainty and attention around introduction and adoption of CBDC, and can be used for further analysis of the impacts of CBDC on various financial markets. These indices not only track current CBDC's news trend, but also presents its variations over time and relationships with other uncertainty and attention measures. Second, this is the first paper to focus on the effects of CBDC news on financial markets using very large and comprehensive dataset. We have thoroughly investigated how CBDC can impact cryptocurrency markets, commercial banking, foreign exchange markets, stock markets, uncertainty indices, and gold, and made our data available for replication.

3. Data

3.1. CBDC indices data collection

We conduct multiple search in LexisNexis News & Business using combinations of keywords relevant to CBDC. There is no doubt that 'Central Bank Digital Currency' and 'CBDC' were set as our key search terms. Moreover, due to our identification of the strongest currencies (see the literature review, above), we considered what the official non-English terms for 'Central Bank Digital Currency' in these countries. The official language of the US, EU, and the UK is English[1]. Therefore, the aforementioned search terms have been translated to Chinese, Japanese, Russian to ensure comprehensive coverage of the stories in the main countries that are leading the CBDC development. Furthermore, considering Spanish, Portuguese, French, and German are essential languages in the EU we also translated 'Central Bank Digital Currency' into these four languages. Additionally, as CBDC is a type of digital currency, and some countries value CBDC as a tool to counter cryptocurrencies. Therefore, we included 'Digital currency' as another key term. Once done, we searched for the most popular synonyms for digital currency, which we found to be 'digital money', 'electronic currency', 'electronic money', 'e-currency', and 'e-money'. Therefore, we also set these five synonyms as key search terms.

Knowing that USD, EUR, GBP, CHF, RUB, JPY, and CNY are heading towards CBDC, we substituted the keywords 'currency' or 'money' with the official name of these currencies. For example, search terms for the currency of the United States also included 'digital dollar', 'electronic dollar', 'e-dollar', 'digital USD', 'electronic USD', and 'e-USD'. For countries where English is not the official language, we not only kept the English search terms, but also translate them into the particular official language. Considering that Germany and France have the EU's strongest economies, we also translated 'digital euro', 'electronic euro', and 'e-euro' into German and French. As we considered Switzerland an English speaking country, we applied 'digital Swiss franc', 'electronic Swiss franc', 'e-franc', 'digital CHF', 'electronic CHF', and 'e-CHF'. Compiling these key search terms together generated our search string for CBDCAI. Based on the CBDCAI's search term, we then added a new search term, 'uncert!', with the link of 'and', not 'or'. Therefore, we obtained a new search string for CBDCUI. Additionally, we set the option for Group Duplicate to MODERATE so as to avoid duplicate results as much as possible.[2] The search strings for CBDCUI

[1] Although the official languages in Switzerland are German, French, Italian, and Romansh, its population is relatively small, meaning that we consider Switzerland an English-speaking country

[2] Weekly values can be downloaded from: https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices?authuser=0

and CBDCAI are as follows:

(("Central Bank Digital Currency") OR ("CBDC") OR ("央行数字货币") OR ("Moneda digital del banco central") OR ("Moeda Digital do Banco Central") OR ("Национальная криптовалюта") OR ("中央銀行のデジタル通貨") OR ("Merkez Bankası Dijital Para Birimi") OR ("Monnaie numérique de la Banque centrale") OR ("Digitales Zentralbankgeld") OR ("Digital currency") OR ("Digital money") OR ("Electronic currency") OR ("Electronic money") OR ("E-currency") OR ("E-money") OR ("Digital dollar") OR ("Electronic dollar") OR ("E-dollar") OR ("Digital USD") OR ("Electronic USD") OR ("E-USD") OR ("Digital Euro") OR ("Electronic Euro") OR ("E-Euro") OR ("Digital EUR") OR ("Electronic EUR") OR ("E-EUR") OR ("Digital pound") OR ("Electronic pound") OR ("E-pound") OR ("Digital GBP") OR ("Electronic GBP") OR ("E-GBP") OR ("Digital RMB") OR ("Electronic RMB") OR ("E-RMB") OR ("Digital CNY") OR ("Electronic CNY") OR ("E-CNY") OR ("Digital CNH") OR ("Electronic CNH") OR ("E-CNH") OR ("Digital Renminbi") OR ("Electronic Renminbi") OR ("E-Renminbi") OR ("电子人民币") OR ("数字人民币") OR ("E-人民币") OR ("Digital ruble") OR ("Electronic ruble") OR ("Cryptoruble") OR ("Digital RUB") OR ("Electronic RUB") OR ("E-RUB") OR ("Цифровой рубль") OR ("крипторубль") OR ("Digital Yen") OR ("Electronic Yen") OR ("E-Yen") OR ("Digital JPY") OR ("Electronic JPY") OR ("E-JPY") OR ("デジタル通貨") OR ("電子通貨") OR ("E-通貨") OR ("Euro numérique") OR ("Monnaie numérique") OR ("Digitaler Euro") OR ("Elektronischer Euro") OR ("E-Währung") OR ("Digital Swiss franc") OR ("Electronic Swiss franc") OR ("E-franc") OR ("Digital CHF") OR ("Electronic CHF") OR ("E-CHF")) and (uncert!)

Figure 1: CBDC uncertainty index search string

("Central Bank Digital Currency") OR ("CBDC") OR ("央行数字货币") OR ("Moneda digital del banco central") OR ("Moeda Digital do Banco Central") OR ("Национальная криптовалюта") OR ("中央銀行のデジタル通貨") OR ("Merkez Bankası Dijital Para Birimi") OR ("Monnaie numérique de la Banque centrale") OR ("Digitales Zentralbankgeld") OR ("Digital currency") OR ("Digital money") OR ("Electronic currency") OR ("Electronic money") OR ("E-currency") OR ("E-money") OR ("Digital dollar") OR ("Electronic dollar") OR ("E-dollar") OR ("Digital USD") OR ("Electronic USD") OR ("E-USD") OR ("Digital Euro") OR ("Electronic Euro") OR ("E-Euro") OR ("Digital EUR") OR ("Electronic EUR") OR ("E-EUR") OR ("Digital pound") OR ("Electronic pound") OR ("E-pound") OR ("Digital GBP") OR ("Electronic GBP") OR ("E-GBP") OR ("Digital RMB") OR ("Electronic RMB") OR ("E-RMB") OR ("Digital CNY") OR ("Electronic CNY") OR ("E-CNY") OR ("Digital CNH") OR ("Electronic CNH") OR ("E-CNH") OR ("Digital Renminbi") OR ("Electronic Renminbi") OR ("E-Renminbi") OR ("电子人民币") OR ("数字人民币") OR ("E-人民币") OR ("Digital ruble") OR ("Electronic ruble") OR ("Cryptoruble") OR ("Digital RUB") OR ("Electronic RUB") OR ("E-RUB") OR ("Цифровой рубль") OR ("крипторубль") OR ("Digital Yen") OR ("Electronic Yen") OR ("E-Yen") OR ("Digital JPY") OR ("Electronic JPY") OR ("E-JPY") OR ("デジタル通貨") OR ("電子通貨") OR ("E-通貨") OR ("Euro numérique") OR ("Monnaie numérique") OR ("Digitaler Euro") OR ("Elektronischer Euro") OR ("E-Währung") OR ("Digital Swiss franc") OR ("Electronic Swiss franc") OR ("E-franc") OR ("Digital CHF") OR ("Electronic CHF") OR ("E-CHF")

Figure 2: CBDC attention index search string

We should also explain our decision to launch an extra CBDCUI, as well as the differences between 'volatility' and 'uncertainty'. We are living in a period of great uncertainty. Indeed, in recent years, various financial and political events have shaken the world. For example, the US financial crisis, the European sovereign debt crisis, terrorist attacks, Brexit, and the current global COVID-19 pandemic, to name but a few. This series of events has meant that uncertainty has become an important variable in modern economies. The CBDCUI not only helps us identify the uncertainty of CBDC itself, but also allow us to capture how these uncertainties can disrupt the modern economies. Uncertainty differs from volatility in the way it is designed and measured, and these have been analysed differently in the academic literature. In fact, volatility captures the variability in the price of financial assets. Therefore, it can be interpreted as a measure of 'the present'. Simply out, volatility is akin to a 'photographs' of the current situation. Uncertainty tries to capture 'the future' through studying economic, social, and political sentiment, that in our case, can be extracted from analysis of wide news coverage of CBDC.

3.2. CBDC indices' construction

The CBDCUI is calculated as in Equation 1:

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

where $CBDCUI_t$ is the value of the CBDCUI in the weeks t between January 2015 and June 2021, N_{1t} is the weekly observed value of news articles on LexisNexis concerning CBDC uncertainty, μ_1 is the mean of these same articles, and σ_1 is the standard deviation of such.

The CBDCAI is calculated as in Equation 2:

$$CBDCAI_t = (\frac{N_{2t} - \mu_2}{\sigma_2}) + 100, \quad (2)$$

where $CBDCAI_t$ is the value of the CBDCAI in the weeks t between January 2015 and June 2021, N_{2t} is the weekly observed value of LexisNexis news articles concerning the uncertainty of cryptocurrency price news articles, μ_2 is the mean of these and, σ_2 is the standard deviation of such.

Figure 3 shows the weekly values for the derived indices based on 663,881,640 news items collected between January 2015 and June 2021. According to [Turrin, 2021], Ecuador was the first country to launch CBDC, which it did in February 2015 to promote anti-dollarisation. This implementation is why we selected January 2015 as the beginning of our observation period. The weekly CBDCUI and CBDCAI indices were annotated in Figure 4 and display which events can drive spikes on the indices. The plot allowed us to clearly see how new CBDC developments could raise the indices, while they could also be stimulated by other significant events related to cryptocurrencies. We have listed all of the events captured by our indices in Appendix-A.

3.3. Financial market variable selection

To justify the selections of financial markets in our sample, we consider previous literature that reported which markets were susceptible to shocked transmitted from CBDC, or reverse, were immunised from these shocks. According to the viewpoints expressed by the central banks around the world, CBDC is a national tool to counter cryptocurrency volatility and uncertainty [Tronnier et al., 2020; Larina and Akimov, 2020; Lee et al., 2021; Koziuk, 2021]. We thus hypothesise that CBDCUI and CBDCAI may have significant effects on cryptocurrency markets. Specifically, we assume that debates around CBDC may affect cryptocurrency price and policy uncertainty, therefore we decided to also include UCRY Policy and UCRY Price indices in our sample. It is important to assess how the new CBDC indices are related to other indices capture uncertainty of the cryptocurrency markets as a whole. Furthermore, taking into account the increased attention to the environmental impacts of cryptocurrency growing energy consumption, we included the ICEA in our sample, since this index could be also strong determinant of the increased debates toward the necessity of regulation of cryptocurrency markets and proactive government intervention in the decentralised asset ecosystem. We also selected the most important cryptocurrency markets leader, i.e. Bitcoin, as one of our financial variables [Corbet et al., 2020b], since this digital asset attract the highest attention from media and general public, and also often used a proxy of overall cryptocurrency market volatility. We omitted the Bloomberg Galaxy Crypto Index because it only began in 2017, and thus does not cover our entire research period.

While the above studies would overwhelmingly suggest that introduction of CBDC will affect commercial banks, there are insufficient quantitative analysis results that can prove this perspective.

Therefore, we selected the MSCI World Banks Index[3] to represent the commercial banking sector, and investigated the impacts of CBDC indices on commercial banking. It is a popular belief, that CBDC is a simply digital version of a fiat currency, while many scholars consider it to be a 'national stablecoin'. Therefore, it is pertinent to examine its effects on the fiat currencies of countries that according to the literature are heading towards adopting the CBDC, such as China, the US, the EU, the UK, Canada, Russia, and Japan [Alonso et al., 2021]. Moreover, Ciner et al. [2013]; Fatum et al. [2017]; Fong and Wong [2020] and Shehadeh et al. [2021] suggest that USD, EUR, GBP, RUB, JPY, and CNY are the strongest currencies in the world, and these countries (or blocs) are leading the CBDC progress worldwide. We also set the F.X. Spot unit of all the currencies as USD, meaning that USD units per 1 of another currency. Therefore, the increase in the exchange rate implies the appreciation of the EUR/GBP/JPY/RUB/CNY against the USD, and vice versa.

To analyse the relationship between our new CBDC indices and other popular global uncertainty measures we selected the VIX and the USEPU indices. We did not choose the EPU (global) because it contains only monthly data. While in this paper, we utilise weekly data for all variables. The effects of CBDCUI and CBDCAI on stock markets is also captured by including the FTSE All-World Index in our analysis.[4] Lastly, we selected gold as our safe-haven [Baur and Lucey, 2010; Lucey et al., 2017], because our sample covers the period of COVID-19 pandemic, and safe-haven properties of gold has been often compared to the other assets [Le et al., 2021 and Chemkha et al., 2021].

4. Methodology

The existing literature provides numerous examples of effective methodologies that can be used to capture the impact of Uncertainty and Attention indices on financial markets. The DCC-GARCH model, wavelet analysis, and the VAR model (SVAR structural shock analysis) are the three most popular and straightforward methodologies for analysing of the relationships between different financial variables. Applying the DCC-GARCH model, Akyildirim et al. [2020] analysed the relationship between the price volatility of cryptocurrencies and the implied volatilities of VIX and VSTOXX (EURO STOXX 50 indices Volatility Index). Çepni et al. [2021] investigated the time-varying co-movements between Turkish sovereign yield curve factors and oil price shocks. Xie and Zhu [2021] examined the stabilisation effects of economic policy uncertainty (EPU) on gold futures market and

[3]The MSCI World Banks Index is constructed on large and mid-capitalisation stocks across 23 developed market countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US). All stocks in the MSCI World Banks Index are classified in the Banks industry group.

[4]The FTSE All-World Index is an international equity index which tracks the market performance of large- and mid-capitalisation stocks of companies from developed and developing markets worldwide. The FTSE All-World Index includes roughly 3,900 stocks in approximately 50 countries.

spot market price volatility. Several recent studies have used wavelet-analysis to investigate the structure of financial indices' correlation with various financial asset classes. For instance, Conlon et al. [2018] used the continuous wavelet transformation to check the relationship between gold and inflation, as well as gold's ability to hedge against inflation dynamically. Sharif et al. [2020] analysed the connection between COVID-19, oil prices, stock markets, geopolitical risks, and EPU in the United States by applying the time-frequency coherence wavelet method. Moreover, Shahzad et al. [2021] examined the dynamics relationships between realised variances and semi-variances of the six strongest currencies by fitting wavelet squared coherence and wavelet cohesion. The VAR model, and its SVAR structural analysis tools, are widely used in issuing new financial indices. Baker et al. [2016] launched the EPU index and analysed its impact on economic activities (S&P 500 index, VIX, industrial production, and unemployment rate). Huang and Luk [2020] issued China Economic Policy Uncertainty Index (China's EPU) to examine the impact of its shocks on macroeconomic variables (equity price, deposit rate, unemployment rate, and output volume). Lucey et al. [2021] and Lucey et al. [2021] built the UCRY Policy, UCRY Price and ICEA. Then, these studies performed the IRF, FEVD, and HD tests to further investigate the impacts of the three indices on financial and commodities assets. In this paper, we used the VAR model to check the effectiveness and validity of two new CBDC indices. Moreover, the SVAR model can investigate how CBDC indices can affect the financial variables and contribute to their variations. Furthermore, to determine the interconnections between CBDC indices and each financial variable, we employed the DCC-GARCH model as the most suitable and straightforward method for achieving this goal.

4.1. Structural shock model specification

The main uses of the VAR model are forecasting and structural analysis Lütkepohl [2005]. The standard VAR is a reduced form model, and can be expressed as Equation 3:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_{p-1} y_{t-(p-1)} + \Delta y_{t-p} + \Xi^+ D_t + u_t, \tag{3}$$

where y_t is a $K \times 1$ dimensional vector of variables observed at time t. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. D_t is a vector of deterministic terms, and Ξ^+ is the coefficient matrices corresponding with D_t. 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.

In order to investigate the relationship between our indices and economic activities, we established a variable system based on the VAR model. The CBDCUI, the CBDCAI, the UCRY Policy, the UCRY Price, the ICEA, the MSCI World Banks Index, the VIX, the US EPU, the FTSE All-World Index, and the EUR/USD, GBP/USD, JPY/USD, RUB/USD, and CNY/USD exchange rates, as well as the price of gold and Bitcoin, were selected as the system variables. We ordered variables as indicated by Equation 4:

$$\mathbf{Y}_t = \begin{bmatrix} CBDC1_t \\ CBDC2_t \\ UCRY\ Policy_t \\ UCRY\ Price_t \\ ICEA_t \\ MSCI\ World\ Banks\ Index_t \\ VIX_t \\ USEPU_t \\ FTSE\ All\ World\ Index_t \\ EUR/USD_t \\ GBP/USD_t \\ JPY/USD_t \\ RUB/USD_t \\ CNY/USD_t \\ Gold_t \\ Bitcoin_t \end{bmatrix} \tag{4}$$

where, CBDCUI or CBDCAI was ordered first and second because we believed that the UCRY Policy Index, UCRY Price Index, ICEA, MSCI World Banks Index, VIX, USEPU, FTSE All-World Index, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin could react contemporaneously to uncertainty or attention shocks.

The standard VAR is a reduced form model designed for stationary data forms. If economic theory is used to provide links between forecast errors and fundamental structural shocks, the SVAR model can be used. Accordingly, structural shocks on the system variables y_t based on the VAR can be calculated as Equation 5:

$$\bar{A}_0 y_t = \bar{A}_1 y_{t-1} + \bar{A}_2 y_{t-2} + \cdots + \bar{A}_{p-1} y_{t-(p-1)} + \bar{A}_p y_{t-p} + \bar{\Xi} D_t + \varepsilon_t, \tag{5}$$

where ε_t is a $K \times 1$ dimensional vector white noise process with covariance matrix Σ_ε, also meaning structural shocks. $A_1, A_2, \cdots, A_{p-1}, A_p$ are $K \times K$ coefficient matrices. Pre-multiplying the Equation 3 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. Therefore, from this we can reach Equation 6:

$$u_t = \bar{A}_0^{-1} \varepsilon_t, \tag{6}$$

The SVAR model allows for three tools: the impulse response function (IRF), forecast error variance decomposition (FEVD), and historical decomposition (HD). These are used to capture the dynamic and instantaneous impacts of structural shocks within the variable system (see Equation 4). The three elements can be broadly defined as follows.

4.1.1. Impulse Response Function

When a VAR process is stationary, it can be said it has a moving-average (MA) representation. In the MA representation, the IRF can trace the marginal effect of a shock to one variable by counterfactual experiment. The MA representation can be expressed as Equation 7:

$$y_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i}, \Phi_0 = I_k, \tag{7}$$

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.

