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ORIGINAL PAPER

Economic policy uncertainty and cryptocurrencies

Chiara Oldani[1] · **Giovanni S. F. Bruno**[2] · **Marcello Signorelli**[3]

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Abstract
The paper focuses on the relationship between cryptocurrencies and economic policy uncertainty (EPU) shocks by adopting robust econometric techniques. Results on monthly data from 2016 to 2022 confirm that the volumes of cryptos are stationary, and the short- and long-run impacts of uncertainty shocks are significantly positive, and, in most cases, begin to show already in the first six months after the shock. When uncertainty significantly prevails, investors increase their demand for cryptos. The ARDL(12,11) specifications for Bitcoin show a significant increase in volumes of around 1% occurring over a year after a unit increase in economic policy indices. Conclusions from the findings are related to supervision, and monitoring of markets and financial stability.

Keywords Autoregressive distributed lag model · Cryptocurrency · Economic policy uncertainty · Financial stability · Financial regulation

JEL Classification C22 · E6 · G18 · O38

1 Introduction

The high complexity and interconnectedness of the global economy amplify the effects that uncertainty can have on investment decisions. Uncertainty in economic policy has a relevant impact on macroeconomic and financial variables; economic actors, such as firms, tend to act more conservatively during times of high uncertainty, 'thereby slowing investments in production and employment' (Al-Thaqeb & Algharabali, 2019).

✉ Chiara Oldani
coldani@unitus.it

[1] Department of Economics and Engineering, Università Degli Studi Della Tuscia, via del Paradiso, 01100 Viterbo, Italy

[2] Department of Economics, Bocconi University, via Roentgen 1, 20136 Milan, Italy

[3] Department of Economics, University of Perugia, via A. Pascoli 20, 06123 Perugia, Italy

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A part of the literature investigated to what extent economic policy uncertainty (EPU) impacted financial assets like bonds, stock indexes, and currencies, and found a negative relationship (Arouri et al., 2016; Ghorbel et al., 2022); however, the growth and development of digital technology are changing the structure of the financial system. The most popular and fastest-growing digital financial asset class is that of cryptocurrencies (Dwyer, 2015). According to CoinBase, the market capitalization of cryptos reached €3 trillion in 2022 and fell to €1 trillion in March 2023. The size of cryptocurrency trading cannot be ignored by policymakers.

This paper contributes to the growing literature, especially with new empirical investigations on the relationship between uncertainty indexes and the main cryptos' volumes, by adopting robust econometric techniques. The choice of the dependent variables (i.e., volumes and not prices/returns) is innovative and conditioned on the fact that the prices of cryptocurrencies are not market-efficient (Nadarajah & Chu, 2017; Tran & Leirvik, 2020; Urquhart, 2016), while volume reflects effective trades.

Blockchain technology developed following the cypher-punk movement (Hughes, 1993) that pursues global freedom of information and privacy of data, opposing Silicon Valley firms and their 'surveillance capitalistic' business structure (Zuboff, 2019). According to the economic literature, blockchain technology is a new political economy player (Brekke, 2021; Magnuson, 2020); decentralized networks disrupt surveillance and control, and provide security and privacy for users. Blockchain technology and related transactions attracted critics, as well as supporters. Supporters believe that decentralized trading systems might create a true peer-to-peer economy, while critics think that the blockchain will reproduce the capitalist structure through the enforcement of its property rights (Caliskan, 2020; Garrod, 2019).

Bitcoin (BTC) and Ethereum (ETH) are the most traded cryptos and employ two very different mining systems in their blockchains. Bitcoin miners use the proof-of work consensus mechanism, where 50% + 1 of the nodes of the blockchain should confirm the transaction to be valid; this system can ensure the integrity of data but is very slow and consumes a large amount of electricity. Ethereum's miners use the proof-of-stake consensus mechanism, which randomly chooses miners to confirm the transaction. This system is faster than the proof of work and is successfully used on different blockchains that trade fungible and non-fungible tokens (NFT) and smart contracts. A third very successful and special type of crypto is Ripple (XRP), which is traded on a centralized ledger managed by Ripple and is faster to trade than Bitcoin and Ethereum. XRP is very attractive for many operators because it is a bridge between centralized and decentralized systems.

Prices and volumes of cryptocurrencies are not free to adjust in the market, following demand and supply forces. Therefore, the properties of the prices of cryptocurrencies have been studied in the literature (Poyser, 2019), and no consensus has yet been reached over their financial nature (i.e., currency or financial asset). The algorithm of the blockchain at the Initial Coin Offering (ICO) and during the life of the coin (i.e., the mining process) defines the supply.

Being decentralized allows blockchains to be fully deregulated, lacking the geographical dimension; this leads to a fragmented regulatory financial environment for global investors, where most countries adopted a wait-and-see approach (Bellini & Vassalli, 2022). In response to this, the Financial Stability Board proposed a set of principles to regulate crypto-assets activities and intermediaries, in line with the principle "same activity, same risk, same regulation" (Financial Stability Board, 2022, 2023). After 2021, G-20 countries' leaders, central bankers, and finance ministers softly agreed toward this approach, and the first steps have been taken, for example, regarding the monitoring of cross border transactions, and their taxation.

The lack of monitoring and control constitutes a perverse incentive to access and trade these innovative tools. The financial risks of these digital assets are enormous; cryptocurrencies attract investors as well as pure speculators, and even criminals.

Investors in blockchain-related assets are difficult to track because of the absence of a monitoring system and the privacy of the blockchain's encryption. Some authors surveyed cryptocurrencies' investors, and, although their samples are not statistically robust, the results are pretty similar over different periods and geographical areas (Auer & Tercero-Lucas, 2022; Hackethal et al., 2022; Xi et al., 2020). The average investor in crypto is mainly male, born between 1989 and 2000, interested in IT, has a mid-to-low degree of financial literacy, and looks for high-risk and high returns in his or her investment decisions (Xi et al., 2020). These characteristics are relevant for policymakers.

