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WHERE DO WE STAND IN CRYPTOCURRENCIES ECONOMIC RESEARCH? A SURVEY BASED ON HYBRID ANALYSIS

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Abstract. This survey develops a dual analysis, consisting, first, in a bibliometric examination and, second, in a close literature review of all the scientific production around cryptocurrencies conducted in economics so far. The aim of this paper is twofold. On the one hand, proposes a methodological hybrid approach to perform comprehensive literature reviews. On the other hand, we provide an updated state of the art in cryptocurrency economic literature. Our methodology emerges as relevant when the topic comprises a large number of papers, which make unrealistic to perform a detailed reading of all the papers. This dual perspective offers a full landscape of cryptocurrency economic research. First, by means of the distant reading provided by machine learning bibliometric techniques, we are able to identify main topics, journals, key authors, and other macro aggregates. Second, based on the information provided by the previous stage, the traditional literature review provides a closer look at methodologies, data sources, and other details of the papers. In this way, we offer a classification and analysis of the mounting research produced in a relative short time span.

Keywords. Bibliometrics; Cryptocurrencies; Web of Science

1. Introduction

Cryptocurrency literature has been experimenting a sustained growth. As a new object of study, cryptocurrencies offer a rich field to implement both old and new methodologies, in order to uncover the salient characteristics of this market. After some years of continuous research, it is necessary to draw a situation map of current research and comment of literature gaps and research perspectives. In this sense, this work precisely aims at becoming a reference guide for researchers. We developed our paper in two complementary steps. First, we implement a biblometric analysis, in order to get the most relevant features arising from text mining analysis of titles, abstracts, keywords, authors, and journal titles. Second, we produce an in-depth analysis of 106 papers, from the most important journals detected in the previous step.

There are some previous experiences of literature review, but with a broader scope. Liu (2016) uses exclusively co-word analysis of 256 papers from Scopus database, in order to classify them into technological, economic, and legal aspects of Bitcin. Miau and Yang (2018) and Holub and Johnson (2018) analyze the whole blockchain research area.

The two closest papers to ours are Corbet *et al.* (2019) and Merediz-Solà and Bariviera (2019). The first one produces a systematic review of 52 quantitative investigations of cryptocurrency markets. The second one, provides a classification and identification of key elements of 1162 papers dealing

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with Bitcoin, across different disciplines. Our methodological approach is different. To the best of our knowledge, this is the first paper that combine bibliometric analysis and close literature review into the same paper, in order to produce a comprehensive landscape of the current cryptocurrency research exclusively within economics.

On the one hand, bibliometric analysis provides a semiautomatic classification of papers, using machine learning. This first approach is very useful, specially when considering a large number of papers. On the other hand, in-depth reading of individual papers helps to identify methodologies, data sets, and results. As a consequence, this paper harmonizes machine-based classification with the insight of the specialized reader.

Our paper contributes to the literature in several ways: (i) it presents a hybrid methodology, by combining distant (bibliometric) and close (in-depth) reading in order to produce a literature survey; (ii) it comprises more up-to-date literature by considering also articles in press, in addition to those already abstracted in Scopus or Web of Science; (iii) it allows to infer emerging research lines in cryptocurrency literature.

The rest of the paper is structured as follows. Section 2.1 describes the data set and comments the main findings of our bibliometric study. Based on these results, Section 2.2 works with a new data set and produces a detailed analysis of papers published in some economics journals. Section 4 identifies literature gaps and explores open research lines. Finally, Section 5 draws the main conclusions.

2. Methodological Design

2.1 *First Step: Distant Reading by Means of Bibliometric Analysis*

Our first approach to this survey is to extract articles' metadata from Web of Science Core Collection (WoS), Clarivate Analytics. We conducted the following query:

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ALL=(bitcoin OR ethereum OR litecoin OR monero OR iota) NOT AU=(Iota) AND
WC=(Business OR Business, Finance OR Economics)
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We retrieved papers from all the years included in the core collection of the Web of Science, which gave a total of 626 papers. We restrict our sample only to articles, which means that we discard conferences proceedings and book chapters. This amounts 444 articles. Finally, we take out of our sample articles published in Forbes. The reason is that Forbes has a great impact among practitioners, CEOs, and general public, but it is seldom cited in scientific publications. Thus, the total number of articles in our bibliometric analysis is 438. The analysis of this section was conducted using bibliometrix R package, developed by Aria and Cuccurullo (2017). The detail of the top sources is displayed in Table 1.

Our sample contains 38 Highly Cited Papers (HCP)[1]. Among all HCP, 15 were published in *Economics Letters*, and 12 in *Finance Research Letters*.