4.1.2. Forecast Error Variance Decomposition

The forecast error variance of the k-th element of the forecast error vector can be denoted as Equation 8:

$$E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{j=1}^{K} (\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2), \tag{8}$$

where $\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2$ can represent the contribution of the j-th ε_t innovation to the h-step forecast error variance of variable k. $\frac{\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2}{E(y_{j,t+h} - y_{j,t}(h))^2}$ 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.

4.1.3. Historical Decomposition

u_t can be decomposed into different structural components in the HD – much like what has been analysed above. Equation 7, the MA representation can be further denoted as Equation 9:

$$y_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i} + \sum_{i=t}^{\infty} \Phi_{i,t} u_{t-i}, \tag{9}$$

where the time series can be decomposed into the estimate structural shocks ε from time 1 to time t, and the inestimable structural shocks ε preceding the dataset's start point.

In a stationary VAR 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 10:

$$\hat{y}_t = \sum_{i=1}^{t-1} \Phi_{i,t} u_{t-i}, \tag{10}$$

Therefore, the HD is equal to the weighted sums, which can be measured as the contribution of shock j on variable k in the stationary VAR process. Consequently, the HD can be denoted as Equation 11:

$$\hat{y}_{kt}^{(j)} = \sum_{i=0}^{t-1} \Phi_{kj,t} u_{j,t} \tag{11}$$

Based on the prior ordering in the SVAR Cholesky decomposition, the relationship between reduced form residuals and structural shocks are shown in Equation 12:

$$\begin{bmatrix} u_t^{CBDC_1} \\ u_t^{CBDC_2} \\ u_t^{UCRY\ Policy} \\ u_t^{UCRY\ Price} \\ u_t^{ICEA} \\ u_t^{MSCI\ World\ Banks\ Index} \\ u_t^{VIX} \\ u_t^{USEPU} \\ u_t^{FTSE\ All\ World\ Index} \\ u_t^{EUR/USD} \\ u_t^{GBP/USD} \\ u_t^{JPY/USD} \\ u_t^{RUB/USD} \\ u_t^{CNY/USD} \\ u_t^{Gold} \\ u_t^{Bitcoin} \end{bmatrix} = \begin{bmatrix} S_{11} & 0_{12} & 0_{13} & \dots & 0_{114} & 0_{115} & 0_{116} \\ S_{21} & S_{22} & 0_{23} & \dots & 0_{214} & 0_{215} & 0_{216} \\ S_{31} & S_{32} & S_{33} & \dots & 0_{314} & 0_{315} & 0_{316} \\ S_{41} & S_{42} & S_{43} & \dots & 0_{414} & 0_{415} & 0_{416} \\ S_{51} & S_{52} & S_{53} & \dots & 0_{514} & 0_{515} & 0_{516} \\ S_{61} & S_{62} & S_{63} & \dots & 0_{614} & 0_{615} & 0_{616} \\ S_{71} & S_{72} & S_{73} & \dots & 0_{714} & 0_{715} & 0_{716} \\ S_{81} & S_{82} & S_{83} & \dots & 0_{814} & 0_{815} & 0_{816} \\ S_{91} & S_{92} & S_{93} & \dots & 0_{914} & 0_{915} & 0_{916} \\ S_{101} & S_{102} & S_{103} & \dots & 0_{1014} & 0_{1015} & 0_{1016} \\ S_{111} & S_{112} & S_{113} & \dots & 0_{1114} & 0_{1115} & 0_{1116} \\ S_{121} & S_{122} & S_{123} & \dots & 0_{1214} & 0_{1215} & 0_{1216} \\ S_{131} & S_{132} & S_{133} & \dots & 0_{1314} & 0_{1315} & 0_{1316} \\ S_{141} & S_{142} & S_{143} & \dots & 0_{1414} & 0_{1415} & 0_{1416} \\ S_{151} & S_{152} & S_{153} & \dots & 0_{1514} & 0_{1515} & 0_{1516} \\ S_{161} & S_{162} & S_{163} & \dots & 0_{1614} & 0_{1615} & 0_{1616} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{CBDC_1} \\ \varepsilon_t^{CBDC_2} \\ \varepsilon_t^{UCRY\ Policy} \\ \varepsilon_t^{UCRY\ Price} \\ \varepsilon_t^{ICEA} \\ \varepsilon_t^{MSCI\ World\ Banks\ Index} \\ \varepsilon_t^{VIX} \\ \varepsilon_t^{USEPU} \\ \varepsilon_t^{FTSE\ All\ World\ Index} \\ \varepsilon_t^{EUR/USD} \\ \varepsilon_t^{GBP/USD} \\ \varepsilon_t^{JPY/USD} \\ \varepsilon_t^{RUB/USD} \\ \varepsilon_t^{CNY/USD} \\ \varepsilon_t^{Gold} \\ \varepsilon_t^{Bitcoin} \end{bmatrix} \tag{12}$$

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

4.2. Dynamic conditional correlation model specification

The DCC model, proposed by Engle [2002], enables the identification of the time-varying correlation among different variables. Many studies have applied multivariate GARCH-DCC models to estimate the DCCs [Celık, 2012; Jones and Olson, 2013; Ciner et al., 2013]. However, finding a suitable GARCH-type model is an extremely challenging task. Considering several popular standard GARCH competing models: GARCH(p,q), EGARCH(p,q), GJR-GARCH(p,q), and FI-GARCH(p,d,q), we selected GJR-GARCH(1,1) as the best volatility model based on AIC, SIC, and Log(L) criteria.[5]

The DCC-GJR-GARCH model is an innovative extension of the GARCH model, expanded by including an additional leverage term that detects asymmetries, and it can assess an asymmetric response to positive and negative shocks. The latest research suggests that the DCC-GJR-GARCH model outperforms other standard GARCH competing models in identifying financial variables' DCC [Laurent et al., 2012; Al Mamun et al., 2020; Corbet et al., 2021].

We first set $r_t = [r_{1,t}, \ldots, r_{n,t}]'$ and $\varepsilon_t = [\varepsilon_{1,t}, \ldots, \varepsilon_{n,t}]'$ as the $(n \times 1)$ vector of financial time series returns and the vector of return residuals, respectively. μ denotes a vector of constant with length n. ψ represents the coefficient vector of the autoregressive terms. Second, set $h_{i,t}$ as the parallel conditional volatilities captured from the univariate GARCH process. Therefore, the mean equation with zero mean normally distributed return series can be given as Equation 13:

$$r_t = \mu + \psi r_{t-1} + \varepsilon_t, \varepsilon_t = z_t h_t, z_t \sim N(0,1). \tag{13}$$

Second, we set $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$, otherwise $I_{t-1} = 1$. Moreover, the asymmetric effect of positive and negative shocks are identified by λ (the leverage coefficient). Based on the GJR - GARCH (1,1) model, the conditional volatility $h^2_{i,t}$ can be expressed as Equation 14:

$$h^2_{i,t} = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \lambda\varepsilon^2_{t-1} I_{t-1}, \tag{14}$$

where, when $\lambda < 0$, the negative shocks can have a less of a significant effect on volatility than positive shocks, and when $\lambda > 0$, the positive shocks can have a less significant effect on volatility than negative ones. If parameters ω, α, β, and λ can satisfy the conditions of $\omega > 0$, α, β, $\lambda \geq 0$, and $\lambda + (\alpha + \beta)/2 < 1$, Equation 14 can always hold for a positive and stationarity volatility process [Glosten et al. [1993] and Al Mamun et al. [2020]].

Third, based on the constant conditional correlation model [Bollerslev, 1990], the constant conditional correlation H_t can be denoted as Equation 15:

$$H_t = D_t \times R \times D_t, \tag{15}$$

where, $D_t = diag\sqrt{h_{i,t}}$ and it is the diagonal matrix of the conditional variances, $R = [\rho_{ij}]$ is the $n \times n$ correlation matrix. Since $\varepsilon_t = D_t^{-1} r_t$, we can reach $E_{t-1}[\varepsilon_t] = 0$ and $R = E_{t-1}[\varepsilon_t \varepsilon'_t] =$

[5]The statistical details of GARCH(1,1), EARCH(1,1), GJR-GARCH(1,1), and FIGARCH(1,d,1) are not reported here for the sake of brevity. Moreover, the estimated residuals' lack of autocorrelation effects can be confirmed with the results of the standardised squared residual diagnostic tests. After testing for the existence of potential higher-order moments within the GJR model, we can confirm there are none as the residuals of the marginal models are good enough to identify the return distributions. All results are available upon reasonable request.

$D_t^{-1} \times H_t \times D_t^{-1}$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-n}$.

Based on the Equation 15, a simple estimate of R is the unconditional correlation matrix of the standardised residuals. When R is set as time-varying, we can reach a dynamic correlation model, which can be denoted as Equation 16:

$$H_t = D_t \times R_t \times D_t, \tag{16}$$

where, $R_t = [\rho_{ij,r}]$ is the $n \times n$ time-varying correlation matrix that is computed by the standardised residuals (i.e., $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ computed from the univariate GARCH estimates).

Moreover, based on the DCC model explanations in [Engle, 2002], we can further reach Equation 17, and Equation 18, and Equation 19:

$$R_t = (Q_t^*)^{-\frac{1}{2}} \times Q_t(Q_t^*)^{-\frac{1}{2}}, \tag{17}$$

$$Q_t = (1 - \alpha - \beta)Q_s + \alpha Z_{t-1}Z_{t-1}^{'} + \beta Q_{t-1}, \tag{18}$$

$$(Q_t^*)^{-\frac{1}{2}} = diag\left[\frac{1}{\sqrt{Q_{11,t}}}, \ldots, \frac{1}{\sqrt{Q_{ij,t}}}\right], \tag{19}$$

where, $Q_t = (q_{ij,t})$ denotes the time-varying correlation matrix of Z_t, and $Q_t^* = diag(Q_t)$. Q_s denotes the $n \times n$ unconditional variance matrix of Z_t, and $Q_s = E\left[Z_t Z_t^{'}\right]$. α, and β are non-negative scalars as long as $\alpha + \beta < 1$.

Finally, we can give the element of the conditional correlation matrix $\rho_{ij,t}$ as Equation 20:

$$\rho_{ij,t} = \frac{q_{ij,t}}{q_{ii,t} \times q_{jj,t}} \tag{20}$$

5. Results

To investigate the indices' structural shocks on cryptocurrency, foreign exchange and stock markets as well as banking sectors, uncertainty indices and safe-haven gold, we applied the IRF, FEVD and HD tests derived from the SVAR model. By using the DCC-GJR-GARCH model, we can further examine the interconnections between CBDC indices and financial markets. We will discuss the results of these tests, including their potential underlying causes in full detail in the following subsections. We demonstrate that CBDC indices have a significant negative relationship with the volatilities of the MSCI World Banks Index, USEPU and the FTSE All-World Index, and a positive one with that of cryptocurrency markets, foreign exchange markets, VIX and gold. Considering that the empirical findings from the two econometrics models are identical, we will not interpret them in each subsection for the sake of brevity. However, we will develop an independent subsection at the end of the current one to fully explain the empirical findings and further discuss the underlying excuses.

5.1. Descriptive statistic results

The time-varying of the dynamic returns for each variable can be seen in Figure 5. Table 1 shows the descriptive statistics for the variable system Equation 4. We opted for weekly data to process the empirical analysis. Following [Long et al., 2021], digital currency markets are enormously volatile, meaning that there are many outliers in the very short-term data period (1-min, 30-mins, or daily data). Weekly data is most suitable for analysing digital currency variables and effectively showcases the data's characteristics. We collected CBDCUI and CBDCAI from LexisNexis News & Business. UCRY Policy Index, UCRY Price Index, and ICEA were all collected from Cryptocurrency Indices[6]. We collected the MSCI World Banks Index, VIX, FTSE All-World Index, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, and gold and Bitcoin prices from Thomson Reuters. USEPU[7] was collected from the EPU. Panel A presents the descriptive statistics for the raw data; panel B displays the descriptive statistics for the log return of the raw data; and panel C shows the descriptive statistics for the continuously compounded returns of the raw data. We calculated the continuously compounded returns by processing the first-difference in the logarithmic values of two consecutive prices, expressed as: $CCR_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100$, 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.

As shown in Table 1, we will explain our raw data from the three perspectives of frequency distribution, central tendency, and dispersion. The indices had the same mean values – even when we expanded the decimal point to six. The value of CBDCUI's range was greater than the CBDCAI's, causing the former to have a lower minimum value and a higher maximum value than the latter. The standard deviation values of CBDCUI and CBDCAI were almost identical, and the differences in standard deviation were apparent when we set the decimal point to nine. The CBDCAI had higher skewness and kurtosis valued than the CBDCUI. Furthermore, the skewness and kurtosis values of these two variables were positive. These results indicate that an asymmetrical probability distribution of both indices (the mean was greater than the median, and the tail is on the right side), their being leptokurtic, and rejecting the normal distribution, which was confirmed by the Jarque-Bera tests. Based on the unit root test (ADF, KPSS, and PP) results, unit roots contained in all the (raw) variables were a non-stationary time series.

According to Lütkepohl [2005] and Durlauf and Blume, 2010, a VAR model requires every variable running in the model to be stationary. Therefore, we calculated the log return to Equation 4.

[6] https://sites.google.com/view/cryptocurrency-indices/home?authuser=0
[7] https://www.policyuncertainty.com/index.html

The results are shown in Table 1 in Panel B. Unfortunately, unit roots still existed in all variables confirmed by the ADF, PP, and KPSS tests. Therefore, we calculated the continuously compounded returns to Equation 4. The results are shown in Table 1 Panel C. All the variables showed stationarity in the continuously compounded returns. Baker et al. [2016] used EPU raw data, the log of the S&P 500 Index, and the employment and industrial production log to process the IRF analysis. However, Lütkepohl [2005] and Corbet et al. [2021] indicated that continuously compounded return is more suitable than the log return for analysing the volatility characteristics. As such, we used the continuously compounded returns of Equation 4 to run the VAR and DCC-GARCH models.

[INSERT Table 1 HERE]

Table 2 unveils the Pearson correlation relationship between each variable. We can observe that both indices positively correlated with the volatility of UCRY Policy, UCRY Price, and ICEA indices at the 1% significance level. When compared with CBDCAI, CBDCUI has a stronger positive correlation relationship with the volatility of UCRY Policy ($0.577 > 0.354$) and UCRY Price ($0.578 > 0.355$), but the correlation relationship is weaker with the volatility of ICEA ($0.412 < 0.536$). Furthermore, both indices are also significantly positively correlated with the volatility of VIX, and all exchange rates EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, as well as with gold, and Bitcoin. However, we found negative correlation between both CBDC indices and the volatility of the MSCI World Banks Index, USEPU, and the FTSE All-World Index.

[INSERT Table 2 HERE]

5.2. VAR model estimation results

As for CBDCUI, the coefficient values of CBDCAI, UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin were all greater than 0 at the 10% significance level. In particular, the CBDCAI and ICEA were able to pass the significance tests at the 1% level. These statistics indicate that the CBDCUI positively effects the volatilities of the financial variables. The coefficient values of the MSCI World Banks Index, USEPU, and FTSE All-World Index were less than 0 at the 10% significance level, meaning that the CBDCUI negatively affects the volatilities of these financial variables. Considering the R^2, we found the adjusted R^2 to be 0.824, meaning that this VAR model estimation can explain 82.4% of the CBDCUI's variations. Furthermore, the residual standard error was low (0.450), and the F statistic equalled 3.988 at the 1% significance level. These statistics further prove that this VAR model estimation about CBDCUI is satisfactory and has a strong predictive capability.

As for the CBDCAI, the coefficient values of CBDCUI, UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin were greater than 0 at the 10% significance level – thereby suggesting the CBDCAI's positive effect on the volatilities of the financial variables. The coefficient values of the MSCI World Banks Index, USEPU, and FTSE All-World Index were less than 0 at the 10% significance level, indicating the CBDCAI's negative effect on the financial variables' volatilities. Considering the R^2, the adjusted R^2 was 0.822, meaning that this VAR model estimation could explain 82.2% of the CBDCAI's variations. Furthermore, the residual standard error was low (0.297), and the F statistic equalled 1.466 at the 1% significance level. These statistics further prove that this VAR model estimation about CBDCAI is satisfactory and has a strong predictive capability.

[INSERT Table 3 HERE]

5.3. CBDC shocks on the dynamics of financial variables volatility

In this subsection, we examine the effects of the indices' shocks on the financial variables' volatilities in Equation 4 from different time horizons. Figure 6 and Figure 7 show that the impulse response of financial variables in the structural CBDCUI is to continuously compound returns, as well as for CBDCAI shocks in short-, mid-, and long-term time horizons. 0–2, 2–4, 4–6, 6–8, 8–10, and >10 represent the very short-term, short-term, mid-term 1, mid-term 2, long-term, and very long-term, respectively.

As for CBDCUI shocks on the dynamics of financial variables' volatility, we can draw several inferences from Figure 6. First, we have empirically verified that CBDCUI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in the very short-term period. However, this increase tends to quickly drop to a negative value at the end of this period (expect for RUB/USD and CNY/USD). Moreover, CBDCUI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index in the very short-term period – although this decrease tends to reverse rather rapidly (except for the MSCI World Banks Index). Second, CBDCUI shocks can slightly decrease the volatilities of UCRY Policy, UCRY Price, ICEA, the MSCI World Banks Index, VIX, USEPU, FTSE All World Index, EUR/USD, GBP/USD, JPY/USD, and gold in the short-term, and maintains an increasing growth trend. Additionally, CBDCUI shocks can slightly increase the volatilities of RUB/USD, CNY/USD, and Bitcoin in the short-term period, and maintains a decreasing growth trend. Third, although CBDCUI can still slightly affect financial variables from the mid-term, the selected financial markets and indices' responses tend to quickly show a convergence trend. Fourth, based on these three inferences, we can draw two short conclusions that, CBDCUI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin as a whole. Moreover, CBDCUI shocks can also significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index overall.

[INSERT Figure 6 HERE]

As for CBDCAI shocks, we can also draw several inferences from Figure 7. First, we empirically verified that CBDCAI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX and CNY/USD in the short-term period. CBDCAI shocks on UCRY Policy, UCRY Price, and VIX show an increasing trend, whereas CBDCAI shocks on the ICEA and CNY/USD display a decreasing trend. CBDCAI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index in the short-term, which maintains an increasing trend. CBDCAI shocks can significantly increase, but also can slightly decrease (the initial significant increase is followed by a slight decrease), the volatilities of EUR/USD, GBP/USD, JPY/USD, RUB/USD, gold, and Bitcoin in the short-term. Additionally, for these financial variables, positive shocks tend to have a greater effect in the very short-term. Second, slightly negative shocks from the CBDCAI have a greater short-term effect for all of the variables. However, as for the variables which receive positive shocks from the CBDCAI at the very short-term period, the small negative shocks from CBDCAI at the short-term are not significant enough to contribute a significantly negative effect as a whole, the positive shock results are still dominant in the final results. Third, although the CBDCAI can still have positive or negative effects on financial variables at the mid- or long-term, the responses of the financial variables begin to converge from the former. Fourth, these three inferences can lead to three short conclusions. First, the results of CBDCAI shocks on the dynamics of financial variables' volatility are the same as those relating to CBDCUI shocks. Second, CBDCAI shocks can significantly increase the volatilities of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin. Third, CBDCAI shocks can significantly decrease the volatilities of the MSCI World Banks Index, USEPU, and the FTSE All-World Index.