The behavior of the prices of financial assets and currencies has been deeply studied, and the literature agrees that the prices of most capitalized cryptos are not market-efficient (Nadarajah & Chu, 2017; Tran & Leirvik, 2020; Urquhart, 2016). The inefficiency can be due to the peculiarities that make the crypto market very different from other financial assets. In particular, while transactions of shares or bonds on exchanges can be settled in a matter of a few seconds, a Bitcoin trade can take up to an hour. Moreover, not all transactions on the blockchain are successful, since there might be no counterpart available at that price to buy or sell. These inefficiencies can also be caused by the presence of bubbles in crypto during certain periods (Hafner, 2020).

The literature investigated the relationship between the EPU index and various financial assets, like bonds and stocks; an increase in policy uncertainty reduces stock returns significantly, and this effect is stronger and more persistent during extreme volatility periods (Arouri et al., 2016). The EPU index is monitored by central banks and global financial authorities and was introduced by Baker et al. (2016). The fundamental relationship can be represented as follows:

$$r_t = \sum_{s=1}^{p} \gamma_s r_{t-s} + \sum_{s=0}^{q} \beta_s x_{t-s} + \lambda' w_t + \varepsilon_t \tag{1}$$

where r is the price or return of the financial asset, x is the uncertainty index, and w is a vector of control variables. The prices of cryptocurrencies are interconnected and exhibit high volatility that increases when markets are more uncertain (Yi et al., 2018). Country-level EPU is related to the returns of cryptocurrencies, and the Chinese EPU can predict the Bitcoin monthly returns, while the U.S. EPU does not (Cheng & Yen, 2020). During the period 2014–2018, the effects of EPU on the relationship between Bitcoin and traditional financial markets were analyzed. Results confirmed the investment attractiveness of Bitcoin, as a hedging tool, against uncertainty shocks (Matkovskyy et al., 2020).

The paper focuses on the relationship between cryptocurrencies, the most popular blockchain-traded assets, and EPU. Some authors showed that there is a dynamic connectedness between country-level EPU and the cryptocurrency index (Cheng & Yen, 2020; Lucey et al., 2022), but since crypto assets are not country-specific, the paper considers how the global economic policy uncertainty (GEPU) indices relate to cryptos. After investigating the stationarity properties of the crypto volumes through unit root tests, the econometric methodology is that of autoregressive distributed lag (ARDL) (p,q), widely applied in the literature (Pesaran & Shin, 1999). Econometric results on monthly data from 2016 to 2022 confirm that the short- and long-run impacts of uncertainty shocks are significantly positive, and, in most cases, they begin to show in the first six months after the shock. The conclusion from the findings and the possible future path of research are discussed in the conclusion.

2 Methodology

The paper considers the relationship between the EPU index and volumes of trades of cryptocurrencies. The fundamental relationship can be represented as follows:

$$\mathrm{v}_{\mathrm{t}} = \sum_{s=1}^{p} \gamma_s \mathrm{v}_{\mathrm{t}-\mathrm{s}} + \sum_{s=0}^{q} \beta_s \mathrm{EPU}_{\mathrm{t}-\mathrm{s}} + \lambda' \mathrm{w}_{\mathrm{t}} + \varepsilon_{\mathrm{t}} \tag{2}$$

where v denotes the (log of) traded volumes, EPU stands for the uncertainty measure of choice (as described in the following paragraph), and w is a vector of controls: the constant term, linear and quadratic time trend components and 11 monthly dummies. With this relationship, we want to test the following research hypothesis:

H1: there is a statistically significant relationship between EPU index and crypto volumes

To test this hypothesis, we consider the cryptos with higher market capitalization and that are more popular among investors after 2016; they are Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP); in fact, the blockchain technology evolved fast, but spread substantially after 2016, leading to the Decentralized Finance (DeFi) developments.

3 Data and results

3.1 Data

The paper uses two different measures of EPU, the GEPU index and the European News-Based Uncertainty Index (ENBI) and considers how they relate to cryptos.

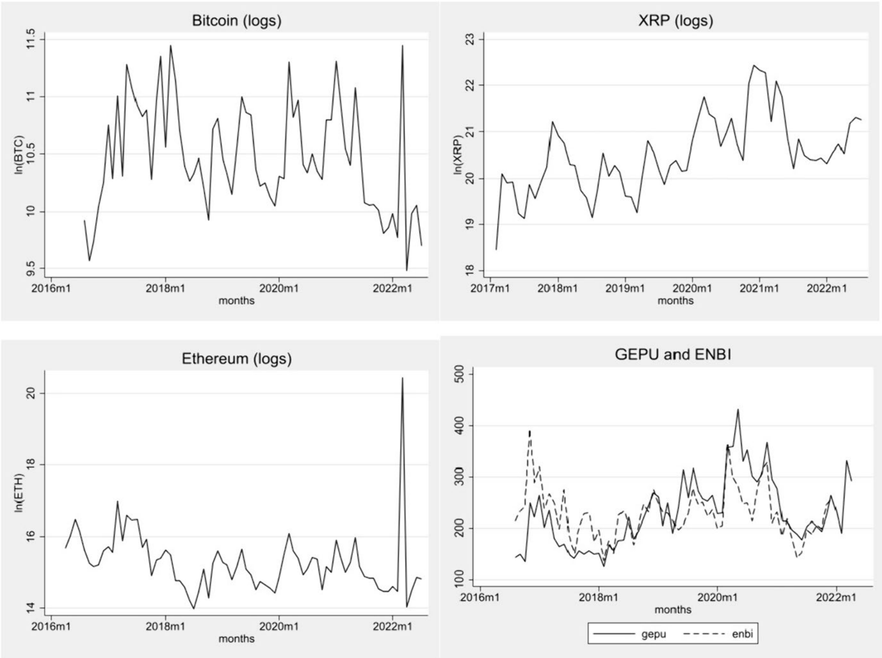

Fig. 1 Log of monthly data 2016–2022. Source: Investing.com/crypto/

The GEPU is computed by the US Federal Reserve of St. Louis and is a GDP-weighted average of national EPU indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. The European News-Based Uncertainty Index (ENBI) is a news-based index of uncertainty computed from news related to policy-related economic uncertainty (Baker et al., 2016).