Our bibliometric analysis identified the most cited papers. We detect that four and 6 out of the 20 most cited were published in *Finance Research Letters* and *Economics Letters*, respectively (see Table 2).

Finally, the analysis of authors' keywords and Keyword-Plus,[2] allows to detect the main topics of papers in our sample. These keywords helped to form the groups developed in the following section. Both groups of keywords, indicate that: (i) bitcoin seems to be the predominant object of the studies, (ii) most words are finance-related, and (iii) there are clusters of literature devoted to informational efficiency, safe haven condition, volatility, hedge properties, and price bubbles.

2.2 *Second Step: Close Reading of Cryptocurrency Literature*

Bibliometric analysis conducted in the previous section, shows main characteristics of the data set. However it has two drawbacks. First, although powerful machine learning techniques are used,

Table 1. Most Frequent Sources.

#	Sources	Articles
1	*Finance Research Letters*	56
2	*Economics Letters*	42
3	*Journal of Risk and Financial Management*	21
4	*Research in International Business and Finance*	20
5	*International Review of Financial Analysis*	16
6	*Applied Economics Letters*	15
7	*Applied Economics*	12
8	*Journal of Risk Finance*	9
9	*Economics Bulletin*	6
10	*Journal of International Financial Markets Institutions & Money*	6

Table 2. Top 20 Manuscript per Citations.

Paper	Total citation	Citation per year
Böhme *et al*. (2015)	198	39.6
Urquhart (2016)	179	44.8
Cheah and Fry (2015)	164	32.8
Dyhrberg (2016a)	154	38.5
Katsiampa (2017)	120	40
Dwyer (2015)	119	23.8
Bouri *et al*. (2017b)	118	39.3
Ciaian *et al*. (2016)	116	29
Nadarajah and Chu (2017)	110	36.7
Dyhrberg (2016b)	108	27
Bariviera (2017)	95	31.7
Corbet *et al*. (2018c)	85	42.5
Balcilar *et al*. (2017)	84	28
Baek and Elbeck (2015)	77	15.4
Urquhart (2017)	68	22.7
Baur *et al*. (2018b)	66	33
Bouri *et al*. (2017a)	65	21.7
Cheung *et al*. (2015)	64	12.8
Selgin (2015)	59	11.8
Fry and Cheah (2016)	58	14.5

bibliometric analysis is not a substitute, but rather a complement of a comprehensive literature review. Second, papers included in Web of Science experience a time delay to be introduced into the database. There are numerous accepted papers that published online in their respective journal websites, but they are not yet indexed in Web of Science.

Considering this situation, based on the previous bibliometric analysis we conduct a close reading of all the papers (including articles in press), from the most frequent journals sources. The reason for this selection is twofold. On the one hand, publication is highly concentrated among a small number

Table 3. Most Relevant Keywords.

Author Keywords (DE)	Articles	Keywords-Plus (ID)	Articles
Bitcoin	257	Bitcoin	101
Cryptocurrency	124	Inefficiency	79
Cryptocurrencies	75	Volatility	65
Blockchain	47	Economics	49
Volatility	23	Gold	49
GARCH	17	Hedge	40
Digital Currency	15	Returns	34
Ethereum	15	Safe Haven	23
Market Efficiency	15	Dollar	20
Safe Haven	13	Exchange	20
Money	10	Market	19
Crypto Currency	9	Time Series	18
Gold	8	Prices	17
Hedge	8	Currency	15
Virtual Currency	8	Money	15
Forecasting	7	Cryptocurrencies	14
Long Memory	7	Markets	14
Bubbles	6	Unit Root	14
Commodities	6	Model	13
Distributed Ledger	6	Models	13

of journals. Almost 30% of the papers has been published in *Applied Economic Letters*, *Economics Letters*, *Finance Research Letters*, or *International Review of Financial Analysis*. On the other hand, almost all the 38 HCP in this area has been also published in these three journals. Then, we can say that mainstream research of this topic is conveyed around these four journals. In addition, we include in our analysis the papers by Böhme *et al*. (2015) and Gandal *et al*. (2018), Fisch (2019) and Momtaz (2020), published in the *Journal of Economic Perspectives*, the *Journal of Monetary Economics*, and the *Journal of Business Venturing*, because they are the only papers published in journals classified at level 4 (worldwide exemplars of excellence) by the Chartered Association of Business Schools (2018).

3. Close Reading Findings

The data set in this section is different from the one used in Section 2.1. Of the 444 originally identified articles, we selected 106 according to the number of citations and representativeness in the different topics discussed in Section 3.3. The distribution of papers read per source is detailed in Table 4. A meticulous analysis of each paper, detailing cryptocurrencies studied, data frequency, source of data, quantitative methodology, aim of the paper, and main results, is displayed in Table A1 in the Appendix. In the following subsections, we will highlight the salient features of some representative papers.