[INSERT Figure 7 HERE]

5.4. Contributions of CBDC disturbances to the variation of financial variables' volatility

From Figure 8 and Table 6, we can see that a shock from the CBDCUI (100% to 85%) could play a non-trivial role in explaining variations in the CBDCUI FEVD. CBDCAI (7.8% to 9.1%) was also a relatively significant variable in explaining variations in the CBDCUI FEVD. Considering the three cryptocurrency indices, the ICEA (2.3957% to 2.4317%) had a greater contribution to the CBDCUI's fluctuations – a novel finding. Cryptocurrency environmental attention contributed more to the CBDCUI variations than cryptocurrency policy uncertainty and cryptocurrency price uncertainty. As for the five foreign exchange rate variables, JPY/USD (0.8302% to 0.8636%) was the most important for CBDCUI variations. Gold (0.03%) and Bitcoin (0.1%) can only be used to explain a small part of the CBDCUI's variations.

From Figure 8 and Table 6, the dominant role that a shock from the CBDCAI (94.73% to 93.83%) could play in explaining variations in the CBDCAI FEVD. However, the CBDCUI's explanation power in the FEVD of CBDCAI was significantly lower than that of the CBDCAI. Due to the dominant role of the CBDCAI, and the lower importance of the CBDCUI's contributions in the FEVD of CBDCAI, the contributions from the other variables become more significant on the percentage level (despite each variable's contribution value being lower than those in the CBDCUI FEVD). For example, the contributions from the three cryptocurrencies have become more critical to the CBDCAI FEVD. Compared with the joint contributions of the ICEA with UCRY Policy and UCRY Price, ICEA (0.9661% to 1.2249%) still had the leading role. Compared with the two world indices, the MSCI World Banks Index was more relevant (0.4105% 0.4409%) than the FTSE All-World Index in explaining the CBDCAI's FEVD. Compared with the two uncertainty indices together, the VIX (0.584% to 0.5957%) was relatively more important than the USEPU in explaining the FEVD of CBDCAI. Although JPY/USD (0.4968% to 0.4988%) was still important for the FEVD of CBDCAI among other foreign exchange rates, the RUB/USD (0.8836% to 0.8882%) had the greatest contribution to the CBDCAI's variations. Surprisingly, although China is leading the CBDC revolution, CNY/USD (0.0168% to 0.0485%) was relatively less important in explaining the variations in the CBDCAI FEVD. Compared with the role of Bitcoin in CBDCUI FEVD, Bitcoin is relatively more important (0.3602% to 0.3898%) in explaining the FEVD of CBDCAI. Moreover, we found that gold (4.10E-05) did not greatly contribute to the CBDCAI's variations.

5.5. Cumulative contributions of CBDC disturbances to the financial variables' volatility

While Figure 8 and Table 6 assess the timing and magnitude of the indices' responses to a typical structural shock, they do not quantify how much of each shock explains the historical fluctuations in the CBDCUI and CBDCAI. Therefore, it is essential to investigate the historical evolution of both indices, and the contribution of each of the structural shocks to fluctuations in both, mainly following major historical episodes. Based on the HD method introduced in the previous section, Figure 9 and Figure 10 present the cumulative contributions of CBDCUI and CBDCAI disturbances to the volatilities of financial variables under dynamic economic environments. The contribution of CBDCUI shocks is given in the red, while the contribution of CBDCAI is presented in light blue.

Several conclusions can be drawn from Figure 9 and Figure 10. Firstly, we found that both the cumulative positive and negative effects of CBDCUI disturbances on financial variables were larger than those of the CBDCAI. The reasons seem abundantly clear: the uncertainty index fluctuates more than the attention index, and financial markets are also more sensitive to shocks from uncertainty indices. Our findings reconfirm those of [Lucey et al., 2021 and Lucey et al., 2021]. Secondly, the contributions of the estimated CBDCUI shocks to the evolution of the financial variables' volatilities changed over time, and we found that they tended to be larger between March 2015 to July 2015, February 2017 to December 2018, June 2019 to August 2019, and April 2020 to July 2021. Generally speaking, these positive or negative shocks appear perfectly reasonable. Indeed, in the first larger cluster period, we found that some good news about CBDC could have significantly negative shocks on the CBDCUI's HD results. For example, dollarisation and the launch of an electronic monetary system in Ecuador. Furthermore, new government CBDC regulations also negatively affected the CBDCUI's HD results. For example, the Chinese government revised its Anti-Money Laundering Law because digital currency makes Anti-Money Laundering enforcement challenging. Regarding the positive shocks in the first larger cluster, we clearly found that the new digital money process in commercial banks could have significant positive effects on the CBDCUI's HD results. For example, M-payment progresses in Brazil, Colombia, and Peru, and PayPal's announcement of their acquisition of Xoom.

It is worth noting that CBDC's progress in the UK may have significantly and positively affected the CBDCUI's HD results in the first larger cluster. In other words, between March 2015 to July 2015, the UK's new CBDC progress could have increased the CBDCUI. Analysing the second larger cluster period with the third and fourth also yielded several interesting findings. First, new CBDC developments (e.g., the digital-CAD, digital-EUR, digital-USD, etc,) significantly decreased CBDC uncertainties. However, it is also worth noting that the UK's CBDC performed differently, and thus increased CBDC uncertainty before the larger cluster in period four. Besides, perhaps because the Renminbi is not a free-float currency, it is hard to place it into the first portfolio position. Alternatively, many regulators and investors are concerned that the digital-RMB could challenge the USD's international hegemony. The new developments of digital-RMB could increase CBDC uncertainty, that is, until Hong Kong helps with its offshore digital-CNH test. Second, negative CBDC news can significantly increase CBDC uncertainties. For example, the Danish Central Bank's cancellation of its CBDC plans, the Deutsche Bundesbank's warning that there will be no CBDC in the Euro-zone, and the Deutsche Bundesbank and the Schweizerische Nationalbank's anti-CBDC plans. Furthermore, significant cryptocurrency events, as well as COVID-19, have seemingly increased CBDC uncertainties.

The contributions of the estimated CBDCAI shocks to the evolution of the financial variables' volatilities are changing over time, and we clearly noted the presence of four larger clusters between May 2016, December 2017, January 2018, June 2019 to July 2019, and March 2021 to July 2021. We also successfully captured which significant events could cause these larger positive or negative shocks. These shocks match the expectations of the public to a certain extent. For example, digital-CAD, digital-USD, digital-RMB, and the Bahamas Sand Dollar prepaid card, as well as other forms of new CBDC progress, could significantly and positively affect the CBDCAI's HD results. However, during the 2021 cryptocurrency bull market, South Korea-based Shinhan Bank and the Central Bank of Russia's new CBDC announcements showed a significantly negative impact on the CBDCAI's HD results.

Furthermore, we can notice that certain significant events from the cryptocurrency market could also have significantly positive impacts on the CBDCAI's HD results. For example, Bitcoin's one-year bull market, and its record highs for both price and transaction values. In terms of the negative shocks, some negative CBDC news could have significantly negative impacts on CBDCAI's HD results. For instance, the Swiss town of Zug is planning to allow its residents to use Bitcoin to pay for municipal services; and the aforementioned plans of the Danish Central Bank, the Deutsche Bundesbank, and the Schweizerische National Bank. Additionally, potential CBDC concerns, such as how it cannot be applied to less developed areas due to poor internet connections. Moreover, due to its reliance on smart devices and technology, CBDC may not be ideally suited to the elderly. Other concerns include CBDC's energy consumption and environmental issues, and free-float concerns regarding the digital-RMB. More details about these events can be found in the Appendix-A.

[INSERT Figure 9 HERE]

[INSERT Figure 10 HERE]

5.6. Dynamic conditional correlations

Table 4 and Table 5 displays the bivariate AR(1)-GJR-GARCH(1,1)-DCC model results for CBDCUI/CBDCAI and each financial variable in Equation 4.

Regarding the interconnections between the CBDCUI and financial variables, as shown in Panel A of Table 4, the ARCH and GARCH parameters were negative and statistically significant at the 5% level for the volatility of the MSCI World Banks Index, USEPU, and FTSE All-World Index. The ARCH and GARCH parameters were positive and statistically significant at the 10% level for the volatility of the others' financial variables. The GJR parameters were significant for all variables. Panel B of Table 4 reveals the DCC between the CBDCUI's volatility and other financial variables. This allowed us to obtain three findings. First, the CBDCUI had a positive and statistically significant DCC with the volatility of UCRY Policy, UCRY Price, ICEA, VIX, EUR/USD, GBP/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in both the short- (a) and long-term (b). Second, the CBDCUI had a significantly small positive DCC with the volatility of the MSCI World Bank Index and FTSE All-World Index in the short-term, but a significantly negative DCC with both indices in the long-term. The value of b was significantly greater than a. Therefore, we can infer that the CBDCUI had a significantly negative DCC with the MSCI World Bank Index and FTSE All-World Index in general. Third, the CBDCUI had a significantly negative DCC with the volatility of USEPU in both the short- and long-term.

In terms of the interconnections between the CBDCAI and financial variables, as shown in Panel A of Table 5, the ARCH and GARCH parameters were also negative and statistically significant for the volatility of the MSCI World Bank Index, USEPU, and FTSE All-World Index, and the ARCH and GARCH parameters were positive and statistically significant for the volatility of the others' financial variables. The GJR parameters were significant for all variables. Panel B of Table 5 reveals the DCC between the CBDCAI and other financial variables, thus leading to three results. First, the CBDCAI had a significantly positive DCC with the volatility of UCRY Policy, UCRY Price, ICEA, VIX, and GBP/USD in both the short- and long-term. Second, the CBDCAI had a significantly small negative DCC with the volatility of EUR/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in the short-term, but has a significantly positive one in the long-term. Furthermore, the value of b was significantly greater than that of a. Therefore, we can infer that the CBDCAI has a significantly positive DCC with the volatility of EUR/USD, JPY/USD, RUB/USD, CNY/USD, gold, and Bitcoin in general. Third, the CBDCAI had a significantly negative DCC with the volatility of the MSCI World Banks Index, USEPU, and FTSE All-World Index in both short- and long-term, although the long-term effects were significantly stronger.

Regarding the CBDCUI and CBDCAI DCC results, it is worth noting that the volatilities of the same financial variables reacted differently to both indices. For example, compared with the CBDCUI, the volatility of the UCRY Policy had a stronger long- and short-term DCC relationship with the CBDCAI. Moreover, the volatility of the UCRY Price and ICEA had a stronger short-term DCC relationship with the CBDCAI. However, these stronger relationships did not exist in the long-term, and the volatility of the UCRY Price and ICEA were more sensitive to the CBDCUI in the long-term ($0.8457 > 0.8452$, $0.6829 > 0.000001$).

[INSERT Table 4 HERE]

[INSERT Table 5 HERE]

Figure 11 and Figure 12 displays the time-varying correlations between CBDCUI/CBDCAI and each financial variable in Equation 4.

As for the CBDCUI, the dynamic correlations between changes in the Bitcoin, CNY/USD, EUR/USD, gold, ICEA, RUB/USD, UCRY price, and VIX were significantly positive across the entire research period – thus providing a potential safe haven ability. However, some details require further explanation. The maximum dynamic correlation value between the CBDCUI and Bitcoin, i.e., 0.2786, occurred on 2020-03-20, while the minimum value, i.e., 0.0318, occurred on 2021-04-30. The dynamic correlations between the CBDCUI and CNY/USD showed a significant increase trend after China's Central Bank began to both test and launch CBDC. Three peaks are visible in the dynamic correlation between the CBDCUI and EUR/USD. The first one is the cryptocurrency bear market and the China–US trade war of 2018–19. The second was due to Brexit in the second half of 2019, and the third occurred due to the cryptocurrency bull market in 2021. Regarding the CBDCUI and gold, there was a significant cliff-like drop in 2017–18, which may have been caused by the Federal Reserve's interest rate hike. The most volatile dynamic correlation relationships exist in the CBDCUI and VIX, which may explain why some refer to the VIX as a fear index. The dynamic correlation values between the CBDCUI and GBP/USD, CBDCUI and JPY/USD, CBDCUI and MSCI World Bank Index, and the CBDCUI and UCRY Policy were both significantly partially positive and negative[8]. From the negative dynamic correlation periods, we found that,

[8] For the sake of brevity, we list these negative dynamic correlation periods in the *Appendix-C*.

generally speaking, the partial significantly positive dynamic correlations were the most significant relationships between the CBDCUI and the UCRY Policy, GBP/USD, and JPY/USD. Moreover, the partial significantly negative dynamic correlations were the foremost relationships between the CBDCUI and MSCI World Bank Index. We found the degrees of dynamic correlations between changes in the CBDCUI and USEPU, and the CBDCUI and FTSE All-World Index were negative throughout the entire research period, thereby providing the potential ability of the hedging strategy.

Regarding the CBDCAI, the degrees of dynamic correlations between changes in the CBDCAI and Bitcoin, CNY/USD, EUR/USD, GBP/USD, gold, ICEA, UCRY Policy, and VIX were positive and statistically significant throughout the whole research period. These empirical results imply that one unit increase in CBDC attention can increase the volatilities of Bitcoin, CNY/USD, EUR/USD, GBP/USD, Gold, ICEA, UCRY Policy, and VIX. The dynamic correlation values between the CBDCAI and JPY/USD, the CBDCAI and RUB/USD, and the CBDCAI and UCRY Price were both significantly partially positive and negative[9]. From the negative dynamic correlations periods, we found that, generally speaking, the partial significantly positive dynamic correlations to be the most important relationships between the CBDCAI and UCRY Price, RUB/USD, and JPY/USD. The degrees of dynamic correlations between changes in the CBDCAI and FTSE All-World Index, CBDCAI and MSCI World Banks Index, and CBDCAI and USEPU were negative throughout the whole research period, thus evidencing the potential availability of the hedging strategy.

[INSERT Figure 11 HERE]

[INSERT Figure 12 HERE]

5.7. A comprehensive interpretation in empirical findings

To start, we want to discuss the potential reasons why CBDC indices have a significant positive relationship with the volatility of cryptocurrency markets. It is clear that CBDCUI represents uncertainty, which has conduction effects on financial markets [Cao et al., 2017], so one variable's uncertainty may cause such in other variables. Thus, there exists a definite correlation between CBDC and cryptocurrency in terms of uncertainty. Second, upon examining the high CBDCUI periods in detail from Figure 4 and Figure 9, we find that the high CBDCUI values are aroused by unfavourable news regarding CBDC or cryptocurrency flash events. As we mentioned many times above, CBDCs can be viewed as 'cryptocurrency counters' launched by central banks. Consequently, the negative news for CBDC results in an acceptable signal for cryptocurrency. Under this condition, cryptocurrency investors could increase their transaction and speculation activities, which will raise

[9] For the sake of brevity, we list these negative dynamic correlation periods in the *Appendix-C*.

uncertainty in relevant markets. For example, during cryptocurrency flash event periods (e.g., Bitcoin value record high and Bitcoin transaction volume record high). As a result, cryptocurrency markets experienced extreme volatility and uncertainty, and these fluctuations can be conducted to the CBDC. This is also can explain why CBDCUI has a meaningful positive relationship with the volatility of cryptocurrency markets.

Third, the reasons CBDCAI sport a substantial association with the cryptocurrency market's volatility are similar to those with CBDCUI. From Figure 4 and Figure 10, we can clearly observe that CBDCAI is occasionally dragged up by major cryptocurrency events. For example, during Bitcoin's one-year bull market, Bitcoin hit a record-high $63503 while volumes recorded 1.26358E+11, among others. Moreover, CBDC is a well-known fiat digital currency, which aims to be 'anti-cryptocurrency.' Therefore, a heated discussion on or intensive attention of CBDC will trigger the fluctuations in the cryptocurrency markets. Fourth, we also desire to explain why CBDC indices can influence the volatility behind ICEA. Importantly, although the central banks launch CBDCs, they are still digital currencies. As such, CBDCs also will consume energy and thus pollute the environment. ICEA is an index that captures the cryptocurrency attention on environmental issues. Therefore, CBDC indices and ICEA volatility showcase a meaningful correlation with one another.

Now, we will explain why the CBDC indices have a significant positive relationship with the volatility of the foreign exchange markets. First, one possible explanation is that the rise in CBDC uncertainty and attention can motivate foreign exchange traders to reduce or increase their net long positions, thus directly inducing fluctuations in the foreign exchange rate. Second, many scholars studying the CBDC have not realised this point until now. The essence of CBDC is the fiat currency. With the development of CBDCs, the public has access both to cash and digital currency, which leads to increased supplies of both in general. The supply influx may lead to inflation. Undoubtedly, liquidity will increase by developing CBDCs, but excess supply will cause disruptions and major inflation. Under this circumstance, increasing one country's inflation rate will increase the volatility of its currency exchange rate. Moreover, because of a conduction effect, the same will occur between one country's currency exchange rate and that of other currencies. Third, CBDCUI is an uncertainty index. High uncertainty maybe can cause high volatility. Fourth, from Figure 4 and Figure 10, we can see that excellent news about CBDCs spikes the high CBDC attention value (e.g., the CBDCs' new developments). As we mentioned, CBDCs can increase the liquidity of currencies, which also means the cost of currency circulation is reduced, and foreign exchange transactions will become easier to perform. Therefore, the cost of the foreign exchange speculation transactions will lower, and the foreign exchange speculation activities will also increase, bringing more fluctuations to foreign exchange markets. This is especially true for CNY due to the progress of cross-border transactions involving e-CNY. The exchange rates of CNY will definitely become more volatile.

Thirdly, we want to explain the relationships between CBDC and uncertainty indices (i.e., VIX and USEPU). Moreover, we will further elucidate on the inconsistency between the two sets of relationships. Our empirical findings indicate CBDC indices have a significant positive relationship with the volatility of VIX but conversely have a negative one with that of USEPU. First, one possible explanation behind the latter case concerns the 'stablecoin' characteristic of CBDC. This empirical evidence reconfirms the notion of [Larina and Akimov, 2020; Copeland, 2020; McLaughlin, 2021 and Buckley et al., 2021] that CBDCs positively impact the financial and policy stability. Second, based on our unconditional correlation table Table 2 and the literature about USEPU and VIX, the USEPU and the VIX should express a positive relationship. Why are the relationships between CBDC indices and USEPU, the relationships of CBDC indices and VIX inconsistent? The potential explanations could be that the VIX-EPU relationship is not always positive and is time-variant, and USEPU and VIX are more coherent to the developed market (i.e., France, Germany, Japan and the United Kingdom), which is confirmed by [Tiwari et al., 2019].