Cryptos with higher markets' capitalization at the global level in July 2022 are considered in the estimates, and are Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) (Fig. 1). The choice of these crypto is also relevant due to their different mining systems. The (similar) econometric results with other cryptos can be provided by authors upon request.

The period goes from 4/2016 to 6/2022 (T = 74). Statistical data are monthly and refer to prices and volumes of cryptocurrencies, to the GEPU index, to the European News-Based Index (ENBI), to the Volatility Index (VIX), and money aggregates that are control variables. While data on cryptos are available at a high frequency, the economic policy indices are updated monthly. The use of monthly data can smooth the econometric problems related to (excess) volatility of daily cryptocurrency data.

Table 1 Descriptive statistics, monthly data (up to July 2022)

Series name	Start date	Mean	S.D
Bitcoin (BTC) price	01/01/2016	14,280.38	1029.90
Ethereum (ETH) price	01/04/2016	746.59	1017.17
Ripple (XRP) price	01/02/2017	0.42	0.31
Global Economic Policy Uncertainty Index (GEPU)	01/01/2016	222.70	65.53
European News Based Index (ENBI)	01/01/2016	233.65	57.92
Bitcoin (BTC) volume	01/01/2016	395,193.75	196,781.44
Ethereum (ETH) volume	01/04/2016	14,863,289.47	86,262,018.01
Ripple (XRP) volume	01/02/2017	1,156,240,000.00	1,157,121,007.34
VIX	01/01/2016	18.71	7.68
M3	01/01/2016	131.89	21.92

Source: Investing.com for cryptos (volume and price) https://www.investing.com/crypto/

St. Louis FED for GEPU, VIX; https://fred.stlouisfed.org/series

OECD for M3; https://data.oecd.org/money/broad-money-m3.htm#indicator-chart

ENBI www.PolicyUncertainty.com

3.2 Descriptive statistics

Table 1 provides the descriptive statistics of variables used in the empirical investigation. Crypto data (prices and volumes) come from Investing.com, the indices GEPU and the VIX come from the St. Louis FED database (FRED); the index ENBI comes from the Baker et al. (2016) website; money aggregate M3 data comes from the OECD.

The price of Bitcoin has an average value of $14,280, with a standard deviation of $1029; the price of Ethereum has an average value of $746, with a standard deviation of $1017. Ripple has an average price of $0.42, with a standard deviation of $0.31. The volume of cryptos is relevant for Ethereum and Ripple, thanks to their faster and more efficient trading systems. The GEPU and ENBI had a peak during the pandemic crisis of 2020, and have similar average values (GEPU mean = 223; ENBI mean = 234). The financial volatility index (VIX) has an average value of 19, with a standard deviation of 7.7. Global money aggregate M3 is a seasonally adjusted index based on 2015 = 100, has steadily increased during the period under observation, and has an average value of 132.

3.3 Preliminary stationarity results

Preliminary to the regression analysis, we investigate stationarity for the series of the logarithms of the volumes of Bitcoin, Ethereum and XRP and for ln(ENBI) and ln(GEPU). Stationarity is, in fact, a relevant property of time series data, and is essential for modelling their behaviour. We base our analysis on a battery of unit-root tests: the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and DFGLS; results are reported in Table 2. To solve possibly divergent conclusions from the

Table 2 Stationarity test results

Variable	ADF test	DF-GLS test	PP test	KPSS test	Obs
	p max (11)	lag(10)	p (11)	Lag(3) truncation	
Ln(Vol. BTC)	−2.302	−1.661	−40.607***	0.117	72
P-value	0.432	0.376	0.0000	0.1154	
	p max (11)	lag(9)	p (11)	Lag(3) truncation	
Ln(Vol.ETH)	−2.207	−2.212	−72.452***	0.141**	75
P-value	0.486	0.83	0.0000	0.05	
	p max (10)	lag(9)	p (10)	Lag(3) truncation	
Ln(Vol.XRP)	−2.421	−2.429	−23.672**	0.112	65
P-value	0.368	0.41	0.012	0.13	
	p max (10)	lag(1)	p (10)	Lag(3) truncation	
Ln(GEPU)	−2.593	−2.553	−23.664**	0.187**	68
P-value	0.283	0.155	0.027	0.016	
	p max (10)	lag(0)	p (10)	Lag(3) truncation	
Ln(ENBI)	−4.343**	−4.373***	−33.990***	0.112	65
P-value	0.027	0.001	0.0013	0.137	

Note: *, **, *** is significant at 10%, 5% and 1% respectively

unit-root tests, we also carry out tests of stationarity, the KPSS tests (Kwiatkowski et al., 1992).

For all tests, we implement the versions where the null hypothesis is a unit-root process with a possible drift against an alternative trend-stationary process. All testing procedures accommodate serial correlation. ADF and DFGLS do this parametrically assuming an ARMA process for the error term in the estimating equations. Increasing the truncation lag p of the ARMA process aims at reducing size distortion, but with the downside of less power.

We first compute the ADF and DFGLS tests using an upper bound for the truncation lag as determined by the (Schwert, 1989) formula $p_{max} = int[(12 \cdot (T/100)^{1/4}]$, then we refine the test reducing the truncation lag by applying the sequential-t rule by (Ng & Perron, 1995).[1] The sequential-t rule is data-dependent, but, interestingly, the lag orders it selects turn out to be identical between ADF and DFGLS with our data, easing interpretation of results. Ng and Perron (1995) shows that, differently from sequential-t rules, information-based rules (AIC, BIC) tend to select too small truncation lags and are therefore less robust in terms of size properties.

