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Bitcoin attention and economic policy uncertainty

Belén Gill-de-Albornoz [a], Juan A. Lafuente [a,*], Mercedes Monfort [b], Javier Ordoñez [b]

[a] Department of Finance and Accounting and IEI, Universitat Jaume I, Castellón, Spain
[b] Department of Economics and IEI, Universitat Jaume I, Castellón, Spain

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ABSTRACT

This paper explores the role of Economic Policy Uncertainty (EPU) as driver of the Bitcoin public attention. Using Google trends data from January 2010 to November 2021 in a set of 22 countries, a Principal Components Analysis reveals a strong unique commonality on the internet searching patterns for Bitcoin across countries, which suggests that the potential explaining factors of the Bitcoin attention should be global instead of local. The multivariate analysis corroborates this hypothesis since EPU at the country level does not play a significant role in explaining the searching patterns on Google for Bitcoin, while the global EPU does.

1. Introduction

Since they emerged in the early 2000s, cryptocurrencies have created an entire ecosystem worth almost $400 billion in 2021. Bitcoin is the most renowned with more than double the market capitalisation and trading volume than the second one, Ethereum.[1]

Bitcoin-related research is prolific. Economics, finance, and business studies concentrate more than 18% of the articles published in leading journals since 2011 (Aysan et al., 2021). Academics have intensively debated on whether the Bitcoin is a currency, an asset, or a commodity; and studied its use for speculative, diversification, hedging, or safe haven purposes (e.g., Dyhrberg 2016; Klein et al., 2018; Bouri et al., 2020; Conlon and McGee 2020; Matkovskyy and Jalan 2019). Fundamental questions to the understanding of the Bitcoin market that concern researchers include: what factors underlie its value formation and fluctuating prices (eg., Polasik et al., 2015; Kristoufek 2015; Brandvold et al., 2015; Griffin and Shams 2020; Bouoiyour et al., 2016; Gandal et al., 2018; Eross et al., 2019; Urquhart 2017; Panagiotidis et al., 2019; Nadler and Guo 2020); the causes and consequences of this market's tendency to create price bubbles (e.g., Bariviera et al., 2017; Kayal and Balasubramanian 2021; Su et al., 2020; Frehen et al., 2013; Corsi and Sornette 2014; Vogel and Werner 2015); or whether the market is efficient (e.g., Urquhart 2016; Bariviera 2017; Kurihara and Fukushima 2017; Nadarajah and Chu 2017; Sensoy 2019).

This study is framed within the strand of research that concerns with the association between EPU and cryptocurrency markets. There is evidence that EPU affects Bitcoin market fundamentals since it is a predictor of returns and volatility (e.g., Bouri and Gupta 2019; Bouri et al., 2017; Demir et al., 2018; Fang et al., 2019). However, to the best of our knowledge, there is no prior research studying EPU as a driver of Bitcoin attention, which is the purpose of this research. The association is not clear a priori. On the one hand, high EPU levels might generate the fear of investors in the crypto-market and move their attention to other financial markets. On the other hand, considering the hedging effect on the volatility of Bitcoin (Fang et al., 2019), high levels of economic uncertainty may

* Corresponding author.
E-mail address: lafuen@uji.es (J.A. Lafuente).

[1] https://coinmarketcap.com/

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lead investors to look for investing their money in Bitcoin if they consider it to be a safe-haven asset.

We employ *Google Trends* data to proxy for Bitcoin public attention, and we perform a cross country analysis since we aim to offer empirical insights as to whether global or local risk factors are relatively more important for explaining the public interest in this cryptocurrency. While the increasing globalization of the world economy would suggest that global risk factors are more important, country specific drivers like development of financial infrastructure, regulatory environment, access to trade, financial literacy and media influence could also play a non-negligible role. Thus, we consider the geographical location of google searches, and our panel data model includes the global as well as each country's EPU indexes, which are widely accepted measures for economic policy risk.