However, our CBDC indices boast wider coverage (e.g., China, Russia, Swiss, Spain, Portugal, etc.), also including some developing countries (e.g., Ukraine, Panama, Ecuador, etc.). These points potentially can explain the inconsistencies in the relationships between CBDC and uncertainty indices. Third, the likeliest reason for the significant positive relationship between CBDC indices and VIX is that the latter is related to the market's expectations for the volatility in the S&P 500 over the coming 30 transaction days, and the S&P 500 contains 500 large companies listed on stock exchanges in the USA. From the news our indices captured, we know that, although the e-USD is being tested, the progress remains slow. China and its e-CNY are leading in the CBDC. The new progress of e-CNY can spike both CBDCUI and CBDCAI. Moreover, many media, scholars and investors believe that e-CNY is challenging the hegemony of the USD and will supplant it as the most important currency used for international settlements. This kind of viewpoint will shake the confidence of US financial markets and cause panic in the US stock market, especially for large companies with prominent international businesses.

Fourthly, we want to illustrate that why CBDC indices have a significant positive relationship with the safe-haven gold. First, with the increasing of CBDC uncertainties, speculation transaction activities concerning Gold as a safe haven also will increase, thus causing gold price fluctuations. Second, the significant positive relationship between CBDCAI and gold can be similarly explained by the aforementioned gold speculation transactions. This empirical evidence confirms our concerns that CBDC may lead to inflation because favourable CBDC news spike CBDCAI in general, and gold is a safe haven against anti-inflation. If some investors value CBDC from an analyst perspective, they may also find this phenomenon a potential issue. They will increase their net long positions in gold, thus directly inducing fluctuations in gold prices.

Fifthly, CBDC indices have a significant negative impact on the volatility of the MSCI World Bank Index, which is caused by the operating system of CBDC. Currently, multiple countries have adopted the two-level operation system of CBDC. For example, the People's Bank of China converts e-CNY to the designated operating institutions such as commercial banks or other commercial institutions and allows these institutions to convert e-CNY to the public instead of directly issuing and converting CBDC to the public. The conversion of CBDC adopts the conversion process of 1:1, which means commercial banks and other operating institutions must pay the central bank the reserve fund of 100%. The two-level operation system of CBDC guarantees the reasonability of CBDC issuances like the issuance of paper currencies, which will negatively influence the existing financial system and impact the real economy or financial stability such as increasing inflation rate, competing for commercial banks and traditional financial institutions and stimulating the speculative transactions of the financial market. Digital Currency/Electronic Payment (DC/EP) in China adopts the two-level operation mode to guarantee the excess issuance of CBDC. When the currency production requirement meets verification rules, corresponding limit vouchers will be sent, which will neither negatively influence the inflation rate nor compete with the traditional business model of commercial banks. This empirical finding reconfirm the notion of [Sissoko, 2020 and Zams et al., 2020] that CBDC can balance the banking system and reduce the shadow banking, but different from [Yamaoka, 2019; Zams et al., 2020; Sinelnikova-Muryleva, 2020; Williamson, 2021 and Fernández-Villaverde et al., 2021], who believe that CBDC can upset commercial banking and central banks will become deposit monopolists by issuing CBDCs.

In point three, we demonstrate why the CBDC indices have a significant relationship with the volatility of the VIX. However, the FTSE All-World Index is also an index related to the stock market, and its volatility shows a significantly negative relationship with CBDC indices. As for why this phenomenon exists, we need to differentiate between the scopes of the VIX and the FTSE All-World Index and also focus on the characteristics of CBDC. As we justified above, VIX focuses on the big companies in the U.S. financial market, but FTSE All-World Index covers over 3,100 companies in 47 countries. Therefore, we can assign the FTSE All-World Index as a representative for the all-world stock markets. Moreover, CBDC is a 'stablecoin,' and the significant negative relationships between CBDC indices and the volatility of the FTSE All-World Index can prove the characteristics of 'stablecoin' of CBDC. These two empirical proofs consistent with [Zams et al., 2020; Tong and Jiayou, 2021; Barrdear and Kumhof, 2021; Fantacci and Gobbi, 2021], who suggest that CBDC can improve financial inclusion, mitigate systemic financial risk and raise GDP.

5.8. Robustness test

As we sought to identify the effects of CBDC indices on financial markets, we selected the SVAR and DCC-GJR-GARCH models as the two econometrics models that would most effectively help us achieved our research aim. In order to obtain a more rigorous conclusion, we considered it necessary to design and process several robustness tests. The core heart of the indices' effects on financial markets with SVAR and DCC-GJR-GARCH models is the relationships between the indices and the financial variables. From our empirical analysis, we concluded that both CBDC indices had a significantly negative relationship with the MSCI World Bank Index, USEPU, and

FTSE All-World Index. Moreover, both CBDC indices had a significantly positive relationship with the other financial variables. Therefore, our robustness tests could focus on how to confirm these relationships between the CBDC indices and those financial variables.

In order to evaluate the reliability of the empirical results, we first further analysed the relationship between CBDC indices risk and financial variables' volatility. Our hypothesis is as follows:

H_0: CBDC indices risk increases, financial variables' volatility also increases.

Or

H_0: CBDC indices risk increases, financial variables' volatility decreases.

To evaluate the significance of the relationship, we followed the methodologies of [Pástor and Veronesi, 2013; Demir et al., 2018 and Al Mamun et al., 2020]. The regression model is as follows Equation 21:

$$FV_t = \beta_1 + \beta_2 CBDC_t + \beta_3 FV_{t-1} + \varepsilon_t, \tag{21}$$

where, FV denotes financial variable volatility, and $CBDC$ denotes the $CBDC$ uncertainty risk or the $CBDC$ attention risk, FV_{t-1} is designed to removing any serial correlation in FV_t. ε is the error term.

We tested this hypothesis as a null hypothesis of when $\beta_2 > 0$, indicates that the volatility of financial variables increases under more uncertainty or attention; when $\beta_2 < 0$, indicates that the volatility of financial variables increase when there is less uncertainty or attention.

First, FV and $CBDC$ are still calculated by the continuously compounded returns. The results are shown in Table 7 columns (1) and (2).

The results in columns (1) and (2) show the significance of the results at the 10% level. The β_2 values of the MSCI World Bank Index, USEPU, and FTSE All-World Index in the CBDCUI and CBDCAI were less than zero, thus implying that the volatility of these three financial variables had a negative relationship with the CBDCUI and CBDCAI. In other words, the volatility of the MSCI World Bank Index, USEPU, and the FTSE All-World Index decrease in the face of greater CBDC uncertainty or attention. The β_2 values of the other financial variables (except for the three just discussed) were greater than zero, thereby indicating a positive relationship between these financial variables and the CBDCUI or CBDCAI. These additional results accord with our former empirical analysis, thus proving our main findings' robustness.

Second, while we still followed the formula of Equation 21, we calculated the FV and $CBDC$ by the realised variance. For example, denoting the nearby weekly variable value at time t as S_t, the realised variance from time 1 to time T, denoted as $RV_{t,T}$, can be computed as: $RV_{t,T} = \frac{1}{T}\sum_{i=1}^{T}(r_{t+i} - \overline{r_{t+i}})^2$, where $r_{t+i} = 100 \times ln(S_{t+i}/S_{t+i-1})$ and $\overline{r_{t+i}} = 100 \times \overline{ln(S_{t+i}/S_{t+i-1})}$ are the one-period return and the average return for T periods. The results are shown in Table 7 columns (3) and (4).

From the results in columns (3) and (4), although we calculated all of the variables in a realised variance, the relationships between the financial variables and the CBDC indices (which we demonstrated in the former empirical analysis) still held in the Equation 21. Moreover, the MSCI World Banks Index, USEPU, and FTSE All-World Index showed a statistically significant negative relationship with the CBDCUI or CBDCAI at the 10% significance level. The statistically significant positive relationships between the other financial variables and CBDC indices were also still at the 10% level. The results from this Equation 21 further prove the robustness of our main empirical findings.

Secondly, the robustness test of our results can be confirmed using the methodology of Whaley [2009]. When $CBDC_t$ displayed a negative relationship with FV_t, we found that the changes in $CBDC_t$ rose at a higher absolute rate when the FV_t fell than when it increased. In other words, when $CBDC_t$ showed a positive relationship with FV_t, the changes in $CBDC_t$ rise at a higher absolute rate when the FV_t rises, than when the FV_t falls. The regression model is as follows Equation 22:

$$CBDC_t = \beta_1 + \beta_2 FV_t + \beta_3 FV_t^- + \varepsilon_t, \tag{22}$$

where $CBDC$ and FV are still calculated by the continuously compounded return and represent the rate of change of the CBDCUI, CBDCAI, and financial variables. FV^- denotes the rate of change of the financial variables conditional on the market going down, and zero otherwise. ε is the error term.

First, if CBDC has a positive relationship with FV, both of the slope coefficients of FV and FV^- would have to be greater than zero. The second condition is that the slope coefficient of FV is more significant than zero, and the slope coefficient of FV^- less than, but the coefficient value of FV would be greater than that of FV^-. If CBDC has a negative relationship with FV, both of the slope coefficients of FV and FV^- should be less than zero.

The results are shown in Table 7 columns (5) and (6). The results of the robustness test confirmed our empirical results reported earlier. Moreover, the results allow us to clearly observe that the CBDCUI and CBDCAI have a statistically significant and negative relationship with the MSCI World Banks Index, USEPU, and FTSE All-World Index. Additionally, the CBDCUI and CBDCAI have a statistically significant and positive relationship with the other variables. For example, if the USEPU rises by 100 basis points, the CBDCUI will fall by: $CBDCUI_t = -0.000,2 \times (0.01) = -0.000,2\%$, and if the USEPU falls by 100 basis points, the CBDCUI will rise by: $CBDCUI_t = -0.000,2 \times (-0.01) - 0.002,5(-0.01) = 0.000,002 + 0.000,025 = 0.000,027 = 0.0027\%$.

[INSERT Table 7 HERE]

6. Conclusions

This paper assesses the impact of CBDC news on financial markets using the over 660m news items collected from LexisNexis News & Business database. Specifically, we introduce two new measures of uncertainty and attention for CBDC that can be used by cryptocurrency researchers, investors, and financial regulators in their subsequent work.

Our new CBDC Uncertainty Index (CBDCUI) and the CBDC Attention Index (CBDCAI) have been constructed and made available for the period from January 2015 to June 2021. We employ a battery of empirical test to examine the behaviour of CBDC indexes in relation to cryptocurrency markets (i.e. UCRY indices, ICEA and Bitcoin), other popular uncertainty measures (i.e. VIX and USEPU), financial markets (i.e. FTSE All-World Index), banking sectors (i.e. MSCI World Bank Index) and exchange rates (i.e. EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD) during this period and capture the dynamics of these interrelationships.

Our empirical results suggest that CBDC indices have a significantly negative effect on the volatilities of the MSCI World Banks Index, USEPU, and FTSE All-World Index. However, CBDC indices have a significantly positive effect on the volatilities of UCRY Policy, UCRY Price, ICEA, and Bitcoin (cryptocurrency markets), EUR/USD, GBP/USD, RUB/USD, JPY/USD, and CNY/USD (foreign exchange markets), as well as VIX and gold. Furthermore, the volatilities of financial variables are more sensitive to CBDCUI when compared with reactions from CBDCAI shocks, highlighting the importance of CBDC uncertainty in this interconnected system. The HD results suggest that both cumulative positive and negative effects of CBDCUI's disturbances on financial variables are larger than those of CBDCAI disturbances. These results display that uncertainty around CBDC news plays more important role that just an attention to this new digital assets, which suggest that introduction of CBDC can bring significant changes to the economy. Our results show that good news and positive government policies can significantly negatively affect the CBDCUI HD results, by decreasing the uncertainty around these assets. However, the HD results for both the CBDCUI and CBDCAI show significant spikes near key CBDC innovations and important digital currency events. The results of the robustness test demonstrate the reliability and validity of our empirical findings.

In terms of methodology, our paper further contributes to the literature by showcasing how to make the most effective use of internet literature database archives to develop and issue new indices of interest to financial areas. This methodology can provide a new channel to more comprehensively understand broad financial developments by systematic online empirical inquiries.

While early research suggests that Bitcoin is by far the most influential cryptocurrency [Corbet et al., 2020a], the most recent evidence indicates that crypto-assets can be categorised as decentralised applications (dapps) and protocols, and have become more attractive for investors than ‘pure’ cryptocurrencies [Katsiampa et al., 2021]. This displays a shift in consumer and investor preferences from pioneer cryptocurrency towards more innovative, scalable, and versatile digital payment instruments and assets. Thus, CBDC may become a competitive product for investors and cryptocurrency users, thereby bridging the gap between cryptocurrency and traditional markets for widespread use.

We believe it pertinent to mention several research pathways for future investigation. As another innovation of a central bank’s financial system, CBDC is aimed at the digitisation, decentration, and disintermediation of sovereign currency. From a global monetary perspective, applying these (central bank-endorsed) digital currencies is a new step towards modern society’s digital transformation. As CBDC continues progressing, the functions of sovereign currency will be enriched, and sovereign currency will be endowed with such new functions as value storage and measurement, and free convertibility instead of a single payment tool. As society increasingly accepts CBDC, the global financial system will be changed dramatically and inevitably in multiple aspects, such as daily individual payment modes, the payment system of society as a whole, the structure of the commercial banking system, and even the operation of the capital market. Countries assuming the leading role regarding CBDC can maintain effective competitive advantages during the digitisation of global currencies. While promoting the internationalisation of sovereign currency, CBDC can improve the financial software power of various countries. In China especially, the RMB has been castigated due to its failure to freely circulate and be converted in the international market. As the progress of digital-RMB is pushed forward, the currency will operate more competitively at the levels of international or reserve currency. We thus expect to see significant local and international impacts of CBDC on competition in the payments and fintech sector.

The role of CBDC in the monetary system, its actual economic performance, and society’s acceptance of it remain to be tested and observed. Therefore, CBDC’s problems require further investigation. First, we can further analyse the CBDCAI and CBDCUI with firm-level data. For example, we can investigate if our CBDC indices are associated with greater stock price volatility, poor financial statement performances in the financial services sector, or other policy-sensitive sectors, such as energy, technology, and real estate. Second, due to constraints regarding the scope of this paper, future studies could examine the effects of CBDCUI and CBDCAI on cryptocurrencies in greater detail. Besides, the predicted powers of CBDC indices can also be further developed. Third, it is worth understanding that cryptocurrencies can have a partial effect between CBDC indices and financial markets or the partial effects of CBDC indices on USEPU and VIX. Fourth, the construction of infrastructures supporting the progress of CBDC, issuance and market supervision of CBDC, and compliance and supervision of the financial institutions responsible should be explored further. Focusing on individual users is another potential research direction. What actual effects, advantages, and disadvantages will CBDC be able to provide a country’s different users? When other digital payment modes still occupy a large market share, can various governments’ CBDC research and efforts expect returns?

There is plenty of room for the development of CBDC in various countries, and there remains much progress to be made. However, digital currency is reshaping our payment system, payment modes, and new financial order. CBDC must be the main battlefield of various countries in the field of fintech. Besides, as money never sleeps, further research into the roles and advantages of CBDC can only be beneficial.

Declaration of Conflicts of Interest

No conflicts of interest to declare.

CRediT authorship contribution statement

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

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Table 1: Descriptive statistics