The PP tests accommodate serial correlation (up to a truncation lag p of choice) and heteroskedasticity nonparametrically using Newey-West standard errors. We consider the same truncation lags as in the ADF and DFGLS and also, when different, the two Newey-West truncation lags, $p_{short} = int[(4 \cdot (T/100)^{2/9}]$ and $p_{long} = int[(12 \cdot (T/100)^{2/9}]$.

[1] We trim the longest lags from the ADF regression, one by one, until the longest remaining has a t-statistic no smaller than 1.6 (p-value < 0.1).

The unit-root tests often lead to divergent conclusions on the stationarity of the process, depending on the procedure, on the number of observations and on the degree of serial correlation accommodated by the procedure. For this reason, we accompany the unit-root analysis with the implementation of a testing procedure developed for the null hypothesis of trend-stationarity, the KPSS test (Kwiatkowski et al., 1992) and its extension by (Hobijn et al., 2004). The Stata implementation of KPSS is carried out through the kpsstest command by (Kagalwala, 2022). Serial correlation is accommodated by specifying the lag truncation $p_{short} = int[(4 \cdot (T/100)^{2/9}]$ and when in doubt also $p_{long} = int[(12 \cdot (T/100)^{2/9}]$.

The testing procedures for BTC lead to different conclusions. ADF and DFGLS tests do not permit to reject the null of unit-root at conventional levels of significance. All PP tests instead reject the null at any conventional level of significance. One may suspect that there is a lack of power in the regression-based tests, ADF and DFGLS, due to the paucity of data, which does not affect the PP test. We try to solve the ambiguity by examining trend-stationarity as a null hypothesis through the KPSS test. The KPSS does not reject the trend-stationarity of BTC at any conventional level.

The ADF tests cannot reject the null of unit-root of ETH at conventional sizes. The PP test always decidedly rejects the null hypothesis of unit root. According to the KPSS test with automatic lag truncation to 3, trend-stationarity cannot be rejected at the 5% level for ETH. Increasing the lag truncation to 6, the resulting KPSS test does not reject the null hypothesis of trend stationarity also at the 10% level.

The ADF tests cannot reject unit root in XRP at any conventional level; the PP tests cannot reject only at the 1% level. The KPSS test cannot reject trend-stationarity of XRP at all conventional levels.

Interestingly, there appears to be some evidence of non-stationarity for the GEPU index. All tests do not reject at conventional levels, except PP with $p = 10$, which does not reject only at the 1% level. This is consistent with the outcome from the KPSS test with $p = 3$, which rejects trend-stationarity at the 5% level. However, when $p = 6$ the KPSS test does not reject trend-stationarity at any conventional level.

There are mixed results from the unit-root tests as well for ENBI. Nevertheless, trend-stationarity is not rejected at any conventional level by the KPSS test.

To sum up, for all variables, ADF and DFGLS on the one hand and PP on the other, tend to lead to contrasting conclusions on the unit-root hypothesis. This ambiguity may be due to the paucity of observations in the current data set.

KPSS tests decidedly support trend-stationarity; the only exception is GEPU where the test does not reject only when the order of serial correlation is increased from 3 to 6. Relying on the evidence from the KPSS tests, we proceed with the analysis of the relationship between volumes of cryptocurrencies and the EPU indices.

Table 3 Log-volumes regressions with non-linear trends

Marginal effects\ Specification	GEPU(0,11) BTC	GEPU(12,11) BTC	ENBI(0,11) BTC	ENBI(12,11) BTC	GEPU(12,11) ETH	ENBI(12,11) ETH	GEPU(0,11) XRP	GEPU(12,11) XRP	ENBI(12,11) XRP
Dynamic effect	–	−0.1875	–	0.2702	−2.9363*** (0.9054)	−0.9147*	–	0.2879	0.5495**
Robust S.E		(0.5973)		(0.4298)	(0.9054)	(0.4864)		(0.1804)	(0.1976)
One-year effect	0.0065***	0.0096***	0.0066**	0.0107**	0.0252***	0.0149**	0.0187***	0.0121*	0.0129**
Robust S.E	(0.0010)	(0.0033)	(0.0028)	(0.0047)	(0.0085)	(0.0061)	(0.0023)	(0.0056)	(0.0053)
Six-month effect	0.0012	0.0044**	0.0007	0.0049*	0.0087**	0.0055	0.0061**	0.0052**	0.0091**
Robust S.E	(0.0017)	(0.0016)	(0.0029)	(0.0026)	(0.0037)	(0.0043)	(0.0025)	(0.0023)	(0.0033)
Long-run effect	–	0.0081**	–	0.0147	–	0.0078**	–	0.0170**	0.0287**
Robust S.E		(0.0041)		(0.0121)		(0.0017)		(0.0067)	(0.0140)
Trend	−0.6821**	−1.2280**	0.1227	−0.3575	−7.8505***	−2.5154**	−2.7916**	−1.7418*	−0.1000
Robust S.E	(0.2668)	(0.4675)	(0.5861)	(0.2741)	(2.1181)	(0.9822)	(1.0068)	(0.8897)	(0.9971)
Trend^2	0.0005**	0.0008**	−0.0001	0.0002	0.0054***	0.0017**	0.0019**	0.0012*	0.0001
Robust S.E	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0015)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
Month dummies F-test	8.68***	3.47***	6.66***	5.12***	10.89***	15.15***	5.77***	14.83***	7.41***
R-squared	0.39	0.76	0.6	0.8	0.73	0.87	0.79	0.94	0.93
# Obs	58	57	58	57	58	54	52	51	47

Note: Robust S.E. are HAC standard errors with Bartlett kernel and 12 lags; *, **, *** is significant at 10%, 5% and 1% respectively

Table 4 Log-volumes regressions with non-linear trends, M3 and VIX (robustness checks)