A Principal Component Analysis (PCA) reveals a common trend in the evolution of public attention to Bitcoin worldwide. In addition, the multivariate regression analysis shows that the global EPU index has a negative and significant association with the Google searches for Bitcoin, but the country specific EPU index has no effect. This evidence suggests that interest in cryptocurrencies could be a story of narrative economics (Shiller 2019) and is consistent with the existence of herding behaviour of investors towards Bitcoin (Bouri and Gupta 2019). Social media trends and global EPU are key elements for driving the appetite of investors worldwide for this decentralised currency. The negative relation of the global EPU index and Bitcoin attention indicates that Bitcoin is not perceived by the public as a haven asset. This evidence adds to our understanding of the role of retail investors in cryptocurrencies markets. Given the speculative nature of cryptocurrencies, they might be more appealing to non-smart investors who interpret public information differently to institutional investors (Lucey et al., 2021). As claimed by Smales (2022), the presence of these "noise" traders could underlie the fact that cryptocurrency prices diverge from fundamental values.

The rest of the paper is organised as follows. Section 2 describes the Bitcoin attention measure employed and presents the analysis carried out to identify worldwide patterns. Section 3 provides the empirical models estimated to test EPU as an additional driver of Bitcoin attention and discusses the findings. Finally, Section 4 concludes.

2. Worldwide Bitcoin attention patterns

Following prior research, we proxy public attention to Bitcoin (*GTB*) from Google Trends (Da et al., 2011; Khalfaoui et al., 2023; Urquhart 2018; Smales 2022). In particular, we collect data for the key word "Bitcoin"[2] from January 2010 to November 2021 period.[3] This proxy makes sense for several reasons: internet searches are a direct measure of attention (Platania et al., 2023); Google accounts for 90 % of global internet search volume, so that we proxy for the search behaviour of the broad population; and Google search volume proxies for information acquisition by retail investors, the most prone to cryptocurrency speculation (Da et al., 2011). Considering data availability of our main research variables, EPU indexes,[4] the sample is composed of the following 22 countries: a) the G7: Canada, France, Germany, Italy, Japan, United Kingdom and the United States; b) advanced economies in the Eurosystem: Greece, Ireland, The Netherlands, Spain; c) emerging and developing Economies: Brazil, Chile, China, Colombia, India, Mexico and Russia; and d) advanced economies other than the G7 and the Eurosystem: Australia, Sweden, Singapore and South Korea.

To identify differences among countries in the searching patterns for Bitcoin (*GTB*) over time, and to provide insights into country clustering, we first perform a PCA, whose results are reported in Table 1. Two factors are suggested: the second largest eigenvalue comes close to 1, and the individual percentage of explained variance is negligible in terms of the first component, which accounts for almost 90% of intragroup variability.[5] Fig. 1 depicts the XY plot of the loadings for the two components, where three relevant aspects emerge: firstly, a cluster for most of the developed countries arises; secondly, according to the magnitude of the loading for the second component, a second cluster is suggested, which includes Japan, South Korea, China and India; finally, Russia is clearly an outlier for both component loadings.

The commonalities across countries for the Bitcoin searching patterns revealed by the PCA indicate a common trend in the time evolution of worldwide searches, as well as some departures for specific countries. This evidence suggests that global risk factors should play an important role for understanding Bitcoin public attention. However, it also leaves some space for local or specific country risk factors to explain Bitcoin attention trends. To figure out the relative importance of global versus local factors, we turn our attention to the Multivariate Analysis.

3. Drivers of Bitcoin attention

To explore local and global policy uncertainty as drivers of Bitcoin public attention, we firstly estimate the panel data model specified in expression (1).

[2] Urquhart (2018) provides evidence that just the term "Bitcoin" adequately captures retail investors' attention to this cryptocurrency (Urquhart 2018: 41). The search queries on Google are not case-sensitive. The data provided by Google Trends represent relative popularity. The collected time series are numbers scaled within a range from 0 to 100 based on the topic's proportion to all searches on all topics. The different regions that show the same search interest for a term do not always have the same total search volume. A zero rating would not mean that no-one searched for Bitcoin, but only a few compared to peaks.

[3] Downloading date 15th February 2022.

[4] Downloaded in February 2022.

[5] The Phillips and Sul (2007, 2009) approach to endogenously check the number of clusters for the searching patterns of countries over time reveals the existence of a unique cluster.

Table 1
Principal component analysis of the searching patterns for Bitcoin (*GTB*) in the 22 countries of the sample. Eigenvalues and percentage of explained variance.