	CBDCUI	CBDCAI	UCRY Policy	UCRY Price	ICEA	MSCI World Banks Index	VIX	USEPU	FTSE All World Index	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
Panel A: price																
Observation	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340
Mean	100.0000	100.0000	100.19	100.20	100.29	88.23	17.45	127.95	325.55	1.14	1.35	0.01	0.02	0.15	1384.81	8323.89
Min	99.12	99.44	99.02	99.03	99.40	56.19	9.14	35.15	235.71	1.04	1.17	0.01	0.01	0.14	1056.20	210.34
Max	106.16	106.02	108.26	109.18	112.00	114.62	66.04	601.16	477.60	1.25	1.59	0.01	0.02	0.16	2010.10	60204.96
Range	7.04	6.58	9.23	10.15	12.60	58.43	56.90	566.01	241.89	0.20	0.42	0.001	0.01	0.02	953.90	59994.63
Std. Dev.	1.00	1.00	1.23	1.26	1.68	12.21	7.76	99.22	53.53	0.05	0.10	0.001	0.001	0.01	241.71	12156.80
MAD	0.50	0.29	0.46	0.48	0.58	11.20	4.51	39.93	53.91	0.05	0.08	0.001	0.001	0.01	130.91	7038.16
Skewness	3.00	3.95	2.78	3.07	3.94	−0.43	2.63	2.59	0.88	0.33	0.79	−0.47	0.22	0.23	1.03	2.67
Kurtosis	11.70	16.40	9.38	11.90	17.70	−0.45	10.63	7.16	0.48	−0.67	−0.38	−0.24	−0.26	−1.03	−0.20	7.12
SE	0.05	0.05	0.07	0.07	0.09	0.66	0.42	5.38	2.90	0.001	0.01	0.001	0.001	0.001	13.11	659.30
J-B test	2482.9***	4755.8***	1707.8***	2577.1***	5387.9***	13.307***	2021***	1122.5***	47.539***	12.454***	37.628***	13.465***	3.5849	17.872***	61.496***	1137.9***
ADF	−2.7817	−2.5028	−2.9183	−2.9066	−2.9971	−1.973	−3.8293**	−3.1866*	−1.7614	−2.516	−1.4776	−2.62	−3.3439*	−1.9712	−2.1804	-2.6065
KPSS	1.8065***	1.549***	1.9293***	2.056***	1.6208***	0.45627*	1.3422***	2.132***	4.3691***	1.2755***	2.3293***	2.3074***	2.0678***	1.9179***	4.2772***	2.7922***
PP	−48.75***	−17.008	−52.702	−46.594***	−11.743	−8.3806	−45.253***	−35.045***	−9.5526	−16.624	−6.6449	−15.1	−16.056	−4.6877	−8.3714	−7.8294
Panel B: log return																
Observation	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340
Mean	4.61	4.61	4.61	4.61	4.61	4.47	2.79	4.67	5.77	0.13	0.30	−4.71	−4.17	−1.90	7.22	8.02
Min	4.60	4.60	4.60	4.60	4.60	4.03	2.21	3.56	5.46	0.04	0.15	−4.83	−4.38	−1.97	6.96	5.35
Max	4.66	4.66	4.68	4.69	4.72	4.74	4.19	6.40	6.17	0.22	0.46	−4.61	−3.91	−1.81	7.61	11.01
Range	0.07	0.06	0.09	0.10	0.12	0.71	1.98	2.84	0.71	0.18	0.31	0.22	0.47	0.15	0.64	5.66
Std. Dev.	0.01	0.01	0.01	0.01	0.02	0.15	0.36	0.56	0.16	0.04	0.07	0.05	0.10	0.04	0.16	1.60
MAD	0.00	0.00	0.00	0.00	0.01	0.12	0.33	0.44	0.17	0.04	0.06	0.04	0.10	0.05	0.11	1.22
Skewness	2.94	3.91	2.72	2.99	3.84	−0.73	0.97	1.03	0.50	0.26	0.68	−0.58	−0.02	0.18	0.84	−0.22
Kurtosis	11.17	16.07	8.84	11.16	16.72	−0.08	1.11	0.87	−0.20	−0.70	−0.51	−0.16	−0.49	−1.06	−0.47	−1.13
SE	0.001	0.001	0.001	0.001	0.001	0.01	0.02	0.03	0.01	0.001	0.001	0.001	0.01	0.001	0.01	0.09
J-B test	2287.2***	4582.7***	1548***	2304.3***	4861.3***	30.458***	72.197***	72.304***	14.563***	10.38***	30.283***	19.708***	3.1647	17.367***	43.413***	20.697***
ADF	−2.7481	−2.4361	−2.9059	−2.9066	−2.9764	−2.1027	−3.4551**	−3.3427	−2.4057	−2.527	−1.4932	−2.5921	−3.216	−1.9756	−2.3738	−2.0129
KPSS	1.8263***	1.5654***	1.9409***	2.0727***	1.6474***	0.43944*	1.5168***	2.998***	4.5332***	1.2814***	2.2613***	2.373***	2.1086***	1.9105***	4.378***	5.0548***
PP	−48.518***	−16.703	−51.967***	−45.332***	−10.838	−9.2871	−41.388***	−69.578***	−14.076	−16.959	−6.9719	−14.908	−15.736	−4.661	−9.7523	−7.0336
Panel C: continuously compounded returns																
Observation	339	339	339	339	339	339	339	339	339	339	339	339	339	339	339	339
Mean	0.0063	0.0091	0.0058	0.0064	0.0164	0.04	−0.05	0.03	0.16	0.00	−0.03	0.02	−0.07	−0.01	0.12	1.44
Min	−1.83	−1.54	−3.58	−3.27	−2.37	−16.02	−55.62	−84.69	−13.30	−3.88	−8.10	−4.63	−8.90	−3.01	−9.74	−40.79
Max	2.32	2.35	3.53	3.92	5.68	15.26	85.37	114.54	9.88	3.69	6.68	4.57	7.93	1.57	9.01	34.70
Range	4.14	3.89	7.10	7.19	8.05	31.28	140.99	199.23	23.19	7.58	14.78	9.20	16.83	4.57	18.75	75.49
Std. Dev.	0.48	0.30	0.61	0.58	0.44	3.31	17.09	28.11	2.26	1.18	1.42	1.17	2.15	0.59	2.06	10.69
MAD	0.32	0.10	0.44	0.32	0.08	2.37	12.88	24.02	1.47	1.06	1.37	0.93	1.67	0.49	1.65	7.28
Skewness	0.49	2.41	0.32	1.61	5.37	−0.35	0.84	0.38	−1.22	−0.26	−0.60	0.30	−0.72	−0.42	−0.10	−0.45
Kurtosis	4.61	21.55	7.41	15.73	82.55	5.17	3.25	1.55	9.11	0.92	4.59	1.85	2.59	2.37	2.69	1.49
SE	0.03	0.02	0.03	0.03	0.02	0.18	0.93	1.53	0.12	0.06	0.08	0.06	0.12	0.03	0.11	0.58
J-B test	320.29***	6978.5***	794.3***	3692.9***	99083***	391.05***	193.08***	43.262***	1274.6***	16.377***	323.61***	54.847***	127.13***	91.052***	105.04***	44.051***
ADF	−7.13***	−6.49***	−7.98***	−7.43***	−6.81***	−6.67***	−8.44***	−9.04***	−7.43***	−6.67***	−7.91***	−7.06***	−6.26***	−5.72***	−6.85***	−6.51***
KPSS	0.022*	0.089*	0.0227*	0.0234*	0.149*	0.084*	0.024*	0.026*	0.125*	0.11921*	0.19924*	0.083*	0.035*	0.246*	0.094*	0.075*
PP	−337.34***	−330.11***	−393.61***	−369.76***	−300.27***	−336.6***	−352.41***	−351.84***	−350.27***	−360.01***	−338.73***	−333.46***	−372.79***	−400.91***	−339.31***	−332.54***

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

Table 2: Unconditional correlation of variables returns

	CBDCUI	CBDCAI	UCRY Policy	UCRY Price	ICEA	MSCI World Banks Index	VIX	USEPU	FTSE All World Index	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
CBDCUI	1															
CBDCAI	0.565***	1														
UCRY Policy	0.577***	0.354***	1													
UCRY Price	0.558***	0.355***	0.903***	1												
ICEA	0.412***	0.536***	0.384***	0.390***	1											
MSCI World Banks Index	−0.015*	−0.047*	−0.044*	−0.012*	0.038*	1										
VIX	0.063*	0.075*	0.119**	0.130**	0.032*	−0.558***	1									
USEPU	−0.081*	−0.158**	0.094*	0.034*	−0.063*	−0.069*	0.082*	1								
FTSE All World Index	−0.021*	−0.031*	−0.101**	−0.071*	−0.015*	0.840***	−0.715***	−0.079*	1							
EUR/USD	0.049*	0.001*	0.053*	0.077*	0.022***	0.209*	0.031*	0.007*	0.231***	1						
GBP/USD	0.056*	0.068*	−0.028*	−0.024*	0.044*	0.426***	−0.134*	−0.040*	0.439***	0.574***	1					
JPY/USD	0.104**	0.031*	0.058*	0.076*	−0.011*	−0.244***	0.293***	0.094**	−0.089*	0.427***	0.114**	1				
RUB/USD	0.005*	0.020*	−0.031*	−0.035*	0.043*	0.383***	−0.313***	−0.068*	0.462***	0.124**	0.198***	0.081*	1			
CNY/USD	0.036*	0.015*	0.058*	0.070*	0.040*	0.162**	0.002*	0.019*	0.210***	0.361***	0.364***	0.220***	0.121*	1		
Gold	0.093**	0.010*	−0.038*	−0.029*	−0.022*	−0.012*	0.041*	0.045*	0.207***	0.393***	0.331***	0.543***	0.163**	0.251***	1	
Bitcoin	0.023*	0.021*	−0.056*	−0.048*	−0.028*	0.152**	−0.159**	−0.045*	0.168**	0.025*	0.049*	0.033*	0.108**	−0.025*	0.056*	1

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

Table 3: CBDC VAR model estimation results

	Dependent variable: y															
	CBDCUI	CBDCAI	UCRY Policy	UCRY Price	ICEA	MSCI World Banks Index	VIX	USEPU	FTSE All World Index	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
CBDCUI		0.040*	−0.160*	−0.118*	−0.145**	0.557*	−1.916*	−2.251*	0.531*	−0.007*	0.030*	−0.177*	0.055*	0.090*	−0.186*	1.919*
		(0.049)	(0.084)	(0.079)	(0.071)	(0.527)	(2.751)	(4.310)	(0.363)	(0.192)	(0.233)	(0.191)	(0.350)	(0.096)	(0.336)	(1.769)
CBDCAI	0.434***		0.324**	0.161*	0.124*	−0.558*	1.327*	−1.127*	−0.137*	0.034*	−0.074*	0.078*	0.047*	−0.072*	−0.219*	−2.588*
	(0.112)		(0.127)	(0.120)	(0.108)	(0.798)	(4.169)	(6.530)	(0.550)	(0.292)	(0.353)	(0.290)	(0.531)	(0.146)	(0.509)	(2.681)
UCRY Policy	0.001*	0.099*		−0.201*	−0.259***	0.336*	−0.267*	9.357*	0.078*	−0.003*	−0.133*	0.003*	−0.053*	0.040*	−0.069*	−1.226*
	(0.100)	(0.066)		(0.108)	(0.097)	(0.719)	(3.756)	(5.883)	(0.496)	(0.263)	(0.318)	(0.261)	(0.478)	(0.131)	(0.458)	(2.416)
UCRY Price	0.026*	0.047*	0.161*		0.184*	−0.061*	−0.337*	−6.403*	−0.181*	−0.085*	0.010*	−0.074*	0.004*	−0.029*	0.178*	1.933*
	(0.103)	(0.068)	(0.116)		(0.100)	(0.735)	(3.836)	(6.008)	(0.506)	(0.268)	(0.325)	(0.267)	(0.488)	(0.134)	(0.468)	(2.467)
ICEA	0.215***	0.091*	0.518***	0.660***		−0.057*	2.808*	−2.567*	−0.183*	0.049*	0.078*	0.123*	0.017*	−0.071*	0.251*	−2.838*
	(0.070)	(0.046)	(0.080)	(0.076)		(0.504)	(2.630)	(4.119)	(0.347)	(0.184)	(0.223)	(0.183)	(0.335)	(0.092)	(0.321)	(1.691)
MSCI World Banks Index	−0.021*	−0.008*	0.0004*	0.008*	0.021*		−0.251*	−0.725*	0.099*	−0.001*	0.088*	−0.012*	0.140*	0.005*	−0.006*	0.003*
	(0.016)	(0.011)	(0.018)	(0.017)	(0.015)		(0.597)	(0.935)	(0.079)	(0.042)	(0.051)	(0.042)	(0.076)	(0.021)	(0.073)	(0.384)
VIX	0.003*	0.003*	0.003*	−0.0002*	−0.0003*	−0.021*		0.147*	−0.012*	−0.001*	−0.002*	0.008*	−0.003*	−0.00002*	−0.016*	0.021*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.017)		(0.137)	(0.012)	(0.006)	(0.007)	(0.006)	(0.011)	(0.003)	(0.011)	(0.056)
USEPU	−0.0004*	−0.0002*	−0.001*	−0.0004*	0.001*	−0.004*	−0.040*		−0.001*	−0.003*	−0.002*	−0.004*	−0.002*	−0.002*	−0.001*	0.013*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.034)		(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.001)	(0.004)	(0.022)
FTSE All World Index	−0.047*	−0.008*	0.017*	−0.001*	−0.019*	−0.301*	−0.178*	−1.921*		−0.052*	−0.120*	0.028*	−0.090*	0.005*	−0.167*	0.543*
	(0.029)	(0.019)	(0.033)	(0.031)	(0.028)	(0.206)	(1.077)	(1.686)		(0.075)	(0.091)	(0.075)	(0.137)	(0.038)	(0.131)	(0.692)
EUR/USD	0.015*	0.001*	−0.024*	−0.038*	−0.017*	−0.635***	2.641**	3.072*	−0.458***		−0.010*	0.084*	0.163*	−0.036*	0.091*	−0.388*
	(0.029)	(0.019)	(0.033)	(0.031)	(0.028)	(0.209)	(1.090)	(1.708)	(0.144)		(0.092)	(0.076)	(0.139)	(0.038)	(0.133)	(0.701)
GBP/USD	0.031*	0.002*	0.055**	0.055**	0.002*	0.279*	0.200*	0.423*	0.021*	−0.045*		−0.107*	−0.191*	−0.003*	−0.181*	0.088*
	(0.024)	(0.016)	(0.028)	(0.026)	(0.024)	(0.174)	(0.909)	(1.424)	(0.120)	(0.064)		(0.063)	(0.116)	(0.032)	(0.111)	(0.585)
JPY/USD	0.051*	0.028*	0.086**	0.083***	0.040*	−0.074*	−2.078*	−1.533*	0.094*	−0.136*	−0.148*		−0.013*	0.019*	0.054*	0.059*
	(0.030)	(0.020)	(0.034)	(0.032)	(0.029)	(0.212)	(1.108)	(1.735)	(0.146)	(0.077)	(0.094)		(0.141)	(0.039)	(0.135)	(0.712)
RUB/USD	0.010*	0.016*	−0.021*	−0.027*	−0.010*	0.024*	0.413*	0.406*	−0.0004*	0.040*	0.025*	0.0004*		0.031*	0.018*	−0.185*
	(0.013)	(0.009)	(0.015)	(0.014)	(0.013)	(0.094)	(0.488)	(0.765)	(0.064)	(0.034)	(0.041)	(0.034)		(0.017)	(0.060)	(0.314)
CNY/USD	0.041*	0.010*	−0.059*	−0.035*	0.020*	0.756**	−3.346*	−5.454**	0.555**	−0.022*	−0.031*	−0.046*	0.441**		−0.297*	−1.027*
	(0.047)	(0.031)	(0.053)	(0.050)	(0.045)	(0.335)	(1.747)	(2.737)	(0.231)	(0.122)	(0.148)	(0.122)	(0.222)		(0.213)	(1.124)
Gold	0.002*	0.001*	−0.026*	−0.012*	−0.006*	0.008*	0.286*	0.997*	0.072*	0.043*	0.082*	0.064*	0.027*	0.015*		−0.506*
	(0.016)	(0.011)	(0.018)	(0.017)	(0.016)	(0.115)	(0.602)	(0.943)	(0.079)	(0.042)	(0.051)	(0.042)	(0.077)	(0.021)		(0.387)
Bitcoin	0.002*	0.002*	0.003*	0.005*	0.004*	0.055***	−0.084*	−0.039*	0.033***	0.005*	0.003*	0.003*	0.011*	0.0003*	0.001*	
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.017)	(0.087)	(0.137)	(0.012)	(0.006)	(0.007)	(0.006)	(0.011)	(0.003)	(0.011)	
Observations	338	338	338	338	338	338	338	338	338	338	338	338	338	338	338	338
R^2	0.865	0.868	0.332	0.336	0.080	0.092	0.076	0.158	0.085	0.046	0.042	0.040	0.044	0.038	0.057	0.041
Adjusted R^2	0.824	0.822	0.299	0.303	0.035	0.047	0.030	0.116	0.039	−0.001	−0.005	−0.008	−0.003	−0.010	0.010	−0.007
Residual Std. Error (df = 322)	0.450	0.297	0.511	0.485	0.437	3.224	16.833	26.368	2.223	1.178	1.427	1.171	2.143	0.588	2.054	10.826
F Statistic (df = 16; 322)	3.988***	1.466*	9.990***	10.199***	1.757**	2.043**	1.653*	3.783***	1.861**	0.972*	0.888*	0.838*	0.928*	0.793*	1.206*	0.855*

Note: *p<0.1; **p<0.05; ***p<0.01. Lags = 1

Table 4: Estimate from the CBDCUI GJR-GARCH-DCC model

Panel A (1): estimates of AR(1)-GARCH(1,1) model														
	CBDCUI	UCRY Policy	CBDCUI	UCRY Price	CBDCUI	ICEA	CBDCUI	MSCI World Banks Index	CBDCUI	VIX	CBDCUI	USEPU	CBDCUI	FTSE All World Index
Const.(v)	0.0048*	0.0094*	0.0027*	0.0054**	0.0042*	0.0016**	−0.0030*	−0.9474***	0.0031*	21.2874***	−0.0233*	−3.4476***	−0.0041*	−0.3035**
	(0.8677)	(1.9222)	(0.9759)	(1.923)	(0.7985)	(0.7124)	(−0.8779)	(−2.3587)	(0.9243)	(6.5871)	(−0.2637)	(−3.0515)	(−0.9847)	(−2.0948)
ARCH(1)	0.1852***	0.1755***	0.2065***	0.2177***	0.1693***	0.4502***	−0.2033***	−0.0171*	0.2076***	0.000092*	−0.0582*	−0.0272*	−0.2012***	−0.0689**
	(2.9619)	(3.9854)	(3.6433)	(2.8688)	(3.0564)	(2.7573)	(−3.0502)	(−0.3867)	(3.3069)	(0.0288)	(−0.2764)	(−0.3032)	(−3.2419)	(−0.9216)
GARCH(1)	0.7899***	0.8420***	0.8221***	0.8768***	0.8065***	0.7643***	−0.8212***	−0.7078***	0.8190***	0.9592***	−0.9782***	−0.7743***	−0.7922***	−0.6856***
	(7.3271)	(15.6031)	(11.9939)	(12.0024)	(8.1141)	(4.7883)	(−10.0654)	(−7.3188)	(10.4843)	(2113.9894)	(−14.7319)	(−2.7395)	(−9.0582)	(−11.5944)
GJR	0.0477*	−0.1237***	−0.0590**	−0.3015***	0.0464*	−0.4310***	−0.0511*	0.3539**	−0.0552*	−0.1345***	0.2923*	0.2626*	0.0113*	0.3890**
	(0.2631)	(−0.8861)	(−0.4398)	(−2.3607)	(0.2397)	(−3.0971)	(−0.3541)	(1.9956)	(−0.3857)	(−4.5559)	(0.6655)	(1.7554)	(0.0722)	(2.1039)
Panel B (1): DCC estimates														
a	0.1409*		0.0581*		0.0205*		0.0135*		0.000001*		−0.000001*		0.000001*	
	(1.7584)		(0.2856)		(0.4701)		(0.6689)		(1.3003)		(0.000002)		(0.000002)	
b	0.4720***		0.8457*		0.6829*		−0.9566***		0.3009*		−0.9078***		−0.9495***	
	(2.9921)		(0.6339)		(0.5171)		(10.54563)		(0.3059)		(8.7714)		(9.0846)	
Panel A (2): estimates of AR(1)-GARCH(1,1) model														
	CBDCUI	EUR/USD	CBDCUI	GBP/USD	CBDCUI	JPY/USD	CBDCUI	RUB/USD	CBDCUI	CNY/USD	CBDCUI	Gold	CBDCUI	Bitcoin
Const.(v)	0.0033**	0.0638*	0.0277*	0.3203***	0.0044*	0.0395*	0.0042*	0.1507*	0.0035*	0.0187***	0.0045*	0.3254*	0.0042*	0.8772***
	(0.8943)	(1.1504)	(0.3692)	(2.5007)	(0.8349)	(1.4056)	(0.8676)	(1.6818)	(0.9418)	(8.2973)	(0.8976)	(1.0609)	(7.7588×10^{-1})	(4.2911×10^{2})
ARCH(1)	0.1973***	0.0764**	0.0305*	0.0986*	0.1836***	0.1018***	0.1878***	0.0061*	0.1893***	0.000001*	0.1914***	0.1959*	0.1753***	0.0671***
	(3.3401)	(1.2547)	(0.1998)	(0.6922)	(3.0963)	(2.6788)	(2.8232)	(0.1549)	(3.1339)	(0.0081)	(2.9448)	(1.8621)	(2.5477)	(7.0613×10^{2})
GARCH(1)	0.8195***	0.8466***	0.9742***	0.4535***	0.7891***	0.8585***	0.7969***	0.8592***	0.8149***	0.9635***	0.7916***	0.7989***	0.8069***	0.9816***
	(10.1700)	(9.5910)	(20.7864)	(2.6901)	(7.4884)	(17.5126)	(7.5917)	(14.4046)	(9.5409)	(4508.0829)	(7.5012)	(6.9123)	(7.4144)	(1.6031×10^{5})
GJR	−0.0356*	0.0426*	0.3234*	0.5766***	0.0526*	0.0218*	0.0287*	0.1657*	−0.0106*	−0.0363**	0.0321*	−0.1466*	0.0337*	−0.0993***
	(−0.2468)	(0.7341)	(1.1818)	(2.8659)	(0.3128)	(0.3181)	(0.1861)	(1.7291)	(−0.0814)	(−2.0156)	(0.1921)	(−1.2593)	(2.1941×10^{-1})	(-5.9355×10^{2})
Panel B (2): DCC estimates														
a	0.000001*		0.0082*		0.0193*		0.000001*		0.000001*		0.000001*		0.0146*	
	(0.000001)		(0.5754)		(0.4099)		(0.000003)		(0.000002)		(0.000002)		(3.6812×10^{-1})	
b	0.9305***		0.9907***		0.8528**		0.9284***		0.9449***		0.9208***		0.7588***	
	(13.2015)		(25.2558)		(2.3202)		(20.9329)		(7.7331)		(8.1857)		(2.4951)	