Marginal effects\Specification	GEPU(0,11) BTC	GEPU(12,11) BTC	ENBI(0,11) BTC	ENBI(12,11) BTC	GEPU(12,11) ETH	ENBI(12,11) ETH	GEPU(12,11) XRP	GEPU(12,11) XRP
Dynamic effect	–	−0.8765	–	−0.2950	−2.8802***	−1.3384**	0.6827*	1.7906***
Robust S.E		(0.3815)		(0.3425)	(0.8765)	(0.5152)	(0.3195)	(0.4743)
One-year effect	0.0062***	0.0106***	0.0065*	0.0059	0.0190***	0.0149**	0.0415***	0.0469**
Robust S.E	(0.0014)	(0.0024)	(0.0037)	(0.0075)	(0.0063)	(0.0061)	(0.0037)	(0.0141)
Six-month effect	0.0009	0.0059	0.0008	−0.0014	0.0026	0.0055	0.0082**	0.0099**
Robust S.E	(0.0025)	(0.0042)	(0.0037)	(0.0054)	(0.0067)	(0.0043)	(0.0032)	(0.0062)
Long-run effect	–	0.0057***	–	0.0045	–	–	0.1309	–
Robust S.E		(0.0015)		(0.0066)			(0.1353)	
Trend	−0.5579	0.2070	0.2689	−0.9125	−9.2840***	−4.3078***	−14.1227***	−7.2699*
Robust S.E	(0.3781)	(0.8997)	(0.4493)	(0.9993)	(2.5545)	(0.9769)	(0.0197)	(3.2828)
Trend^2	0.0004	−0.0002	−0.0002	0.0006	0.0065***	0.0030***	0.0099***	0.0052*
Robust S.E	(0.0003)	(0.0007)	(0.0003)	(0.0007)	(0.0018)	(0.0007)	(0.0000)	(0.0023)
L6.M3	0.0088	0.0623	0.0051	−0.0389	−0.0845	−0.0563**	−0.2711***	−0.2524
Robust S.E	(0.0174)	(0.0438)	(0.0239)	(0.0453)	(0.0530)	(0.0246)	(0.0188)	(0.1407)
L6.vix	0.0161**	0.0091	0.0101	0.0355	0.0479	0.0203	−0.0199	−0.0152
Robust S.E	(0.0076)	(0.0136)	(0.0083)	(0.0242)	(0.0413)	(0.0193)	(0.0209)	(0.0271)
Month dummies F-test	7.37***	10.44***	5.76***	11.28***	5.50***	17.27***	35.70***	13.91***
R-squared	0.62	0.81	0.61	0.82	0.76	0.88	0.97	0.96
# Obs	58	57	54	53	58	54	51	47

Note: Robust S.E. are HAC standard errors with Bartlett kernel and 12 lags; *, **, *** is significant at 10%, 5% and 1% respectively

Table 5 Log-volumes regressions with non-linear trends and pandemic dummy (robustness check)

Marginal effects\Specification	GEPU(0,11) BTC	GEPU(12,11) BTC	ENBI(0,11) BTC	ENBI(12,11) BTC	GEPU(12,11) ETH	ENBI(12,11) ETH	GEPU(12,11) XRP	ENBI(12,11) XRP
Dynamic effect	–	0.0080	–	0.4619	−2.9272***	−0.9527**	−0.7245**	0.1298
Robust S.E		(0.4754)		(0.4921)	(0.9007)	(0.4389)	(0.3053)	(0.3180)
One-year effect	0.0066***	0.0188***	0.0046	0.0152*	0.0265**	0.0111**	0.0216***	0.0201**
Robust S.E	(0.0014)	(0.0056)	(0.0037)	(0.0077)	(0.0120)	(0.0043)	(0.0053)	(0.0070)
Six-month effect	0.0012	0.0094**	−0.0009	0.0088	0.0094**	0.0019	0.0032	0.0054
Robust S.E	(0.0017)	(0.0037)	(0.0033)	(0.0062)	(0.0045)	(0.0031)	(0.0029)	(0.0031)
Long-run effect	–	0.0190	–	0.0282	–	0.0057***	0.0125***	0.0231***
Robust S.E		(0.0119)		(0.0372)		(0.0015)	(0.0028)	(0.0075)
Trend	−0.6876**	−2.6014**	0.4226	−0.8924	−8.0084***	−1.9836***	−3.8986***	0.0146
Robust S.E	(0.3002)	(0.9110)	(0.6862)	(0.6098)	(2.5154)	(0.6004)	(0.9327)	(1.1185)
Trend^2	0.0005**	0.0018**	−0.0003	0.0006	0.0055***	0.0014***	0.0027***	0.0000
Robust S.E	(0.0002)	(0.0006)	(0.0005)	(0.0004)	(0.0017)	(0.0004)	(0.0006)	(0.0008)
Pandemic	−0.0075	−0.7159**	0.2733	−0.3258	−0.1762	0.3788**	1.3289***	1.1803*
Robust S.E	(0.1327)	(0.2821)	(0.2242)	(0.2850)	(0.4751)	(0.1636)	(0.4222)	(0.5430)
Month dummies F-test	7.55***	8.48***	5.31***	7.20***	7.40***	15.32***	4.36***	10.74***
R-squared	0.59	0.81	0.61	0.81	0.73	0.88	0.95	0.94
# Obs	58	57	54	53	58	54	51	47

Note: Robust S.E. are HAC standard errors with Bartlett kernel and 12 lags; *, **, *** is significant at 10%, 5% and 1% respectively

3.4 Econometric results

Tables 3, 4, 5 present results for the ARDL(12,11) models, and robustness checks. In all specifications, the Huizinga Heteroskedasticity-robust autocorrelation test evidences the presence of autocorrelation in errors, and therefore, we compute Heteroskedasticity–Autocorrelation Consistent (HAC) standard errors by the Newey-West covariance estimator, using a Bartlett kernel with 12 lags. Following the comments received by a referee, we have also tried other types of standard errors, other three HAC types, the Just-Heteroskedasticity Consistent (HC) and the plain, non-robust standard errors with no substantial difference in the significance of our results; we discuss this further in the robustness-checks section of the paper.