Component	Percentage of explained variance		
	Eigenvalue	Individual	Cumulative
1	19.669	0.894	0.894
2	1.006	0.046	0.940
3	0.612	0.028	0.968
4	0.277	0.013	0.980
5	0.113	0.005	0.985
6	0.072	0.003	0.989
7	0.060	0.003	0.991
8	0.044	0.002	0.993
9	0.031	0.001	0.995
10	0.027	0.001	0.996

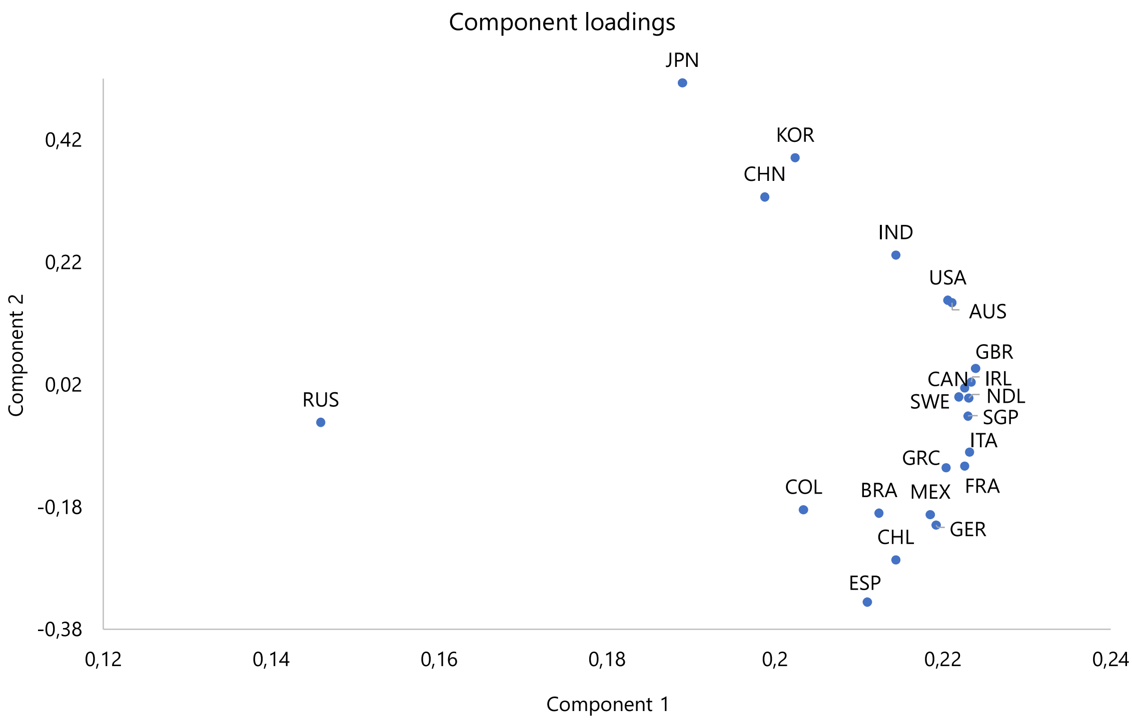

Fig. 1. Principal component analysis. Loadings for the two components.

$$GTB_{i,t} = \alpha_1 + \beta_1 EPU_{i,t} + \beta_2\ GEPU_t\ +\ \beta_3 VIX_t + \beta_4 RA_t +\ \beta_5 GEOPRISK_t + \beta_6 BTCVOLAT_{t-1} +\ \beta_7 BTCRETURN_{t-1} + \beta_8 BTCVOLUME_{t-1} + \beta_9\ t +\ \varepsilon_{i,t} \tag{1}$$

where, the dependent variable is the Google Trend searches for Bitcoin in country i and month t ($GTB_{i,t}$), and as independent variables we include the EPU index for country i in month t ($EPU_{i,t}$) and the Global EPU Index in month t ($GEPU_{i,t}$), both collected from the EPU website; and a set of control variables which the literature suggests that relate with investors' attention, as follows:

- Expected volatility, proxied by the Chicago Board Options Exchange Volatility Index in month t (VIX_t). Bouri et al. (2019) finds that Bitcoin acts as a hedge against uncertainty, and Glaser et al. (2014) suggest that uninformed users who approach digital currencies seek a new investment instrument rather than an alternative payment method.
- Investors' risk aversion. We use the Risk Aversion Index developed by Bekaert et al. (2021) in month t (RA_t). This index is a proxy for investor sentiment toward risky assets that is based on a separate identification of the aversion to risk and the amount of risk.
- Geopolitical risk, proxied by the Geopolitical Risk Historical Index developed by Caldara and Iacoviello (2022) in month t ($GEOPRISK_t$), available in the EPU website. There is evidence that geopolitical risk negatively affects investment levels (Wang et al., 2023), reduces markets' liquidity (Fiorillo et al., 2023), and that Bitcoin can be considered as a hedging tool against it (Aysan et al., 2019).