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

Table 5: Estimate from the CBDCAI GJR-GARCH-DCC model

Panel A (1): estimates of AR(1)-GARCH(1,1) model														
	CBDCAI	UCRY Policy	CBDCAI	UCRY Price	CBDCAI	ICEA	CBDCAI	MSCI World Banks Index	CBDCAI	VIX	CBDCAI	USEPU	CBDCAI	FTSE All World Index
Const.(v)	0.0013*	0.0093*	0.0013*	0.0055*	0.0029*	0.0014*	−0.0017*	−0.7918**	0.0048*	3.2251***	−0.0163*	−3.2242***	−0.0016*	−0.3176*
	(1.9087)	(1.8120)	(1.5935)	(1.7201)	(1.0917)	(0.1321)	(−1.3207)	(−2.3191)	(0.0234)	(4.0131)	(−0.0859)	(−3.0266)	(−1.3712)	(−1.7539)
ARCH(1)	0.5288***	0.1548***	0.5231**	0.2113***	0.3094***	0.3906***	−0.5238***	−0.00059*	0.3263*	0.4947***	−0.4152*	−0.0231*	−0.4676***	−0.0886*
	(20.3448)	(3.7060)	(2.2679)	(3.3912)	(3.0216)	(3.0702)	(−2.8854)	(−0.0147)	(1.2392)	(3.4608)	(−1.4535)	(−0.2666)	(−2.6122)	(−0.9773)
GARCH(1)	0.7670***	0.8643***	0.7584***	0.8603***	0.5801***	0.7951*	−0.7433***	−0.7392***	0.9412***	0.4112***	−0.9329***	−0.5106***	−0.7488***	−0.6892***
	(20.0939)	(15.6031)	(20.6359)	(20.4433)	(5.2085)	(1.3843)	(−19.9631)	(−9.4292)	(27.2468)	(2.9420)	(−30.0175)	(−3.1421)	(−14.3742)	(−11.8936)
GJR	−0.5936***	−0.1434*	−0.5649**	−0.2231*	0.2189*	−0.3733*	−0.5361*	0.3787**	0.8831***	−0.1739*	1.0704***	0.2437*	−0.4348*	0.3278*
	(−25.0153)	(−1.7349)	(−2.2012)	(−1.6833)	(0.5515)	(−1.6126)	(−1.9006)	(2.2753)	(3.4623)	(−1.1930)	(3.4552)	(1.6828)	(−1.3385)	(1.7767)
Panel B (1): DCC estimates														
a	0.0467*		0.0732**		0.2322*		−0.000001*		0.000001*		−0.000001*		−0.000001*	
	(1.1837)		(2.2918)		(1.247532)		(0.0071)		(0.0285)		(0.0188)		(0.000006)	
b	0.8325***		0.8452***		0.000001*		−0.9042***		0.8930***		−0.8805***		−0.9217***	
	(4.0646)		(12.9301)		(0.0661)		(8.037396)		(3.6646)		(4.4211)		(10.1536)	
Panel A (2): estimates of AR(1)-GARCH(1,1) model														
	CBDCAI	EUR/USD	CBDCAI	GBP/USD	CBDCAI	JPY/USD	CBDCAI	RUB/USD	CBDCAI	CNY/USD	CBDCAI	Gold	CBDCAI	Bitcoin
Const.(v)	0.0014*	0.0583*	0.0391*	0.3431**	0.0026*	0.0453*	0.0025*	0.1532*	0.0702*	0.0862***	0.0024*	0.2289*	0.0026*	0.9453***
	(1.2329)	(1.1390)	(0.2276)	(2.4791)	(0.9869)	(1.3657)	(0.9726)	(1.6683)	(3.9045×10^{-1})	(1.9338×10^{1})	(0.7893)	(0.7083)	(9.8787×10^{-1})	(1.0553×10^{2})
ARCH(1)	0.5119**	0.0757*	0.2789*	0.1084*	0.2883**	0.1014***	0.2829***	0.0074*	0.2608*	0.0216*	0.3085*	0.1719*	0.2891***	0.0555***
	(2.0227)	(1.4179)	(1.3574)	(0.7446)	(2.3987)	(2.6579)	(2.8084)	(0.1718)	(1.2410)	(9.7291×10^{-1})	(1.7366)	(1.3358)	(2.9371)	(2.9794×10^{2})
GARCH(1)	0.7551***	0.8549***	0.9393***	0.4265**	0.6581***	0.8581***	0.6490***	0.8516***	0.9295***	0.9259***	0.6657***	0.8331***	0.6658***	0.9903***
	(19.3449)	(10.7939)	(28.3969)	(2.3780)	(5.2388)	(15.0118)	(6.0123)	(13.2041)	(2.5945×10^{1})	(8.6684×10^{4})	(3.7912)	(6.1930)	(6.8731)	(1.4925×10^{4})
GJR	−0.5359*	0.0391*	0.8743***	0.5663***	0.1051*	0.0125*	0.1341*	0.1782*	0.8785***	−0.0861***	0.0496*	−0.1145*	0.0881*	−0.0935***
	(−1.9671)	(0.6952)	(4.1450)	(2.8378)	(0.2088)	(0.1796)	(0.3082)	(1.7084)	(4.0370)	(-2.7836×10^{1})	(0.0744)	(−0.8677)	(1.9239×10^{-1})	(-2.8211×10^{2})
Panel B (2): DCC estimates														
a	−0.000001*		0.000001*		−0.0095*		−0.0053*		−0.000002*		−0.000001*		−0.000001*	
	(0.000005)		(0.0359)		(0.8089)		(0.3851)		(9.1802×10^{-1})		(0.0178)		(0.0017)	
b	0.9244***		0.9369***		0.9799***		0.9062***		0.0808*		0.9058***		0.8068*	
	(9.5477)		(15.2649)		(27.4912)		(6.4818)		(5.0000×10^{-6})		(14.5571)		(0.2973)	

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

Table 6: FEVD of variable system due to the CBDCUI and CBDCAI shocks

Panel A: CBDCUI shocks FEVD

Period	CBDCUI	CBDCAI	UCRY Policy	UCRY Price	ICEA	MSCI World Banks Index	VIX	USEPU	FTSE All World Index	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0.87385027	0.078630556	0.001540141	0.001894321	0.023957476	0.000232356	7.64E-06	0.00031172	0.002687329	0.001543235	0.002284958	0.008302064	0.001306907	0.002131092	6.49E-05	0.001255005
3	0.854581571	0.090549541	0.004489565	0.00237922	0.024192082	0.000323839	1.65E-05	0.000682883	0.00280771	0.001785166	0.003070175	0.008668789	0.001994477	0.002568188	0.000218299	0.001672011
4	0.851613435	0.09051325	0.005979219	0.003139056	0.024255979	0.000359452	5.15E-05	0.000688822	0.002859301	0.001845116	0.003258706	0.008640845	0.002252194	0.002583977	0.000293106	0.001666077
5	0.850785984	0.090459906	0.006318764	0.003390846	0.02431586	0.00035921	9.92E-05	0.000692221	0.002878462	0.001891496	0.003265253	0.008634379	0.002285333	0.002593147	0.00034227	0.001687706
6	0.850614243	0.090464765	0.006359403	0.003442059	0.024316012	0.000364857	0.000117579	0.000694831	0.002883038	0.001897954	0.003264591	0.008635246	0.002286439	0.002602169	0.000360638	0.001696177
7	0.850589073	0.090464894	0.006361825	0.003450491	0.024315633	0.000367825	0.000120762	0.000695252	0.002883381	0.001898089	0.003264606	0.008635878	0.002286375	0.002603978	0.00036466	0.001697277
8	0.850585325	0.090464604	0.006361861	0.003451856	0.024316395	0.000368466	0.000121064	0.000695278	0.002883369	0.001898099	0.003264611	0.008635996	0.002286415	0.002604135	0.000365199	0.001697326
9	0.850584613	0.090464527	0.006361856	0.003452107	0.024316727	0.000368553	0.000121087	0.000695278	0.002883374	0.00189812	0.003264609	0.008636006	0.002286433	0.00260414	0.000365245	0.001697325
10	0.850584469	0.090464511	0.006361855	0.00345216	0.024316806	0.000368563	0.000121091	0.000695278	0.002883377	0.001898125	0.003264608	0.008636007	0.002286437	0.00260414	0.000365248	0.001697325

Panel B: CBDCAI shocks FEVD

Period	CBDCAI	CBDCUI	UCRY Policy	UCRY Price	ICEA	MSCI World Banks Index	VIX	USEPU	FTSE All World Index	EUR/USD	GBP/USD	JPY/USD	RUB/USD	CNY/USD	Gold	Bitcoin
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0.947349746	0.003762535	0.005716254	0.003952496	0.009660885	0.004105911	0.005840185	0.000118244	0.00012844	0.001563322	0.000139175	0.0049875	0.008881855	0.000167704	2.36E-05	0.003602186
3	0.9390155	0.005052288	0.006528226	0.004307658	0.012248868	0.004392259	0.005948685	0.000705656	0.000127146	0.003442311	0.000147368	0.00497023	0.008839278	0.000348911	2.79E-05	0.003897713
4	0.938405665	0.005096089	0.006540041	0.004304846	0.012335012	0.004397739	0.005954744	0.000823175	0.000140978	0.003543275	0.000190036	0.004967396	0.008833668	0.000478132	3.89E-05	0.00395028
5	0.938350739	0.005099009	0.006545367	0.004309043	0.012335684	0.004408088	0.005955876	0.000831519	0.000142187	0.003543268	0.000198405	0.004968268	0.008836195	0.000484857	4.08E-05	0.003950693
6	0.938335943	0.005102829	0.006548739	0.0043112	0.012338271	0.004408862	0.005956132	0.000831608	0.000142286	0.003543776	0.000198904	0.004968225	0.008836467	0.000484886	4.08E-05	0.003951071
7	0.938333043	0.005103557	0.006549106	0.004311606	0.012338566	0.004408855	0.005956498	0.00083161	0.000142392	0.003543885	0.000198903	0.004968223	0.00883645	0.000485077	4.09E-05	0.003951306
8	0.938332709	0.005103608	0.006549109	0.004311654	0.012338561	0.004408887	0.00595656	0.000831611	0.000142404	0.003543886	0.000198907	0.004968235	0.008836446	0.000485117	4.10E-05	0.003951337
9	0.938332669	0.005103609	0.00654911	0.004311659	0.01233857	0.004408894	0.005956563	0.000831611	0.000142404	0.003543887	0.000198908	0.004968237	0.008836447	0.00048512	4.10E-05	0.003951338
10	0.938332661	0.005103609	0.006549111	0.00431166	0.012338574	0.004408894	0.005956563	0.000831611	0.000142405	0.003543887	0.000198908	0.004968237	0.008836448	0.00048512	4.10E-05	0.003951338

Table 7: Uncertainty risk and volatility structure risk

	CBDC risk (CCR)		*CBDC risk (RV)*		*CBDC risk (R)*	
	CBDCUI	CBDCAI	CBDCUI	CBDCAI	CBDCUI	CBDCAI
	(1)	(2)	(3)	(4)	(5)	(6)
UCRY Policy	0.7003***	0.6334***	0.6094***	0.7315***	0.4520***	0.1773***
	(0.0529)	(0.0995)	(0.1293)	(0.1524)	0.0056***	−0.0073***
UCRY Price	0.6555***	0.6366***	0.5949***	0.6594***	0.4483***	0.1788***
	(0.0526)	(0.0963)	(0.1495)	(0.1837)	0.0316***	0.0096***
ICEA	0.3969***	0.7964***	0.7685***	0.7884***	0.4022***	3.747e-01***
	(0.0461)	(0.0681)	(0.1187)	(0.1384)	0.1423***	−4.096e-02***
MSCI World Banks Index	−0.0985*	−0.5429*	−0.1455*	−0.6099*	−0.0132*	−0.0112*
	(0.3749)	(0.6023)	(0.6335)	(0.7801)	−0.0206*	−0.0130*
VIX	0.1592**	0.1531**	0.0473*	0.0943*	0.0004*	0.0004*
	(0.0538)	(0.0543)	(0.1177)	(0.1159)	0.0055*	0.0022*
USEPU	−0.2394**	−0.2406***	−3.2239*	−0.2895*	−0.0002*	−0.0011*
	(0.0528)	(0.0522)	(0.675)	(0.1164)	−0.0025*	−0.0012*
FTSE All World Index	−0.0995**	−0.2132*	−0.0649*	−0.2601*	−0.0048*	−0.0031*
	(0.2567)	(0.4129)	(0.4390)	(0.5405)	−0.0005*	−0.0019*
EUR/USD	0.1238*	0.0216*	0.4218*	0.4018***	0.0423*	0.0018*
	(0.1323)	(0.2124)	(0.1013)	(0.1022)	0.0425*	0.0040*
GBP/USD	0.1800*	0.3351*	0.5098*	0.7419*	0.0201*	0.0121*
	(0.1607)	(0.2573)	(0.2653)	(0.3295)	−0.0021*	0.0042*
JPY/USD	0.2524*	0.1240*	0.2555*	0.2731*	0.0203*	0.0044*
	(0.1316)	(0.2120)	(0.1116)	(0.1115)	0.0503*	0.0080*
RUB/USD	0.0281*	0.1526*	0.3585*	0.3608*	0.0196*	0.00682*
	(0.2429)	(0.3894)	(0.1012)	(0.1007)	0.0312*	−0.00665*
CNY/USD	0.0411*	0.0305*	0.0291*	0.1519*	0.0830*	0.0022*
	(0.0664)	(0.1064)	(0.1002)	(0.1229)	0.2111*	0.0187*
Gold	0.3893*	0.0704*	0.1704*	0.2555*	0.0022*	0.0028*
	(0.2329)	(0.3747)	(0.3618)	(0.1133)	0.0488*	0.0087*
Bitcoin	0.4789*	0.6257*	5.6714**	5.428*	0.0141***	0.0041*
	(1.2138)	(1.9506)	(1.8814)	(2.334)	0.0259***	0.0069*
Observations	338	338	78	78	339	339