To evaluate the uncertainty effect over one year, all ARDL specifications present 11 lags for the uncertainty measures, in addition to the current value. Our most general specification is an ARDL(12,11) model, with the choice of 12 autoregressive lags being supported by the Akaike information criterion (AIC), which at that order turns out to be the smallest over all autoregressive orders ≤ 12 for any crypto and any uncertainty measure. Nonetheless, conscious of the paucity of observations in our samples and that AIC can underweight complexity, we consider more parsimonious models selected on a significance criterion: in the event that the dynamic coefficient $\gamma = \sum_{s=1}^{12} \gamma_s$ is found to be not significantly different from 0, results for the ARDL(0,11) models are also reported. For either ARDL model, the uncertainty measure alternates between GEPU and ENBI. For both BTC specifications, the significance criterion agrees with the degrees-of-freedom corrected AIC (AICc) and the Bayesian information criterion (BIC) in selecting ARDL(0,11). In the case of ETH, the significance criterion rejects ARDL(0,11). In the case of XRP, the significance criterion selects ARDL(0,11), while BIC agrees with AIC in selecting ARDL(12,11). Therefore, we report ARDL(0,11) and ARDL(12,11) for the BTC and XRP equations and, to conserve space, just ARDL(12,11) for the ETH equations, although ARDL(0,11) results are in line with ARDL(12,11). For the same reason and for ease of comparison, we do not report other ARDL specifications selected by BIC and AICc: BIC selects ARDL(1,11) for the ETH-GEPU equation and ARDL(2,11) for ETH-ENBI; AICc selects ARDL(1,11) for XRP-ENBI, ARDL(2,11) for XRP-GEPU and ARDL(0,11) for ETH-GEPU. Our main findings from the reported equations are robust to the non-reported specifications, whose results are available on request from the authors.

The tables contain the estimates of the uncertainty effects after the first 6 months, $\sum_{s=0}^{5} \beta_s$ and after one year, $\sum_{s=0}^{11} \beta_s$, and, limited to the ARDL(12,11) models, of the dynamic coefficient γ. When a stable dynamic (with an estimated dynamic coefficient $|\gamma| < 1$) is found, the long-run effect of uncertainty is reported, $\left(\sum_{s=0}^{11} \beta_s\right)/(1-\gamma)$. Tables also portray the trend coefficients, the R-squared, and the robust F-tests for the joint significance of the monthly dummies. The estimation-sample size, accommodating the observations lost to the lags in the specification, is reported at the end of each table.

Regression results are quite clear-cut. For each crypto, the short and long-run impacts of uncertainty shocks, however measured, are significantly positive and, in most cases, they begin to show already in the first six months after the shock.

The ARDL(12,11) specifications for Bitcoin show a significant increase in volumes of around 1% occurring over a year after a unit increase in either GEPU or ENBI (Table 2). In the first six months, the increase was already significant, around a 0.4%. Dynamic is not pronounced, with a barely significant γ coefficient; we therefore estimated the ARDL(0,11) specifications. Results are close to the more general dynamic specifications, with less significant six-month effects, and smaller one-year effects.

The dynamic is, instead, significant for Ethereum, negative dynamic coefficients emerge in either specification, with that of the GEPU specification greater than unity in absolute value (Table 3). In all cases, we observe significantly positive short-run effects of uncertainty. For the stable ENBI specification, where we find well-defined long-run coefficients, we also find a significantly positive long-run effect of uncertainty.

Ripple (XRP) presents pronounced dynamics only in the ENBI specification, which is so implemented only as an ARDL(12,11) model (Table 3). For the GEPU specification, we also tried the ARDL(0,11) model. In all cases, the uncertainty effects, six-months, one-year and long-run, are significant and positive. Based on these results, the H1 can be confirmed, i.e., there is a statistically significant relationship between EPU and crypto volumes.

3.5 Robustness checks

Following the literature (Al-Thaqeb & Algharabali, 2019), as robustness checks, we have extended our specification to two variables, lagged six times: (1) the M3 global aggregate, to capture the impact of global liquidity on investment in cryptocurrencies; (2) the VIX, index of financial volatility.

The ultra-expansionary monetary policies implemented by most central banks during the period under observation provided investors with cheap funding, but also reduced yields, thus leading to excessive risks taking behavior (Iménez et al., 2014). The index of financial volatility is considered in many empirical analyses as a control variable because it directly influences the EPU index.

Results of estimates of Eq. (2) are largely in line with the previous findings, with the uncertainty measures, GEPU and ENBI, always exerting a positive impact at various levels on crypto volumes (Table 4). There are significantly positive short-run effects of uncertainty, and the control variables, the global money aggregate M3 and the VIX, contribute to increase the goodness of fit. Other specifications have been tested, where VIX replaces ENBI and GEPU, as an uncertainty index, with still similar findings (these additional results are available from the authors on request).

We have also extended the baseline specification to a dummy variable for years 2020, 2021 and 2022 to capture the effect of the pandemic crisis (Table 5).

Again, this does not modify our main result on the positive relationship between volumes of cryptocurrency and uncertainty indexes. We only notice that in the XRP specifications the presence of the pandemic dummy modifies the dynamic effect in GEPU(12,11) from insignificant to negatively significant, and in ENBI(12,11) from positively significant to insignificant.

The small size of our samples may raise concerns on the accuracy of coefficient estimates and HAC standard errors. One possibility to increase the degrees-of-freedom count could be turning to high-frequency data, such as daily. But this is a route that we could not follow as daily data, although available for the crypto volumes, are not for the uncertainty measures. Therefore, in order to increase degrees-of-freedom for the coefficient estimates, we have estimated a SURE three-equation model comprising the baseline ARDL equations for BTC, ETH and XRP with cross-equation equality constraints for the coefficients on the current and lagged uncertainty measures. All the estimated SURE models decidedly confirm our finding of significantly positive impacts of the uncertainty measures on the crypto volumes. SURE results are reported in Table A.2 in the Appendix; beyond the SURE models with GEPU and ENBI, we have also considered two SURE models with the VIX index, referred to in the table as VIX(0,11) and VIX(12,11).