- Bitcoin market fundamentals: a) lagged monthly Bitcoin returns ($BTCRETURN_{t-1}$), calculated as the monthly percentage change in price; b) lagged Bitcoin volatility ($BTCVOLAT_{t-1}$) based on the estimation of a GARCH (1,1) model with generalized error distribution, where conditional mean is an AR (1) for such monthly returns; and c) lagged values for the natural logarithm of aggregated monthly Bitcoin trading volume ($BTCVOLUME_{t-1}$).[6] Urquhart (2018) finds that past volatility, returns, and trading volume relate to internet search volume for Bitcoin; while Aalborg et al. (2019) or Ibikunle et al. (2020) show evidence that the volume of internet searches, and tweets, can predict Bitcoin trading volume and volatility.

The model also includes a linear time trend (t) to control for non-stationarity.[7]

Data availability of the research variables limits the sample employed in this analysis to the period beginning in January 2015, being the sample size 1741 observations. Table 2 reports the pairwise correlations between the research variables, which suggests that there are no potential redundant regressors and all the research variables in model (1) could be jointly considered to explain *GTB*.

The results of the estimation of model (1) are shown in the first column of Table 3, where, as indicated by the Hausman test, we report the fixed effects estimation. Our results suggest that global economic policy uncertainty casts down the relative popularity of Bitcoin, since the coefficient of *GEPU* is negative and statistically significant. The effect of country level economic uncertainty (*EPU*) on *GTB* is not statistically significant. This result is consistent with the evidence revealed by the PCA presented in Section 2, and with the growing literature related to the presence of herding behaviour in the cryptocurrency market, where investment is mostly driven by social influence or public sentiment (e.g., Almeida and Gonçalves, 2023).

Regarding the control variables, the positive and significant coefficient of *VIX* indicates that greater expected volatility in the financial market enhances public attention towards Bitcoin. The negative effect of *GEOPRISK* on *GTB* suggests that, despite Bitcoin having limited supply and government interference, it is not perceived as a safe-haven asset, which are often sought-after during periods of geopolitical uncertainty. This evidence is in line with Klein et al. (2018), who claim that Bitcoin is not “the new Gold”. Consistently, *RA* also has a negative and significant coefficient, meaning that lower risk tolerance leads investors to pay less attention to Bitcoin, like other high-risk assets. Regarding the market’s fundamentals, the results are consistent with Urquhart (2018) as *BTCVOLAT*, and *BTCRETURN* positively and significantly relate to *GTB*. The higher the potential profits and risk observed in the Bitcoin market the more interest is paid to this cryptocurrency.

As a robustness check, we account for the potential endogeneity of economic policy uncertainty in our panel data estimation, by implementing a 3SLS approach for Eq. (1), using the following auxiliary regression in the first stage:

$$\begin{aligned} GEPU_t = {} & \alpha_1 + \beta_1\ GTB_{i,t} + \beta_2 BTCVOLAT_{t-1} + \beta_3 BTCRETURN_{t-1} \\ & + \beta_4\ BTCVOLUME_{t-1} + \beta_5 USTPU_t + \beta_6 CHINATPU_t \\ & + \beta_7\ t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where the dependent variable is the global economic policy uncertainty index (*GEPU*), explained by: Bitcoin attention (*GTB*); Bitcoin market fundamentals ($BTCRETURN_{t-1}$, $BTCVOLAT_{t-1}$, $BTCVOLUME_{t-1}$), since there is evidence of their association with economic policy uncertainty (e.g., Demir et al., 2018); and two measures of trade uncertainty collected from the EPU website: the US and China monthly Trade Policy Uncertainty Indexes developed respectively by Baker et al. (2016) and Davis et al. (2019) ($USTPU_t$, $CHINATPU_t$). Trade policy explains the magnitude of EPU spillovers (Balli et al., 2017), and the US and China are the main players within international trade.[8]