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

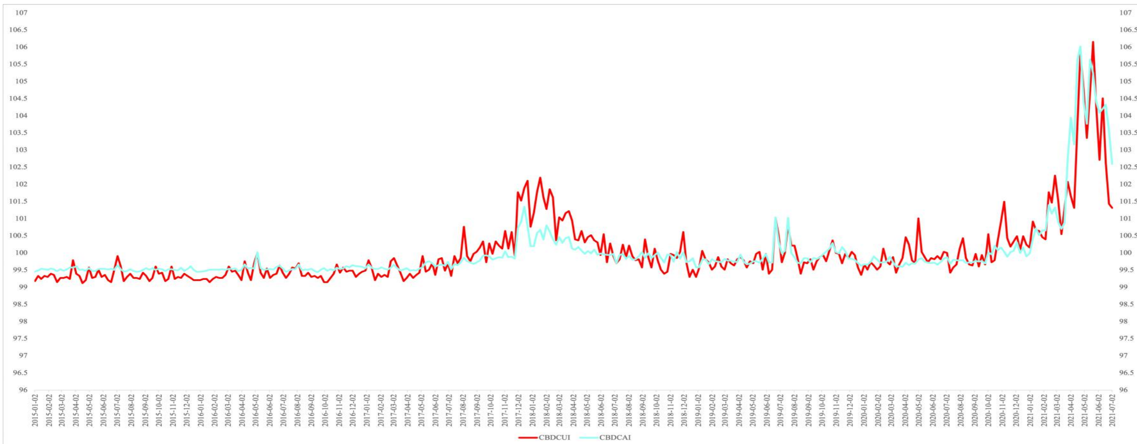


Figure 3: CBDCUI and CBDCAI

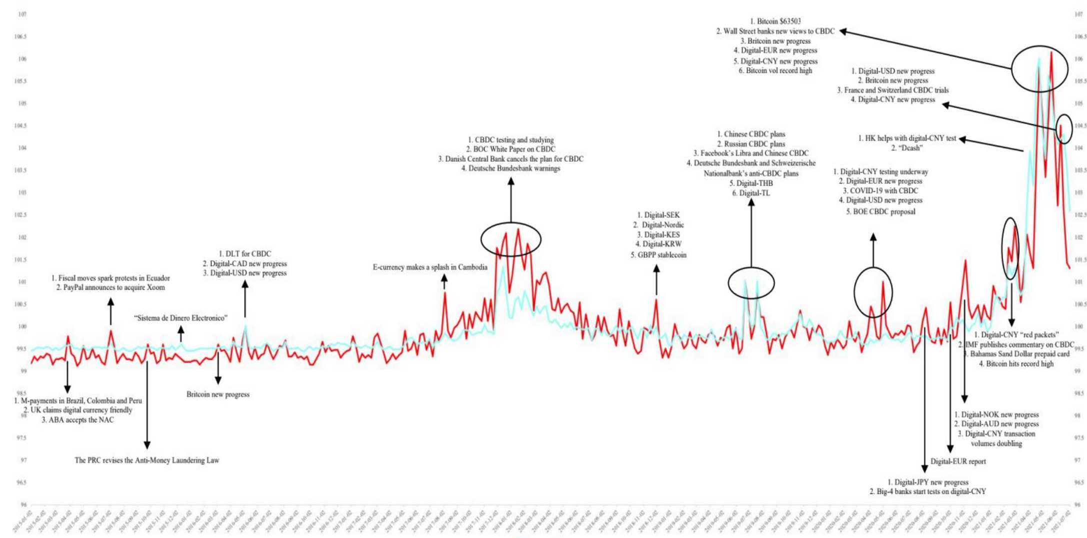
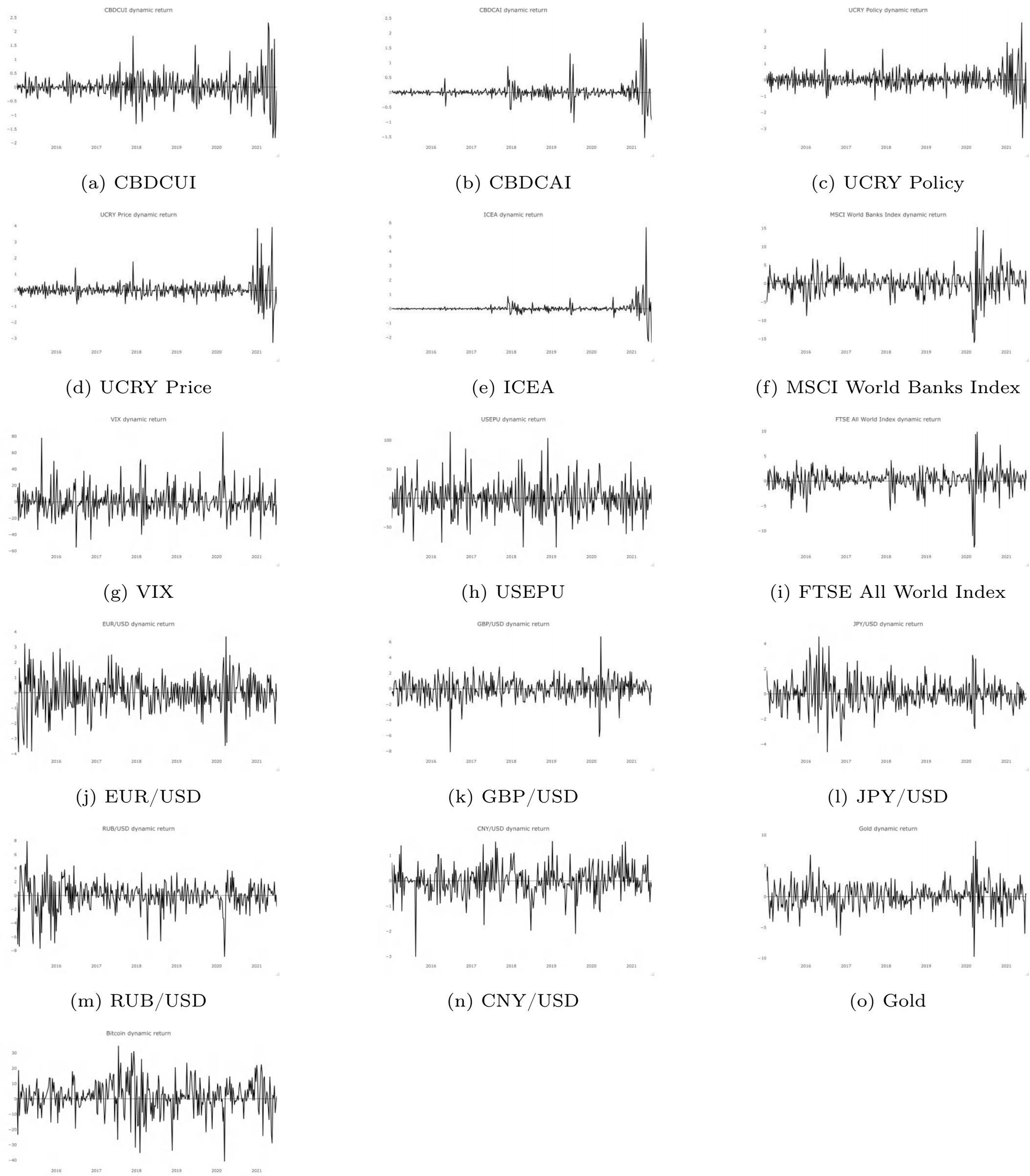


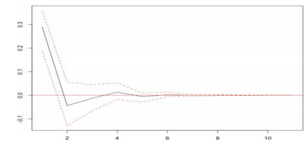
Figure 4: CBDC annotated indices

Figure 5: The dynamics of variables returns

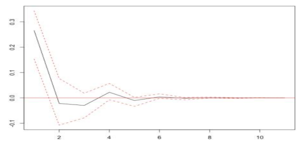


(a) CBDCUI
(b) CBDCAI
(c) UCRY Policy
(d) UCRY Price
(e) ICEA
(f) MSCI World Banks Index
(g) VIX
(h) USEPU
(i) FTSE All World Index
(j) EUR/USD
(k) GBP/USD
(l) JPY/USD
(m) RUB/USD
(n) CNY/USD
(o) Gold
(p) Bitcoin

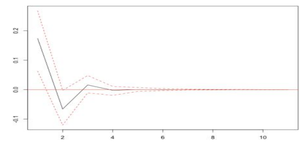
Figure 6: CBDCUI shocks to other variables



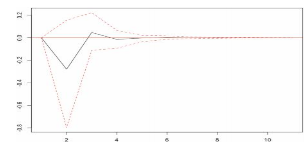
(a) εCBDCUI to UCRY Policy



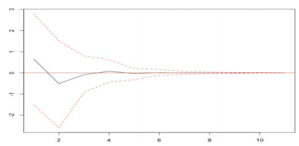
(b) εCBDCUI to UCRY Price



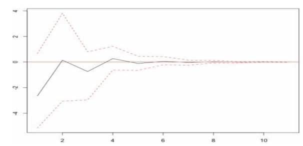
(c) εCBDCUI to ICEA



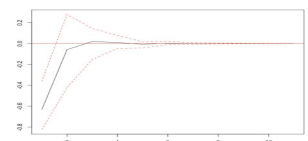
(d) εCBDCUI to MSCI World Banks



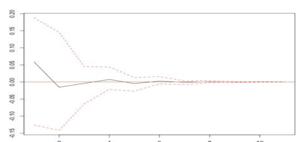
(e) εCBDCUI to VIX



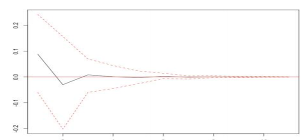
(f) εCBDCUI to USEPU



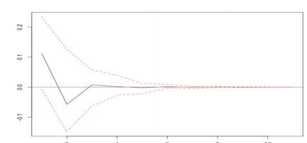
(g) εCBDCUI to FTSE All World Index



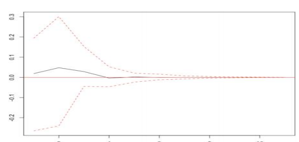
(h) εCBDCUI to EUR/USD



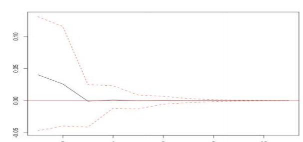
(i) εCBDCUI to GBP/USD



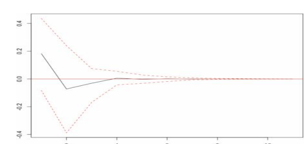
(j) εCBDCUI to JPY/USD



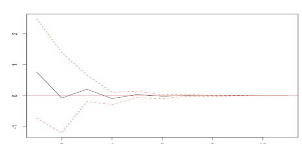
(k) εCBDCUI to RUB/USD



(l) εCBDCUI to CNY/USD



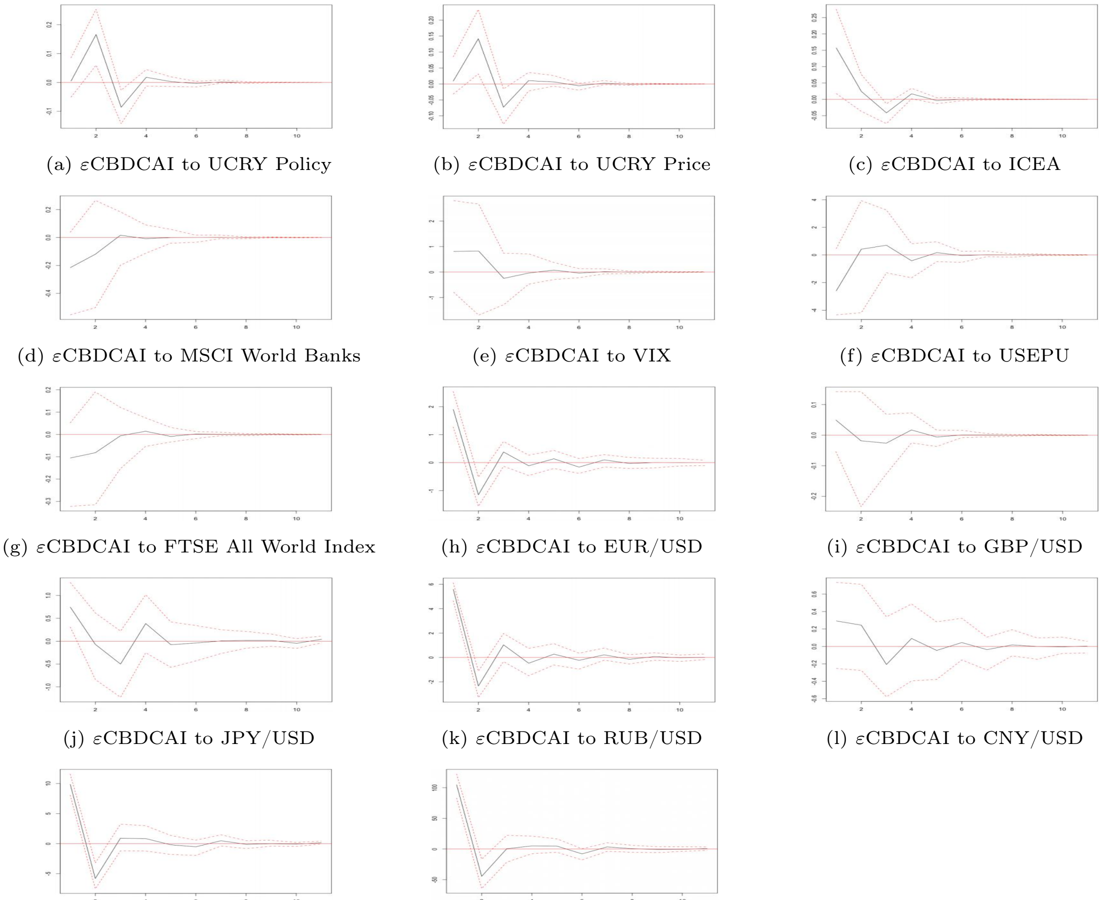
(m) εCBDCUI to Gold



(n) εCBDCUI to Bitcoin

Notes: 99% Bootstrapping, 1000 runs

Figure 7: CBDCAI shocks to other variables



(a) εCBDCAI to UCRY Policy

(b) εCBDCAI to UCRY Price

(c) εCBDCAI to ICEA

(d) εCBDCAI to MSCI World Banks

(e) εCBDCAI to VIX

(f) εCBDCAI to USEPU

(g) εCBDCAI to FTSE All World Index

(h) εCBDCAI to EUR/USD

(i) εCBDCAI to GBP/USD

(j) εCBDCAI to JPY/USD

(k) εCBDCAI to RUB/USD

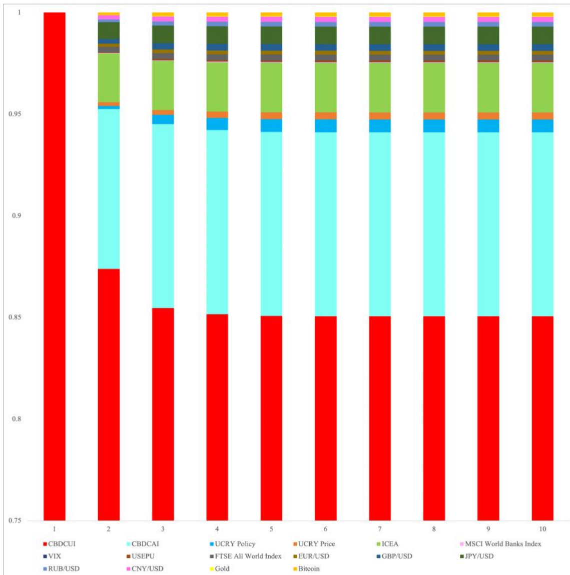
(l) εCBDCAI to CNY/USD

(m) εCBDCAI to Gold

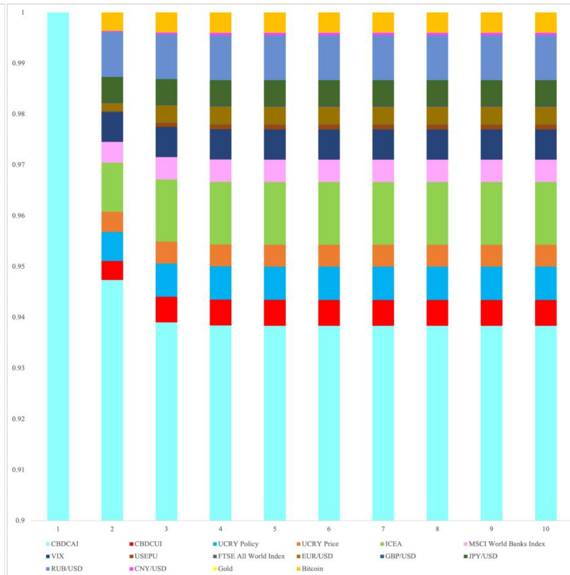
(n) εCBDCAI to Bitcoin

Notes: 99% Bootstrapping, 1000 runs

Figure 8: CBDC FEVD



(a) CBDCUI FEVD



(b) CBDCAI FEVD

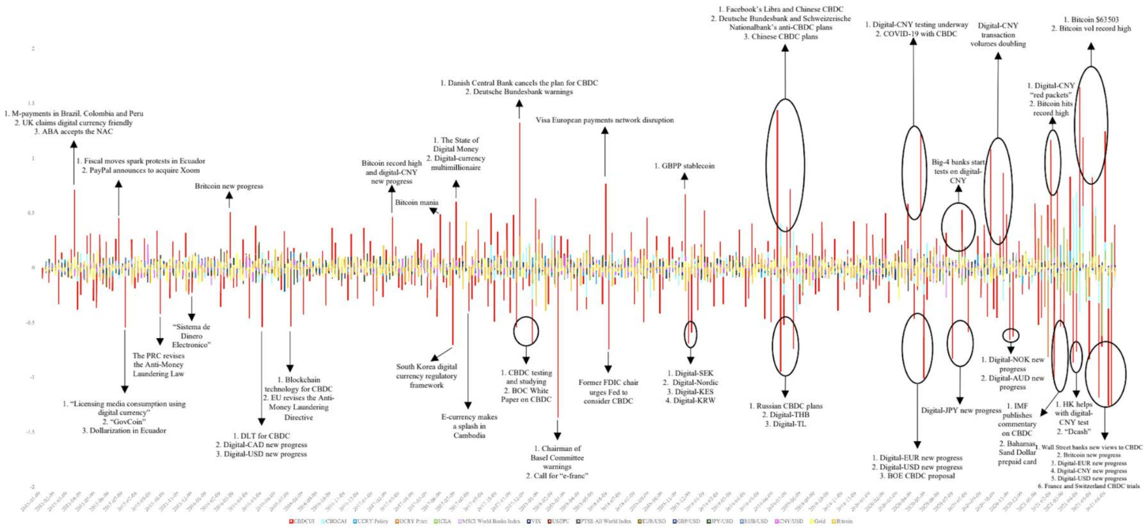


Figure 9: CBDCUI historical decomposition

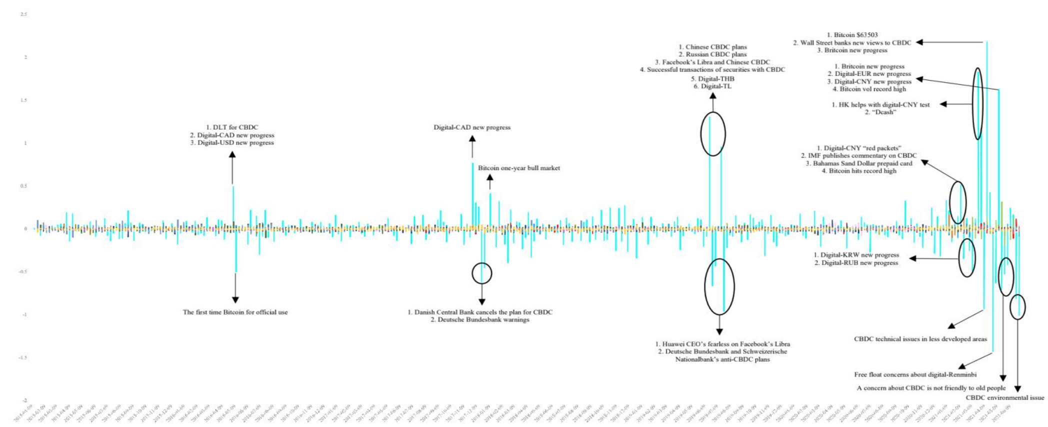
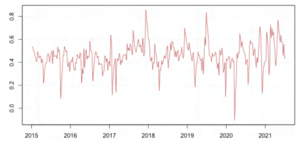


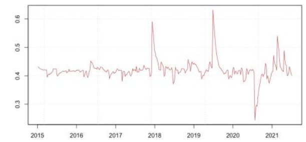
Figure 10: CBDCAI historical decomposition

Figure 11: CBDCUI dynamic condition correlation



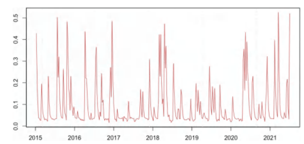
(a) UCRY Policy

(b) UCRY Price

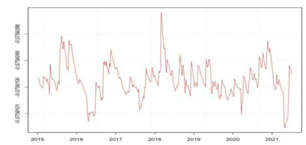


(c) ICEA

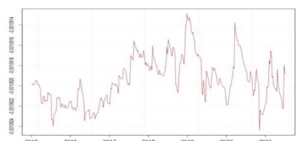
(d) MSCI World Banks Index



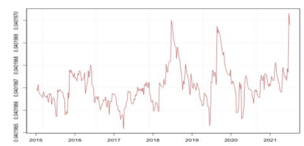
(e) VIX



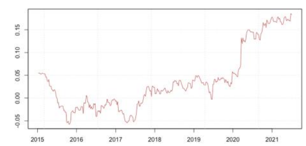
(f) USEPU



(g) FTSE All World Index

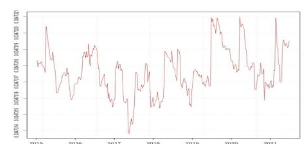


(h) EUR/USD

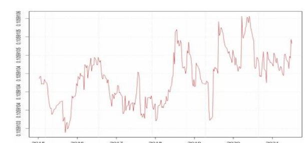


(i) GBP/USD

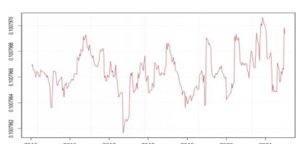
(j) JPY/USD



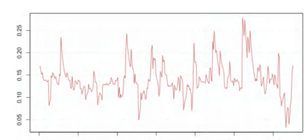
(k) RUB/USD



(l) CNY/USD

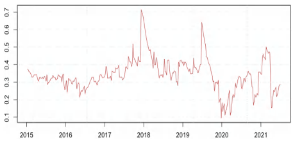


(m) Gold



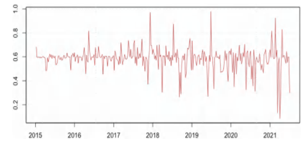
(n) Bitcoin

Figure 12: CBDCAI dynamic condition correlation

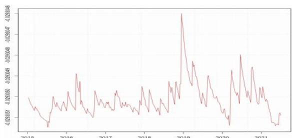


(a) UCRY Policy

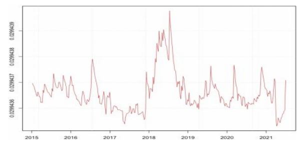
(b) UCRY Price



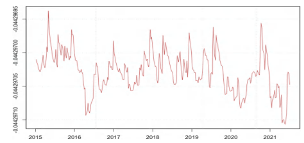
(c) ICEA



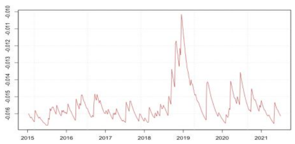
(d) MSCI World Banks Index



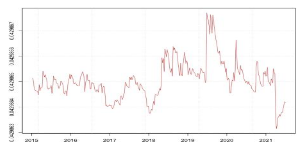
(e) VIX



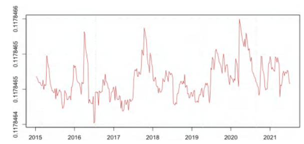
(f) USEPU



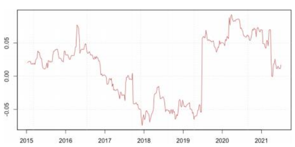
(g) FTSE All World Index



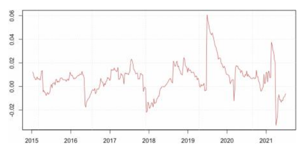
(h) EUR/USD



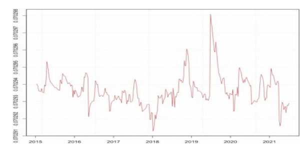
(i) GBP/USD



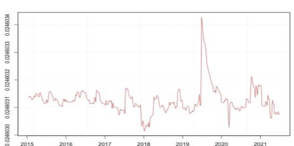
(j) JPY/USD



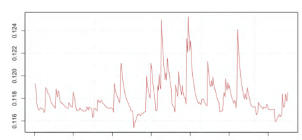
(k) RUB/USD



(l) CNY/USD



(m) Gold



(n) Bitcoin

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Appendix

Appendix A - Big events in annotated indices

- **23/03/2015 - 29/03/2015 (2015-03-27)**

1). M-payments in Brazil, Colombia and Peru (23/03/2015).

