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The link between cryptocurrencies and Google Trends attention

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ABSTRACT

This paper revisits the linkage between cryptocurrencies and public disclosed preferences, proxied by online searches. We show that cryptocurrencies are not related to a general uncertainty index as measured by the Google Trends data by Castelnuovo and Tran (2017). Instead, cryptocurrencies are linked to a Google Trends attention measure specific for this market. In particular, we find a bidirectional flow of information between Google Trends attention and cryptocurrency returns up to six days. Moreover, information flows from cryptocurrency volatility to Google Trends attention seem to be larger than those in the other direction. Finally, we report a significant tail dependence between cryptocurrency returns and Google Trends. These relations hold for the five cryptocurrencies analyzed and different compositions of the proposed Google Trends Cryptocurrency index.

1. Introduction

Since its creation in 2009, Bitcoin has gained a growing attention among investors, researchers financial institutions and policy makers. The first advocates of Bitcoin were libertarians and true believers in cryptocurrencies who were critical of the global financial crisis 2008–09. These investors saw blockchain as a mechanism to bypass the traditional financial system, which was severely criticized because of its lax regulation which led to the aforementioned crisis (Karlstrøm, 2014; Dallyn, 2017). A second wave of Bitcoin enthusiasts were speculators, who saw in Bitcoin (and in newly minted cryptocurrencies) high-yield investment opportunities (Bouoiyour et al., 2015). A third wave of market participants were financial institutions, which aimed to introduce blockchain technology in their industry and offer investors more secure platforms for investment (Guo and Liang, 2016; Patki and Sople, 2020). At the same time, governments begun to worry about the potential negative effects of cryptocurrencies. Several countries have been introducing regulations (e.g., tax laws, anti-money laundering/anti-terrorism financing laws. See Global Legal Research Center (2018)) and issuing warnings about the high risk of this type of investment (Martin, 2021). Finally, a fourth wave of cryptocurrency market players currently taking place, is related to central banks and to the so-called Central Bank Digital Currencies (Fernández-Villaverde et al., 2020; Wang et al., 2021a). For a detailed review on the evolution and the state-of-the-art on cryptocurrencies, we refer to Corbet et al. (2019), Bariviera and Merediz-Solà (2021), among others.

At the same time, the increasing digitalization of the economy has left a digital footprint that, in certain way, reveals preferences, tastes, or consumption habits. Google Trends have been found useful for nowcasting and forecasting economic indicators (Vicente et al., 2015) and predicting political outcomes (Mavragani and Tsagarakis, 2016). Given that cryptocurrencies are digitally native assets, investors tend to gather market information mainly through the internet (social networks, specialized forums, etc.). As a result, Google searches tend to signal investors' attention. Urquhart (2018) is one of the earliest papers to relate cryptocurrency's market attention with Google Trends, finding that realized volatility, volume and returns influence future search for the term 'Bitcoin'.

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Subsequently, Shen et al. (2019) point out that the number of tweets is a significant driver of Bitcoin trading volume and realized volatility.

Other researchers have used news-based uncertainty indices to assess the impact of uncertainty on Bitcoin. Demir et al. (2018) shows that the Economic Policy Uncertainty (EPU) index is negatively associated with Bitcoin daily returns. Using a GARCH-MIDAS framework Walther et al. (2019) finds that the Global Real Economic Activity (GREA) index fares well in cryptocurrency volatility forecasting. In a similar vein, Fang et al. (2020) reports a significant impact of News Implied Volatility (NVIX) on long-term cryptocurrency volatility. Meanwhile, Aysan et al. (2019) detects significant predictive power of the Geopolitical Risk (GPR) index for both Bitcoin returns and volatility. Focusing more on the cryptocurrency market, Lucey et al. (2021) employs weekly data to construct cryptocurrency uncertainty indices based on a variety of news pieces from LexisNexis Business database. The authors carry out a historical decomposition and relate their cryptocurrency uncertainty indices to major economic and political events. Similarly, Wang et al. (2021b) studies the environmental pressure of cryptocurrencies due to the intensive use of energy during the mining process. To this end, they construct a cryptocurrency environmental attention index that captures investors' environmental concern.