The results of the 3SLS estimation with the seemingly unrelated equations (SURE) approach are reported in columns (2) and (3) of Table 3. Column (3) shows the estimates of the auxiliary regression (Eq. (2)), where we observe that all the controls for the endogeneity of *GEPU* are statistically significant at conventional levels. As to the main equation, the estimates, shown in column (2) remain qualitatively and quantitatively the same as those reported in column (1), except for *BTCVOLUME* that becomes significant. Thus, the results of this alternative test corroborate that local risk factors do not play significant role in explaining the public interest in the Bitcoin.

4. Conclusion

The underlying motivation of this study is to cast light on EPU as driver of Bitcoin public attention. Using panel data for a set of 22 countries, we observe a global common trend in the evolution of public attention to Bitcoin, which suggests that global factors should play a more important role in explaining interest in Bitcoin. Indeed, the multivariate regression results show that Global EPU negatively affects interest in Bitcoin, while local EPU does not play a significant role. Consistent with prior research, other drivers of Bitcoin attention include geopolitical risk; and past Bitcoin market’s fundamentals (volatility, returns and volume). Overall, our results are consistent with the view of Bitcoin as a speculative investment rather than a safe-haven asset.

[6] Bitcoin market data is obtained from coinmarketcap.com.

[7] Panel unit root tests of Levin et al. (2002), Harris and Tzavalis (1999) and Breitung (2000) systematically lead to reject the null hypothesis that the panel contains unit root if the data generating process includes a linear time trend.

[8] According to the observatory of economic complexity of the MIT, in 2021, China and the US were the number 1 and 2 in total exports, and the number 2 and 1 in total imports respectively.

Table 2
Pearson pairwise correlations between research variables.

	1	2	3	4	5	6	7	8
1. GTB	1.00							
2. EPU	0.02	1.00						
3. GEPU	0.09***	0.35***	1.00					
4. VIX	0.07***	0.24***	0.56***	1.00				
5. RA	0.01	0.19***	0.44***	−0.14***	1.00			
6. GEOPRISK	−0.41***	−0.13***	−0.44***	−0.17***	−0.14***	1.00		
7. $BTCVOLAT_{t-1}$	0.29***	−0.11***	−0.22***	−0.01***	−0.17***	−0.13***	1.00	
8. $BTCRETURN_{t-1}$	0.33***	−0.00	−0.03	−0.13***	−0.01	0.09***	−0.07***	1.00
9. $BTCVOLUME_{t-1}$	0.13***	−0.01	−0.07***	−0.09***	0.00	0.25***	−0.17***	0.54***

Note: The sample size is 1741 observations. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table 3
Multivariate analysis results.

Variables	(1) *GTB*	3SLS (2) *GTB*	(3) *GEPU*
Constant	−330.25***	−356.31***	−1205.01***
GTB_t			−1.517***
EPU_t	−0.001	0.001	
$GEPU_t$	−0.111***	−0.170***	
VIX_t	0.450***	0.298***	
RA_t	−4.638***	−4.683***	
$GEOPRISK_t$	−0.171***	−0.156***	
$BTCVOLAT_{t-1}$	1.439***	0.669***	−5.517***
$BTCRETURN_{t-1}$	0.325***	0.298***	0.267***
$BTCVOLUME_{t-1}$	0.211	1.212***	4.284***
$CHINATPU_t$			0.055***
$USTPU_t$			0.016***
T	0.538***		1.903***
Hausman test	159.08		
(*p-value*)	(0.000)		
Estimation	Fixed Effects	SURE	
Observations	1741	1741	1741
Groups	22		
R^2		0.50	0.63
F-statistic	245.63***		
Wald χ^2		2387.45***	3693.48***

*, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

CRediT authorship contribution statement

Belén Gill-de-Albornoz: Formal analysis, Investigation, Methodology, Writing – review & editing. **Juan A. Lafuente:** Conceptualization, Formal analysis, Investigation, Supervision, Validation, Writing – original draft. **Mercedes Monfort:** Data curation, Investigation, Resources. **Javier Ordoñez:** Data curation, Investigation, Resources.

Data availability

Data will be made available on request.

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