2). ABA accepts the NAC (23/03/2015). *Explanation: American Bankers Association accepts the National Atan Coin.*

3). UK claims digital currency friendly (24/03/2015).

- **29/06/2015 - 05/07/2015 (2015-07-03)**

1). Fiscal moves spark protests in Ecuador (01/07/2015). *Explanation: A new Electronic Currency System (ECS), the nationwide central bank digital currency progress have sent out danger signals to investors.*

2). PayPal announces to acquire Xoom (02/07/2015).

- **13/07/2015 - 19/07/2015 (2015-07-17)**

1). "GovCoin." (15/07/2015) *Explanation: UK intellectual property office grants trade mark "GovCoin" to GovCoin Limited.*

2). "Licensing media consumption using digital currency." (16/07/2015) *Explanation: The United States Patent and Trademark office has granted a patent to WILDTANGENT, INC, titled as "Licensing media consumption using digital currency" .*

3). Dollarization in Ecuador (17/07/2015) *Explanation: the dollarization of Ecuador process could come to an end within months, weeks or even days. Ecuador's government is trying to creating digital-currency to avoid to print cash. The use of digital-currency transactions has been imposed on private banks.*

- **28/09/2015 - 04/10/2015 (2015-10-02)**

1). The PRC revises the Anti-Money Laundering Law (01/10/2015). *Explanation: Digital currency makes the Anti-Money Laundering enforcement gets tough.*

- **07/12/2015 - 13/12/2015 (2015-12-11)**

1). "Sistema de Dinero Electronico" formally available (05/12/2015). *Explanation: Electronic money system was launched in Ecuador, making Ecuador becomes the first country with a state-run electronic payment system.*

- **29/02/2016 - 20/03/2016 (2016-03-04 to 2016-03-18)**

  1). Britcoin new progress (03/03/2016). *Explanation: Ben Broadent (Bank of England)'s speech about CBDC. In details, what is a CBDC? And what are the economic implications of introducing the CBDC.*

- **02/05/2016 - 08/05/2016 (2016-05-06)**

  1). DLT for CBDC (02/05/2016). *Explanation: Distributed ledger technology for CBDC.*

  2). Digital-CAD new progress & Digital-USD new progress (06/05/2016). *Explanation: Bank of Canada and the U.S. Treasury propose a project about launching dollars in digital.*

- **09/05/2016 - 15/05/2016 (2016-05-13)**

  1). First time Bitcoin for official use. *Explanation: Swiss town of Zug is planning to allow its residents to use Bitcoin to pay for municipal services.*

- **11/07/2016 - 17/07/2016 (2016-07-15)**

  1). EU revises the Anti-Money Laundering Directive (12/07/2016). *Explanation: EU brings virtual currency exchanges and wallet providers under the EU Anti-Money Laundering Directive.*

  2). Blockchain technology for CBDC (15/07/2016). *Explanation: The UK Parliament issued the news about the Economic Affairs Committee takes evidence from the Bank of England, Imperial College London, Z/Yen Group limited, among others for distributed ledger or blockchain technology for CBDC.*

- **20/02/2017 - 26/02/2017 (2017-02-24)**

  1). Bitcoin record high and digital-CNY new progress (25/02/2017). *Explanation: Bitcoin surges to record high ($1200) and China is developing digital-CNY.*

- **05/06/2017 - 11/06/2017 (2017-06-09)**

  1). Bitcoin mania (05/06/2017).

- **03/07/2017 - 09/07/2017 (2017-07-07)**

  1). South Korean digital currency regulatory framework (03/07/2017). *Explanation: Lawmakers of South Korea are preparing a set of bills to give cryptocurrencies legal grounds.*

- **10/07/2017 - 16/07/2017 (2017-07-14)**

1). The State of Digital Money (11/07/2017). *Explanation: Los Angeles' first global fintech and blockchain event.*

2). Digital-currency multimillionaire (16/07/2017). *Explanation: A secret cryptocurrency trader in Amyster turned $55 million of paper wealth into $283 million in just over a month.*

- **31/07/2017 - 06/08/2017 (2017-08-04)**

1). E-currency makes a splash in Cambodia (01/08/2017). *Explanation: the ASC group begins to use Aseancoin in the retail, e-commerce, tourism and import-export sectors all around Association of Southeast Asian Nations.*

- **27/11/2017 - 24/12/2017 (2017-12-01 to 2017-12-22)**

1). Digital-CAD new progress (2017-12-01). *Explanation: a research paper from the BOC points out that the Bank of Canada is considering the merits to creating the CBDC.*

2). Bank of Canada White Paper on CBDC (15/12/2017).

3). Danish Central Bank cancels the plan for CBDC (22/12/2017).

4). CBDC testing and studying (23/12/2017). *Explanation: a digital currency sponsored by the U.S. government and managed by the Federal Reserve is been studying. China's Central Bank is testing a digital currency. Bank of England, Bank of Canada, European Central Bank, Bank of Russia, Bank of Japan, Bank of Australia, among others are studying the Central Bank Digital Currency.*

4). Deutsche Bundesbank warnings (24/12/2017). *Explanation: Deutsche Bundesbank warns that there will be no CBDC in Euro-zone.*

- **08/01/2018 - 14/01/2018 (2018-01-12)**

1). Bitcoin one-year bull market. *Explanation: In January 2017, the price of Bitcoin was still under $1000, and 12 months later, the price of Bitcoin has risen to around $19600, increased by nearly 20 times.*

- **19/02/2018 - 25/02/2018 (2018-02-23)**

1). Chairman of Basel Committee warnings (19/02/2018). *Explanation: Stefan Ingves, the Chairman of Basel Committee warned banks to stay away from cryptocurrency.*

2). Call for "e-franc" (25/02/2018). *Explanation: the chairman of Switzerland's stock exchange urges that Switzerland should launch a cryptocurrency version of the Swiss franc.*

- **04/06/2018 - 10/06/2018 (2018-06-08)**

  1). Visa European payments network disruption (07/06/2018).

- **11/06/2018 - 17/06/2018 (2018-06-15)**

  1). Former FDIC Chair urges Fed to consider CBDC (11/06/2018). *Explanation: Sheila Blair, former chair of the US Federal Deposit Insurance Corporation (FDIC) urges the Federal Reserve to consider a CBDC.*

- **26/11/2018 - 02/12/2018 (2018-11-30)**

  1). Digital-SEK (26/11/2018). *Explanation: Sweden's Central Bank plans to launch CBDC to against cash usage declines.*

  2). Digital-KES (27/11/2018). *Explanation: Central Bank of Kenya is thinking to issue CBDC of Kenyan shilling.*

  3). GBPP Stablecoin (27/11/2018). *Explanation: the first digital pound sterling is mined, minted and used. London Block Exchange works with Alphapoint to create the first digital pound sterling, and the GBPP stablecoin is pegged to the value of pound sterling.*

  4). Digital-KRW (29/11/2018). *Explanation: Bank of Korea gave a presentation about CBDC on an international symposium held by the Financial Supervisory Service.*

  5). Digital-Nordic (30/11/2018). *Explanation: Nordic central banks are considering the CBDC because of the cyber security of digital payment.*

- **17/06/2019 - 21/07/2019 (2019-06-21 to 2019-07-19)**

  1). Chinese CBDC plans (10/06/2019). *Explanation: China's Central Bank publish the lastest plans for Chinese CBDC plan, and the cabinet gives approval to central bank to launch CBDC.*

  2). Russian CBDC plan (18/06/2019). *Explanation: The Central Bank of the Russian Federation is exploring its options when it begins to launching the CBDC.*

  3). Successful transactions of securities with CBDC (21/06/2019). *Explanation: Banque Internationale Luxembourg, LuxCSD and Seba Bank successfully tested use of CBDC for securities transactions.*

  4). Digital-CNY new progress (21/06/2019). *Explanation: Over 3,000 ATMs in Beijing now support CBDC withdrawals.*

5). Digital-THB (25/06/2019). *Explanation: Bank of Thailand is developing its own CBDC (Can not beat them, join them, can not beat the cryptocurrency, launch own digital currency).*

6). Deutsche Bundesbank and Schweizerische Nationalbank anti-CBDC plans (05/07/2019).

7). Facebook's Libra and Chinese CBDC (08/07/2019). *Explanation: the cryptocurrency plan of Facebook have forced China's Central Bank into stepping up research into launching Chinese CBDC.*

8). Digital-TL (11/07/2019). *Explanation: The Turkish Central Bank is planing to launch CBDC).*

- **22/07/2019 - 28/07/2019 (2019-07-26)**

1). Huawei CEO's fearless on Facebook's Libra. *Explanation: Ren, Zhengfei, the CEO of Huawei, has dismissed concerns that Facebook's Libra could dominate the world at the expense of China and its tech firms.*

- **30/03/2020 - 03/05/2020 (2020-04-03 to 2020-05-01)**

1). Digital-USD new progress (30/03/2020). *Explanation: (1) The Digital-Dollar project names 22 new advisory group members. And a partnership between Accenture and the Digital Dollar Foundation aims to promote establishment of a U.S. Central Bank Digital Currency. (2) Digital Dollar Project White Paper.*

2). BOE CBDC proposal (30/03/2020). *Explanation: Bank of England released a 57-page discussion paper about the opportunities, challenges and design of CBDC.*

3). Covid-19 with CBDC (08/04/2020). *COVID-19 has accelerated a move toward CBDC).*

4). Digital-CNY testing underway (21/04/2020). *Explanation: China has started testing the government-backed digital legal tender, CBDC wallet App available in Suzhou, Xiongan, Shenzhen and Chengdu these four cities..*

5). Digital-EUR new progress (02/05/2020). *Explanation: (1). The Banque de France plans to find cooperators to process the experiments in the use of a digital euro in interbank settlements. (2). The Dutch Central Bank intends to actively participate in any related policy discussions around a European CBDC in the future.*

- **03/08/2020 - 09/08/2020 (2020-08-07)**

1). Digital-JPY new progress (07/08/2020). *Explanation: The Bank of Japan has set up a new department to further promote digital Yen progress.*

2). Big-4 banks start tests on digital-CNY (07/08/2020). *Explanation: The Bank of China, China Construction Bank, Industrial and Commetrical Bank of China and Agricultural Bank of China, these big four state-owned commercial banks had started large-scale internal testing of digital-yuan..*

- **28/09/2020 - 04/10/2020 (2020-10-02)**

1). Digital-EUR report (02/10/2020). *Explanation: this report examines the issuance of the digital euro from the perspective of the Euro-system.*

- **02/11/2020 - 08/11/2020 (2020-11-06)**

1). Digital-CNY transaction volumes doubling (03/11/2020). *Explanation: China's CBDC testings has so far been smooth, with transaction volumes doubling over October, and the transactions hit $300 million.*

2). Digital-AUD new progress (04/11/2020). *Explanation: The National Australia Bank and the Commonwealth Bank of Australia will join forces to work with the Reserve Bank of Australia to develop CBDC. And Reserve Bank of Australia considering on Ethereum based digital currency.*

3). Digital-NOK new progress (06/11/2020). *Explanation: Norges Bank's presentation about CBDC and real-time digital payments.*

- **08/02/2021 - 28/02/2021 (2021-02-21 to 2021-02-26)**

1). Bahamas Sand Dollar Prepaid card (17/02/2021). *Explanation: Collaboration of MasterCard, Central Bank of the Bahamas and Island Pay issue the Bahamas Sand Dollar prepaid card, and can give people additional option to use the Bahamas Sand Dollar CBDC. This is the world's first CBDC-linked card.*

2). Digital-CNY "red packets" (18/02/2021). *Explanation: "Red packet" e-currency trials in Beijing, it is a catalyzator to hasten Asia e-currency race.*

3). IMF publishes commentary on CBDC (20/02/2021).

4). Bitcoin hits record high (21/02/2021). *Explanation: Bitcoin hit record high price $57,539.95 on 21/02/2021.*

- **08/03/2021 - 14/03/2021 (2021-03-12)**

1). Digital-KRW new progress. *Explanation: South Korea-based Shinhan Bank has said that it has built a platform for a potential South Korean CBDC.*

2). Digital-RUB new progress. *Explanation: Russian Central Bank Chairperson Elvira Nabiulline said on Association of Russian Banks that Central Bank of Russia will test digital ruble platform on 01/01/2022.*

- **29/03/2021 - 04/04/2021 (2021-04-02)**

1). Hong Kong helps with digital-CNY test (02/04/2021). *Explanation: The People's Bank of China and the Hong Kong Monetary Authority have begun "technical testing" for cross-border use of digital-RMB.*

2). Dcash (31/03/2021). *Explanation: 'Dcash', launched by the international fintech company, Bitt, in partnership with the Eastern Caribbean Central Bank (ECCB), became the world's first retail CBDC to be publicly issued within a formal currency union.*

- **05/04/2021 - 11/04/2021 (2021-04-09)**

1). CBDC technical issues in less developed areas.

- **19/04/2021 - 25/04/2021 (2021-04-23)**

1). Bitcoin $63503 (13/04/2021). *Explanation: Bitcoin hits the historical recording high $63503.*

2). Britcoin new progress (19/04/2021). *Explanation: The Bank of England and the Treasury will set up a new taskforce and joint together to explore the objectives of establishing a CBDC.*

3). Wall Street banks new views to CBDC (20/04/2021). *Explanation: Wall Street banks is warming up to the idea that CBDC as the next big financial disruptor.*

- **26/04/2021 - 02/05/2021 (2021-04-30)**

1). Free float concerns about digital-Renminbi. *Explanation: Some scholars worry about that RMB is not fully convertible, so taking a head position using RMB might be difficult.*

- **10/05/2021 - 23/05/2021 (2021-05-14 & 2021-05-21)**

1). Digital-CNY new progress (11/05/2021). *Explanation: (1). Digital-CNY trials has for the first time included a private bank, Zhejiang E-Commerce Co Ltd. (2). MYbanks joins Digital-RMB platform (12/05/2021)..*

2). Britcoin new progress (14/05/2021). *Explanation: Bank of England officially announces that Britcoin CBDC launch is 'probable'..*

3). Bitcoin vol record high (19/05/2021). *Explanation: Bitcoin transaction volumes hit the record high 1.26358E+11.*

4). Digital-EUR new progress (21/05/2021). *Explanation: The European Central Bank takes a new rush toward the digital-euro. In the coming weeks, The European Central Bank will announce whether it will issue a "digital euro" within the next four years. And many experts believe it will.*

5). CBDC is not friendly for old people (21/05/2021).

- **07/06/2021 - 13/06/2021 (2021-06-11)**

1). Britcoin new progress (07/06/2021). *Explanation: Bank of England publishes discussion paper on the CBDC-Britcoin.*

2). Digital-CNY new progress (08/06/2021). *Explanation: The second stage experiments of digital-RMB in Hong Kong starts, and Hong Kong is to test connecting digital-RMB with its domestic payment network.*

3). Digital-USD new progress (09/06/2021). *Explanation: Senate Banking, Housing and Urban Affairs Subcommittee on Economic Policy Hearing about Building a stronger financial system: opportunities of a CBDC.*

4). France and Switzerland CBDC trials (11/06/2021). *Explanation: two Central Banks of European in France and Switzerland have launched a joint CBDC cross-border trial.*

- **28/06/2021 - 04/07/2021 (2021-07-02)**

1). Digital currency environmental issue.

Appendix B - Table

Table 8: The negative dynamic correlation periods in the CBDC indices and financial variables

CBDCUI & Financial variables	Time period	CBDCAI & Financial variables	Time period
$\boldsymbol{CBDCUI \& GBP/USD}$	2015-07-03 to 2016-03-25	$\boldsymbol{CBDCAI \& JPY/USD}$	2017-01-13 to 2017-07-28
	2016-04-15 to 2017-09-15		2017-08-11 to 2017-09-08
	2019-06-14 to 2019-06-21		2017-09-22 to 2019-06-21
$\boldsymbol{CBDCUI \& MSCIWorldBanksIndex}$	2015-07-10 to 2016-03-04		2021-04-09 to 2021-04-16
	2016-04-29 to 2016-09-30	$\boldsymbol{CBDCAI \& RUB/USD}$	2015-04-17 to 2015-06-26
	2019-08-09		2015-07-10
	2020-12-11		2016-05-13 to 2016-09-23
	2021-04-30 to 2021-06-18		2016-11-04
$\boldsymbol{CBDCUI \& JPY/USD}$	2017-03-31		2017-11-10 to 2018-04-27
	2017-05-12		2018-05-18 to 2018-05-25
$\boldsymbol{CBDCUI \& UCRY Policy}$	2020-03-20		2019-04-26
			2019-06-07 to 2019-06-21
			2020-03-06 to 2020-03-13
			2020-11-06 to 2020-12-04
			2020-04-02 to 2021-07-02
		$\boldsymbol{CBDCAI \& UCRY Price}$	2020-03-20
			2020-10-23