The present paper aims to explore to what extent investors' attention to the cryptocurrency market is captured by a set of keywords as measured by Google Trends. Note that compared to Twitter (where access is limited in time) or to LexisNexis (a subscription-based service), Google Trends has the advantage that it is freely available. In addition, Google Trends is simple to obtain and reflects to a large extent the attention of a broader profile of investors and thus can be used to forecast near-term values of economic indicators as documented by (Choi and Varian, 2012). Moreover, Google Trends could be used as a reliable measure for online searches (Johnson, 2021).

Our contribution to the literature can be summarized as follows. First, we construct a new Google Trends index to capture cryptocurrency market attention. Second, we find that general uncertainty Google Trends indices such as the one proposed by Castelnuovo and Tran (2017) for the macroeconomy does not provide significant information for the cryptocurrency market. Third, we employ a novel methodology, namely Transfer Entropy, based on information theory to show important information flows from Google Trends to the cryptocurrency market and vice versa, which reflects a recurring dialog between market attention and investors' interests. This methodology is non-parametric in nature and has two main advantages: (i) it overcomes some of the limitations of Granger causality, and (ii) gives flexibility to our modeling approach since it does not assume a particular distribution for the data generating process. Finally, our analysis shows that cryptocurrency market attention is well captured by a handful of keywords such as Bitcoin, BTC, blockchain, crypto, cryptocurrency.

The rest of the paper is organized as follows: Section 2 details the proposed Google Trends Cryptocurrency index; Section 3 briefly describes the key methodologies used in the paper; Section 4 describes our data set and discusses the main finding. Finally, Section 5 concludes.

2. Construction of Google Trends Cryptocurrency index

We first update the Google Trends Uncertainty (GTU) index of Castelnuovo and Tran (2017) over the period 2015–2021. Next, we construct a Google Trends Cryptocurrency (GTC) index, using a set of cryptocurrency-oriented keywords. We argue that most cryptocurrency investors would gather information mainly through the internet. Even though there are several search engines (e.g., Google, Yahoo, Bing, Ask), Google clearly dominates the market. According to Johnson (2021) the worldwide search market share of Google is 86.6%. Thus Google Trends could be used as a reliable measure for online searches.

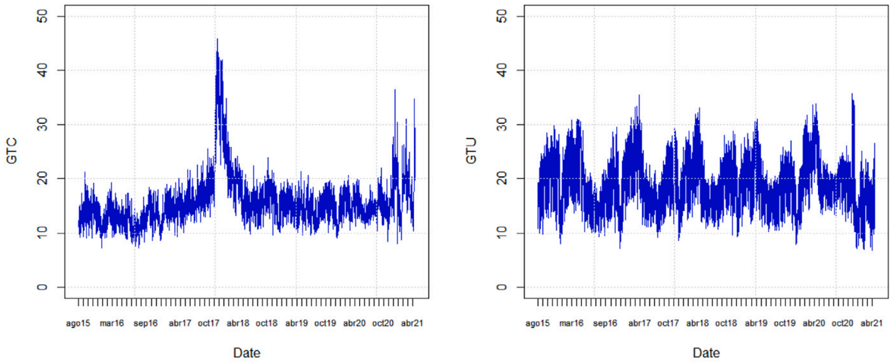
The keywords that constitute our GTC index are selected using a bibliometric analysis of scientific papers in line with Merediz-Solà and Bariviera (2019). The full set is composed by 38 keywords. In order to check the robustness of our results, we reduce the number of keywords, leaving only the ones that we consider more closely related to Bitcoin economics, while dropping more technical words such as 'hash', 'hard fork', 'proof of work', etc. The list of the full set of keywords, as well as the three subsets of keywords of the index are detailed in the appendix. After obtaining the daily Google Trend index for each keyword, we compute the arithmetic mean for all the keywords, constituting the daily GTC index (see Fig. 1).