Böhme *et al*. (2015) is one of the earliest papers to render a full overview of bitcoin and its relationship with the then emerging blockchain technology. The authors point out pros and cons of bitcoin, emerging challenges for the monetary policy, risks, and necessity of regulation. It constitutes an excellent introductory paper, in order to begin the study of this field.

Table 4. Publication Sources Considered in Our Sample.

Journal	# articles	%
Economics Letters	34	32%
Finance Research Letters	49	46%
International Review of Financial Analysis	15	14%
Applied Economic Letters	1	1%
Journal of Business Venturing	2	2%
Journal of Monetary Economics	1	1%
Journal of Economic Perspectives	1	1%
Journal of Economics and Business	1	1%
Managerial Finance	1	1%
Technological Forecasting and Social Change	1	1%
Total	106	100%

Table 5. Source of Data Used in Empirical Studies of Cryptocurrencies.

Source	# Articles	%
Coinmarketcap	27	24%
Coindesk	21	19%
Bitcoincharts	13	12%
Other	44	39%
Not known	5	4%
Not applicable	2	2%
Total	112[a]	100%

[a]Total of articles does not match because some papers use more than one source.

3.1 *Data Sources*

Our first analysis is related to the source of data used in papers. Table 5 displays the data sources used in the papers of our sample. We detect that 55% of the papers use data from either Coinmarketcap, Coindesk, or Bitcoincharts. One of the reasons is, apparently, that these websites allow the use of Application Programming Interfaces (API). An API is a set of subroutine definitions and communication protocols that allow, among other things, to formulate data requests, and download data in an efficient way. In addition, all three websites gather information from several trading platforms and several cryptocurrencies. Thus, they provide a broad coverage of the market. With the exception of three papers, the rest rely on only one source of data.

Considering that these websites generate their own price indices by averaging different cryptocurrencies' platforms, data are not homogeneous across all papers. This situation emerges as a weakness in order to compare results. It is well known in financial economics, that equally weighted indices or capitalization-weighted indices can lead to different results in stock markets. A similar situation can happen in the cryptocurrency market. Special attention should be payed to the use of nontraded prices or nonsynchronous data in multivariate analysis. A very recent and detailed critical review of cryptocurrency data is in Alexander and Dakos (2020), where it is reported that half of the papers published since 2017 uses appropriate data.

Table 6. Data Frequency Used in Empirical Studies of Cryptocurrencies.

Data frequency	# Articles	%
Daily	82	77%
Intraday	13	12%
Weekly	3	3%
Monthly	1	1%
Not known/Not applicable	7	7%
Total	106	100%

3.2 *Data Frequency*

An important issue in our literature review, is to detect the data frequency used in the empirical studies. Unlike stock or bond markets, cryptocurrencies markets offer free, real-time information. Moreover, trading is open 24/7. From a theoretical point of view, if the goal is to understand a stochastic process, recorded in a time series, sampling selection is a key task. In this sense, cryptocurrencies (specially the bigger ones) offer the possibility to select different data granularity. We detect that the large majority of empirical studies (77%) uses daily data, whereas intradaily data are only used by 12% of the papers. It seems that authors consider daily frequency as the "natural frequency" of data, disregarding other options. This situation means that there are still unexplored issues, which could give new insights and possible uncover stylized facts at ultra-high frequency.

3.3 *Main Research Topics*

After a detailed reading of the 106 papers in our sample, we classify them according to their key research topics (see Table 7). Even though some papers cover more than one topic, we assign the one that, in our

Table 7. Articles' Key Research Topics.

Research topic	# Articles	%
Informational efficiency	26	25%
Price discovery	15	14%
Volatility	13	12%
Portfolio formation	10	9%
Bubble	8	8%
Correlation	8	8%
Safe-haven	7	7%
Initial Coin Offering (ICO)	6	6%
Microstructure	6	6%
Price clustering	3	3%
Monetary economics	2	2%
Literature review	1	1%
Overview	1	1%
Total	106	100%

opinion, is the main driver of their research. In the following subsections, we select some articles of each research topic in order to explain the methodologies and main findings.

Classification and detailed characteristics of all 106 papers are displayed in Table A1 (Appendix). Half of them are referred either to classical financial economics topics such as informational efficiency (25%), price discovery (14%), or volatility (12%). There is another portion of literature that studies two related topics: portfolio formation (9%) and safe-haven properties of cryptocurencies (7%). There is only one paper that performs a literature review in our sample (Corbet *et al.*, 2019), whose coverage only partially overlaps with ours.