Small sample sizes could also impair the finite sample accuracy of our reported Newey-West HAC SEs and the size of the significance tests. We therefore considered three HAC refinements that are routinely computed by statistical software: HAC SEs with a quadratic spectral kernel (Andrews, 1991), HAC SEs with Bartlett kernel and Newey-West automatic lag selection (Newey & West, 1994) and HAC SEs with quadrispectral kernel and Newey-West lag selection. We also considered two more conventional SEs, the just heteroskedasticity consistent (HC) SEs and the plain SEs, only consistent under i.i.d. errors. We computed these additional SEs for all models of Table 3 with results reported in Table A.1. In most cases, the new SEs are in line with the SEs of Table 3, so confirming our findings. In particular, for all but one models, all of the new SEs confirm the significantly positive one-year effect of the uncertainty measures. Only for the ENBI(12,11) XRP model we notice that for three of the new SEs (HC, plain and HAC with Bartlett kernel and automatic lag selection) the corresponding t-tests on the one-year effect reversed to non-significant.

We are aware that this evidence is non-conclusive and that the small-sample issues are challenging in empirical work with crypto data, at the moment. Our future research will progress along this direction, by regularly updating the data and focusing on robust methods of estimation and inference.

4 Conclusions

The positive relationship between crypto volumes and global EPU indices, over the period 2016–2022, shows that when uncertainty significantly prevails, investors increase their demand for cryptos. This result is new in the literature; this behavior is coherent with the fact that crypto investors are mainly risk lovers, and then look for high-risk assets, also in periods of high volatility. Crypto trading attracts young investors, especially those with average or low financial literacy, who can suffer disproportionally in the long run, if they concentrate their wealth in high-risk assets, and do not differentiate their portfolios. Given the nature of crypto investors, it would be important to develop better educational strategies for improving financial literacy, with a specific focus on the young and young/adult populations in the digital ecosystem.

Conclusions from the findings are related to supervision, and monitoring of markets and financial stability. The blockchain has certain barriers to entry that induce most (unsophisticated) users to access it through digital intermediaries and exchanges. The monitoring of markets and supervision of crypto assets at the global level can be implemented by applying the same rules to all intermediaries, in line with the principle “same activity, same risk, same regulation” (Financial Stability Board, 2022, 2023). The benefits of treating cryptocurrencies’ intermediaries and exchanges in the same way as traditional financial ones exceed the costs of regulation, that is already in place, and the costs of compliance.

There is no consumer or investor protection system in the blockchain, and this structural asymmetry, regarding traditional financial markets, constitutes a weakness that can alter financial stability. Domestic authorities should make small size investors aware of the extreme risks to which they are exposed in these systems, and the consumer and investor protection system should be extended to blockchain trading, via intermediaries and exchanges.

The monitoring and supervision of digital intermediaries and exchanges will hopefully also contribute to making more granular data available for research. This would allow future research to map the characteristics of digital investors, analyze the relationship between their managerial ability and returns, assess the costs of regulating digital intermediaries, and the related benefits for the economic system as a whole.

Appendix

See Tables A.1 and A.2.

Table A.1 Three-equation system regression (SURE)

Marginal effects\ Specification	GEPU(0,11)	GEPU(12,11)	ENBI(0,11)	ENBI(12,11)	VIX(0,11)	VIX(12,11)
Dynamic effect BTC	–	−1.2845***	–	−0.7334***	–	0.7797***
Robust S.E		(0.2024)		(0.1669)		(0.1808)
Dynamic effect ETH	–	−1.0085***	–	−2.0977***	–	−05957*
Robust S.E		(0.2351)		(0.0840)		(0.3225)
Dynamic effect XRP	–	−0.2630**	–	0.7400***	–	0.2413***
Robust S.E		(0.1057)		(0.1081)		(0.0843)
One-year effect	0.0038***	0.0136***	0.0077***	0.0259***	0.0804***	0.0361***
Robust S.E	(0.0010)	(0.0011)	(0.0012)	(0.0013)	(0.0066)	(0.0091)
Six-month effect	−0.0016	0.0054***	0.0053***	0.0087***	0.0378***	0.0309***
Robust S.E	(0.0012)	(0.0008)	(0.0009)	(0.0009)	(0.0057)	(0.0062)
Long-run effect BTC	–	–	–	0.0150***	–	0.0078**
Robust S.E				(0.0012)		(0.0017)
Long-run effect ETH	–	–	–	–	–	0.0226***
Robust S.E						(0.0067)
Long-run effect XRP	–	0.0108***		0.0998**	–	0.0476***
Robust S.E		(0.0006)		(0.0428)		(0.0108)
# Obs	58	51	58	47	61	54

Note: Robust S.E. are Heteroskedasticity-consistent standard errors. Month dummy coefficients and trend components are equation-specific. Month dummy coefficients are always jointly significant. Trend components are insignificant only in the XRP equations of models GEPU(0,11), VIX(0,11) and VIX(12,11). *, **, *** is significant at 10%, 5% and 1% respectively

Table A.2 Log-volumes regressions with non-linear trends—more SEs (in parentheses)