3. Methods

We measure information linkages between Bitcoin and market attention by means of Shannon Transfer Entropy (for details, see Dimpfl and Peter (2013, 2018)). Shannon Transfer Entropy is a flexible, non-parametric method designed to overcome some of the limitations of Granger causality (for example, the linearity assumption).

Transfer Entropy is a measure based on the Kullback–Liebler distance of transition probabilities, and allows not only to determine the direction of information flows, but more importantly to quantify the strength of those flows. Let consider two processes I and J, with marginal probability distributions $p(i)$ and $p(j)$, and joint probability distribution $p(i,j)$, the Shannon transfer entropy (TE) can be defined as:

$$T_{J\to I}(k,l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) \cdot \log_2 \left(\frac{p\left(i_{t+1} | i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} | i_t^{(k)}\right)} \right), \tag{1}$$



(a) GTC index (b) GTU index

Fig. 1. Google Trends attention indices: GTC and GTU (Castelnuovo and Tran, 2017).

where $T_{J\rightarrow I}$ is a measure of the information conveyed from J to I, and k and l are the lags considered. Considering that TE could be a biased estimator of the information transfer, Marschinski and Kantz (2002) proposed a modified metric, by removing the information produced by shuffled realization of the explanatory process as:

$$ETE_{J\rightarrow I}(k,l) = T_{J\rightarrow I}(k,l) - T_{J_{\text{shuffled}}\rightarrow I}(k,l) \tag{2}$$

The Effective Transfer Entropy (ETE) shows not only the direction, but also the quantity of information transmitted from one process to the other.

It has been previously documented that cryptocurrencies are extremely volatile assets (Chaim and Laurini, 2018). At the same time, online searches could suffer from herd behavior (Preis et al., 2010; Bouri et al., 2019). Consequently, it could be interesting to investigate the effect of extreme cryptocurrency returns and Google searches on the information transfer. In this aspect, Rényi entropy allows to emphasize certain parts of the empirical probability density function of both variables.

Rényi (1970) developed a family of information measures alternative to the classical Shannon entropy. One of those measures is now known as Rényi's entropy:

$$S_q^R(P) = \frac{1}{1-q}\log_2 \sum_{x\in X} p^q(x) \tag{3}$$

where q is a parameter that could be employed to accentuate portions of the probability distribution. In particular, when $0 < q < 1$, marginal events are emphasized for lower values of such interval. On contrary for $q \rightarrow 1$, the Shannon entropy is recovered.

For the sake of brevity we refer the reader to Jizba et al. (2012), Behrendt et al. (2019) for details on the derivation of Rényi's transfer entropy.

4. Empirical analysis

4.1. Data

This paper uses daily data on Google Trends and cryptocurrency prices. We calculate the Google Trends Uncertainty (GTU) of Castelnuovo and Tran (2017) as well as our Google Trends Cryptocurrency (GTC) index proposed in Section 2. Cryptocurrency daily data is used to compute the logarithmic return and Parkinson (1980) volatility[1]. For replication purposes, data used in this paper is available online along this paper. The period under examination spans from 07/08/2015 to 22/04/2021, for a total of 2086 observations.

We focus mainly on Bitcoin, since cryptocurrency market linkages (both in returns and volatilities) have become very strong in recent years (Aslanidis et al., 2021). As shown in the supplementary material, our results can be generalized to other coins such as DASH, ETH, LTC and XRP.

The empirical results of this section are obtained using the GTC index with five keywords (Subset 3), but they are robust to a different selection of keywords. For more details on the different selection of keywords, see Appendix A.

4.2. Google Trends Uncertainty index and cryptocurrencies

We explore by means of Transfer Entropy, the information exchange between the Bitcoin market and the Google Trends uncertainty (GTU) index. We use first differences of the Google Trends data to ensure stationarity. Table 1 displays the descriptive statistics of the working variables.

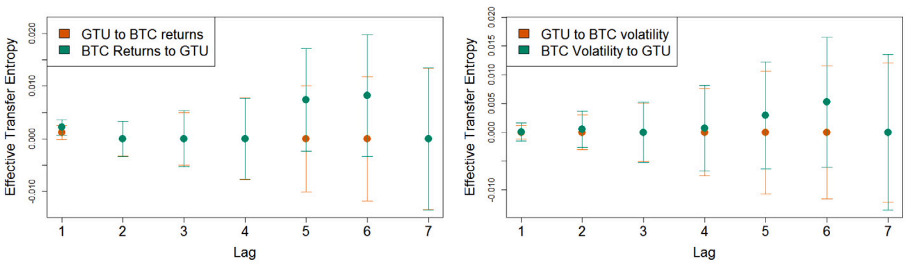
[1] Although not displayed in the paper, results using Garman and Klass (1980) volatility are similar.

Table 1
Descriptive statistics of working variables.

	GTC Index	GTU Index	Daily log return	Daily volatility (Parkinson)
Observations	2086	2086	2086	2086
Mean	9.2802	19.5827	0.2505	0.1782
Median	7.3470	19.5516	0.2335	0.0604
Min	0.4340	6.8474	−47.9934	0.0009
Max	90.0500	35.8035	22.7618	9.8362
Std. Deviation	9.6803	5.5378	4.0015	0.4227
Skewness	2.7540	0.0969	−0.8723	10.1374
Kurtosis	13.4618	2.2816	16.0696	173.6036
Jarque Bera	12149.9634	48.1276	15111.2728	2565488.7983

Table 2
Transfer Entropy between Google Trends Uncertainty (GTU) and Bitcoin (return and volatility).

Direction	TE	ETE	Std.Err.	p-value
GTU→Return	0.0056	0.0012	0.0013	0.0675
Return→GTU	0.0042	0.0021	0.0014	0.4275
GTU→Volatility	0.0017	0.0000	0.0011	0.4150
Volatility →GTU	0.0021	0.0000	0.0015	0.7900



(a) Daily return (b) Volatility (Parkinson)

Fig. 2. Effective Transfer Entropy (ETE) between Google Trends Uncertainty (GTU) and return (a) or volatility (b) using different lags.

First, we quantify the information transfer between GTU and Bitcoin. Table 2 shows that information flows between Bitcoin and GTU are not statistically significant, which indicates a detachment of cryptocurrencies from the general macroeconomic environment. This result is in line with previous findings (Corbet et al., 2018; Aslanidis et al., 2019), who report that major cryptocurrencies are rather isolated from traditional assets such as gold, stocks or bonds. This finding is robust to a selection of different lag lengths, as observed in Fig. 2.

4.3. Google Trends Cryptocurrency index and cryptocurrencies

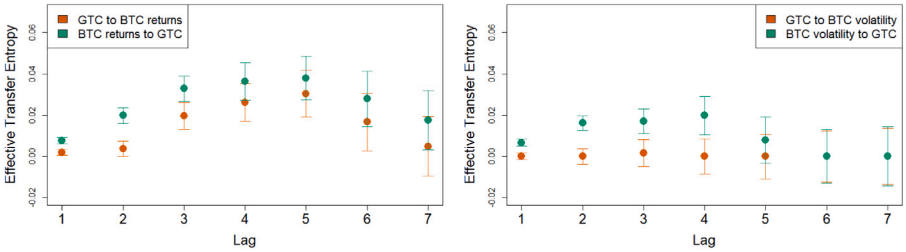
A different picture emerges, however, when analyzing Bitcoin returns/volatility with respect to the proposed Google Trends Cryptocurrency (GTC) index. Table 3 displays the results of Transfer Entropy using just the first lag. As seen, there is a reciprocal flow of information between Bitcoin and GTC. We observe that the amount of information transmitted between Bitcoin and market attention is not symmetric. Specifically, there is more information leaked from Bitcoin return (and volatility) to GTC than in the other direction.