Marginal effects\ Specification	GEPU(0,11) BTC	GEPU(12,11) BTC	ENBI(0,11) BTC	ENBI(12,11) BTC	GEPU(12,11) ETH	ENBI(12,11) ETH	GEPU(0,11) XRP	GEPU(12,11) XRP	ENBI(12,11) XRP
Dynamic effect	–	−0.1875	–	0.2702	−2.9363***	−0.9147*	–	0.2879	0.5495**
HAC		(0.5973)		(0.4298)	(0.9054)	(0.4864)		(0.1804)	(0.1976)
HAC1		(0.6207)		(0.4094)	(0.8328)	(0.4879)		(0.1055)>*	(0.1339)
HAC2		(0.6196)		(0.5241)	(0.8182)	(0.4552)		(0.1459)>*	(0.2637)
HAC3		(0.5510)		(0.2674)	(0.6353)	(0.3722)		(0.1061)>*	(0.1127)
HC		(0.6055)		(0.5788)	(1.1906)	(0.5094)		(0.3641)	(0.4561)<*
Plain		(0.5560)		(0.5070)	(0.9551)	(0.5219)		(0.3379)	(0.4686)<*
One-year effect	0.0065***	0.0096***	0.0066**	0.0107**	0.0252***	0.0149**	0.0187***	0.0121*	0.0129**
HAC	(0.0010)	(0.0033)	(0.0028)	(0.0047)	(0.0085)	(0.0061)	(0.0023)	(0.0056)	(0.0053)
HAC1	(0.0008)	(0.0034)	(0.0029)	(0.0045)	(0.0078)	(0.0063)	(0.0016)	(0.0054)	(0.0038)
HAC2	(0.0009)	(0.0034)	(0.0030)	(0.0049)	(0.0075)	(0.0058)	(0.0019)	(0.0053)	(0.0071)<*
HAC3	(0.0007)	(0.0034)	(0.0031)	(0.0048)	(0.0058)	(0.0053)	(0.0009)	(0.0048)	(0.0032)
HC	(0.0016)	(0.0029)	(0.0023)	(0.0052)	(0.0093)	(0.0053)	(0.0033)	(0.0058)	(0.0090)<*
Plain	(0.0020)	(0.0039)	(0.0026)	(0.0054)	(0.0073)	(0.0050)	(0.0034)	(0.0073)	(0.0105)<*
Six-month effect	0.0012	0.0044**	0.0007	0.0049*	0.0087**	0.0055	0.0061**	0.0052**	0.0091**
HAC	(0.0017)	(0.0016)	(0.0029)	(0.0026)	(0.0037)	(0.0043)	(0.0025)	(0.0023)	(0.0033)
HAC1	(0.0018)	(0.0012)	(0.0030)	(0.0023)	(0.0036)	(0.0046)	(0.0021)	(0.0023)	(0.0030)
HAC2	(0.0018)	(0.0016)	(0.0028)	(0.0031)<*	(0.0035)	(0.0043)	(0.0021)	(0.0023)	(0.0041)
HAC3	(0.0017)	(0.0009)	(0.0030)	(0.0015)	(0.0033)	(0.0043)	(0.0018)	(0.0022)	(0.0028)
HC	(0.0021)	(0.0029)<*	(0.0020)	(0.0032)<*	(0.0047)	(0.0033)	(0.0034)	(0.0027)	(0.0041)
Plain	(0.0023)	(0.0029)<*	(0.0027)	(0.0035)<*	(0.0058)<*	(0.0034)	(0.0031)	(0.0035)<*	(0.0053)<*

Table A.2 (continued)

Marginal effects\ Specification	GEPU(0,11) BTC	GEPU(12,11) BTC	ENBI(0,11) BTC	ENBI(12,11) BTC	GEPU(12,11) ETH	ENBI(12,11) ETH	GEPU(0,11) XRP	GEPU(12,11) XRP	ENBI(12,11) XRP
Long-run effect	–	0.0081**	–	0.0147		0.0078***	–	0.0170**	0.0287**
HAC		(0.0041)		(0.0121)		(0.0017)		(0.0067)	(0.0140)
HAC1		(0.0042)		(0.0118)		(0.0018)		(0.0054)	(0.0116)
HAC2		(0.0045)		(0.0145)		(0.0016)		(0.0058)	(0.0160)
HAC3		(0.0044)		(0.0104)		(0.0014)		(0.0042)	(0.0099)
HC		(0.0046)		(0.0142)		(0.0016)		(0.0094)	(0.0284)<*
Plain		(0.0048)		(0.0138)		(0.0017)		(0.0095)	(0.0336)<*
R-squared	0.39	0.76	0.6	0.8	0.73	0.87	0.79	0.94	0.93
# Obs	58	57	58	57	58	54	52	51	47

Note: *, **, *** is significant at 10%, 5% and 1% respectively. HAC: HAC SEs with Bartlett kernel and 12 lags (the HAC SEs in Table 3); HAC1: HAC SEs with quadrispectral kernel and 12 lags; HAC2: HAC SEs with Bartlett kernel and Newey-West optimal choice of lags; HAC3: HAC SEs with quadrispectral kernel and Newey-West optimal choice of lags; HC: HC SEs; Plain: Non-robust SEs. All SEs are computed with the finite-sample correction n/(n-k). Symbols <* and >* indicate the cases of reversed significance from HAC to the new SE: <* indicates that the new SE does not yield a significant t-test (p-value > 0.1) when HAC does (p-value < 0.1) and >* indicates the opposite. In the absence of <* or >*, the new SE is equivalent to HAC in terms of significance: either the new SE and HAC both yield t-tests with p-value > 0.1 or both yield t-tests with p-value < 0.1

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Data availability Data used in this paper is publicly available; crypto volumes come from https://www.investing.com/crypto/; GEPU and VIX from https://fred.stlouisfed.org/series; ENBI from www.PolicyUncertainty.com; M3 from https://data.oecd.org/money/broad-money-m3.htm#indicator-chart.

Declarations

Conflict of interest The authors report that there are no competing interests to declare and that there is no conflict of interest.

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Economic policy uncertainty and cryptocurrencies

CreditRoles

Giovanni Bruno: Formal analysis; Methodology; Writing
Chiara Oldani: Conceptualization; Data curation; Writing
Marcello Signorelli: Supervision; Validation; Writing - review & editing.