Our analysis goes one step forward and considers the interdependence, using several lags of the variables. As seen in Fig. 3, the amount of information transferred is larger for returns than for volatilities. Further, we show that the interdependence between GTC and returns is bidirectional, increases with the lag length and is significant for up to six days. Instead, the transfer of information between Bitcoin volatility and GTC holds strong but for up to three/four days, and is only significant from volatility to GTC. This implies that news are relatively quickly absorbed by the market, although price swings seem to produce stronger market attention during the week.

The strong bidirectional link between Bitcoin and GTC might be explained by the growing media attention about cryptocurrencies, which encourages high-yield seeking investors to gather information about this new type of financial asset. This generates a "dialog" between online searches and cryptocurrency market profitability and risk metrics.

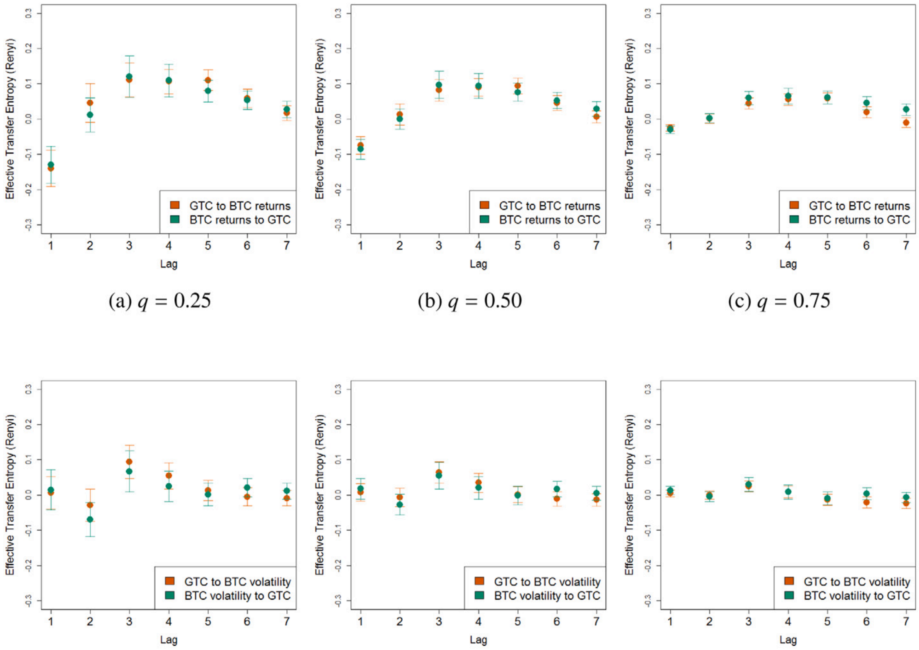
Table 3
Transfer entropy between GTC and Bitcoin (return and volatility).

Direction	TE	ETE	Std.Err.	*p*-value
GTC →Return	0.0063	0.0019	0.0014	0.0500
Return →GTC	0.0112	0.0075	0.0015	0.0000
GTC →Volatility	0.0025	0.0000	0.0016	0.7075
Volatility →GTC	0.0102	0.0066	0.0016	0.0000



(a) Daily return (b) Volatility (Parkinson)

Fig. 3. Effective Transfer Entropy (ETE) between Google Trends Cryptocurrency (GTC) index and return (a) or volatility (b) using different lags.



(a) $q = 0.25$ (b) $q = 0.50$ (c) $q = 0.75$

(d) $q = 0.25$ (e) $q = 0.50$ (f) $q = 0.75$

Fig. 4. Renyi Transfer Entropy (for different q) between Google Trends Cryptocurrency (GTC) and BTC return and volatility using different lags.

4.4. Tail risk and information transfer

Shannon transfer entropy measures the information exchange between two time series, considering the whole probability distribution. As known, cryptocurrencies are highly volatile and prone to large price swings. At the same time, online searches could be influenced by fads, and thus exhibit herd behavior. Therefore, in this section we aim to pin down the information in the tails of the distributions of Bitcoin returns/volatility and GTC. The Rényi transfer entropy measures tail dependence by setting the value of the parameter q between 0 and 1. In our analysis, we compute Rényi transfer entropy for $q = \{0.25, 0.5, 0.75\}$, bearing in mind that the lower the q the greater the weight on the tails. Results are displayed in Fig. 4.

Consistent with previous results, the information flow between GTC index and Bitcoin returns is larger than between GTC index and Bitcoin volatility. Similarly, the shape is maintained over different lags. The information transfer between GTC and returns is

Table A.4
Sets of words considered in the Google Trends Cryptocurrency (GTC) Attention Index.

Full set	AES256	crypto crash	miner	Mount Gox
	altcoin	cryptocurrency	minted	Mt Gox
	anonymity	cryptography	public key	Mt. Gox
	Bitcoin	digital assets	ripple	private key
	block producer	distributed ledger	satoshi	Proof of Authority
	blockchain	ethereum	soft fork	Proof of Burn
	BTC	hard fork	stablecoin	Proof of Stake
	coin	hash	tether	Proof of Work
	consensus	hashing	token	
	crypto	ICO	virtual currency	tether
Subset 1	anonymity	crypto	miner	token
	Bitcoin	cryptocurrency	minted	private key
	blockchain	ICO	public key	Proof of Work
	BTC	cryptography	ripple	
	coin	ethereum	satoshi	
	consensus	hash	stablecoin	
Subset 2	Bitcoin	crypto	ethereum	tether
	blockchain	cryptocurrency	ripple	
	BTC	cryptography	satoshi	
Subset 3	Bitcoin	BTC	cryptocurrency	
	blockchain	crypto		

significant up to six days. Instead, we find an important difference in the size of the information flow. Specifically, when extreme events are given a high weight, the amount of the information transferred is larger, reaching a maximum after three days.

Regarding volatility, the results are generally in line with those obtained using the Shannon Entropy. There is little information transfer between GTC and Bitcoin volatility. Still, focusing on extreme events ($q = 0.25$) there is some information transfer but up to three days.

5. Conclusion

We confirm that the cryptocurrency market is rather detached from the general macroeconomic environment as proxied by Google Trends Uncertainty indices such as the one by Castelnuovo and Tran (2017). Instead, our proposed Google Trends Cryptocurrency index conveys important information flows to (and receives feedback from) the cryptocurrency market.

We show that information transfer between Google Trends and daily returns is found to be bidirectional and to last for up to six days. Moreover, information flows from Bitcoin volatility to Google Trends attention index are found to be larger than vice versa. This paper also reports significant tail dependence, in particular, between the Google Trends Cryptocurrency index and Bitcoin returns reflecting the importance of extreme events for market participants.

Our results are robust to different compositions of the Google Trends Cryptocurrency index. In fact, only five words are sufficient to capture market attention, which reflects an unsophisticated investors' search strategy. Moreover, our findings are not Bitcoin-specific, but also apply for other major cryptocurrencies such as Dash, Ethereum, Litecoin, and Ripple.

Recently, the cryptocurrency market has attracted a great deal of attention among investment banks (e.g., Morgan Stanley, Goldman Sachs), venture capitalists, regulators (the approval of Bitcoin ETFs in Canada) and policy makers (the decision of El Salvador to accept Bitcoin and Ethereum as legal tender) showing that the institutional interest is gaining momentum. Moreover, the Bank for International Settlements (2021) has started a consultative process to gather opinions on the possibility of commercial banks holding Bitcoin and other digital assets. Although our research does not detect any significant relationship between Bitcoin and the general macroeconomy, the institutionalization of cryptocurrencies could make their way into the traditional financial ecosystem. Overall, our research has important implications for fund management and policy making, as it provides important information for portfolio design and rebalancing.

CRediT authorship contribution statement

Nektarios Aslanidis: Conceptualization, Methodology, Writing – review & editing, Formal analysis. **Aurelio F. Bariviera:** Conceptualization, Methodology, Writing – review & editing, Software, Formal analysis. **Óscar G. López:** Writing – review & editing, Software.

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Appendix A. Sets of words to construct the Google Trends Cryptocurrency Attention (GTC) Index

See Table A.4.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2021.102654.

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