3.3.1 *Monetary Economics and Overview of Bitcoin Ecosystem*

Papers in this section conducts general analysis of bitcoin prices and demand, giving an overview of the functioning of this new kind of financial market. Gandal *et al.* (2018) identifies and analyzes the impact of suspicious trading activity on one important trading platflorm, concluding that cryptocurrency markets are vulnerable to manipulation due to the unregulated nature of the activity. Recently, de la Horra *et al.* (2019) focus their analysis on the determinants of the demand for bitcoin, building monetary-theory based demand model. They find that, in the short run, speculation fuels the demand for bitcoin. However, in the long run demand is driven by expectations about its future utility as a medium of exchange.

3.3.2 *Informational Efficiency*

There is a relevant number of papers inquiring on the informational efficiency of cryptocurrencies. Articles within this group are aimed at testing the weak form of the Efficient Market Hypothesis (EMH), developed by Fama (1970), which states that prices in an informational efficient market should follow a random walk. The three most cited within this group are published in the *Economics Letters*. Although some of the articles from other groups also study some characteristics dealing with the efficiency of cryptocurrencies, some difference between them are found.

The methodology used by Urquhart (2016), the highest cited article in this group, to test the EMH has been used subsequently in other articles. In that article, a battery of tests for randomness are employed:

- Ljung and Box (1978) test, in order to test the null hypothesis of no autocorrelation.
- Wald and Wolfowitz (1940) and Bartels (1982) tests to determine whether returns are independent.
- Variance ratio test by Lo and MacKinlay (1988), which under the null hypothesis, the price process is a random walk. Papers also use some variations such as the automatic variance test (AVR) by Choi (1999), or the wild-bootstrapped version by Kim (2009).
- Broock *et al.* (1996) test, in order to verify possible deviations from independence including linear dependence, nonlinear dependence, or chaos.
- Hurst (1951) Rescaled Hurst exponent (R/S Hurst) to detect the presence of long memory in prices time series.

Urquhart (2016) finds that Bitcoin had been informational inefficient at the beginning, but was moving toward a more efficient market.

Nadarajah and Chu (2017) use, in addition to the previous tests, the following ones:

- Spectral shape tests by Durlauf (1991) and Choi (1999) to test for random walk.
- Escanciano and Lobato (2009) robustified portmanteau test for no serial correlation.
- Generalized spectral test by Escanciano and Velasco (2006) to check whether the martingale difference hypothesis holds for the returns.

In this paper, the authors show that some power transformations of Bitcoin returns can be weakly efficient.

In addition, Bariviera (2017) compares results of the Hurst exponent computed by R/S and Detrended Fluctuation Analysis (DFA) methods. The author argues in favor of the latter because it avoids the spurious detection of long-range dependence. The main contribution of this paper is to study daily returns and volatility using sliding windows. Such methodology design allows detecting a diminishing memory in daily returns, but persistent memory in volatility, justifying the use of GARCH modelization in variance.

Vidal-Tomás *et al*. (2019b) studies the informational efficiency of equally weighted and capitalization-weighted cryptocurrency portfolios during the period 2015–2017, finding that the cryptocurrency market is inefficient (in its weak form) due to the behavior of altcoins.

3.3.3 *Price Discovery*

The articles from this group employ different approaches to study the predictability of cryptocurrencies. For example, some papers apply machine learning algorithms in order to measure the forecasting power of past Google or Twitter searches.

Brauneis and Mestel (2018) uses the EMH tests introduced by Urquhart (2016) as measure of how predicable cryptocurrencies are. Furthermore, they also add a Measure Of Efficiency (MOE) (Godfrey, 2017), using different kind of liquidity measures. MOE measures how well a passive strategy performs relative to active trading. The four liquidity measures proposed are the following: (1) log-dollar volume, (2) turnover ratio, (3) Amihud's illiquidity ratio (Amihud, 2002), and (4) bid–ask estimate (Corwin and Schultz, 2012).

Moreover, Urquhart (2018) constructs a time series of daily realized volatility (RV), which was introduced by Andersen *et al*. (2003). This model is built using vector autoregressive model (VAR) to study the dynamics between search queries (Google Trends data), realized volatility, trading volume, and returns. Urquhart (2018) finds that attention of Bitcoin is significantly influenced by the previous day's high realized volatility and volume.

In addition, Aalborg *et al*. (2019) use four OLS models to study returns, volatility, and trading volume of Bitcoin. Some of the independent variables are the trading volume, VIX index, Google trends data, etc. To study the volatility, they use the HAR-RV model proposed by Corsi (2009), to capture long-memory behavior of volatility. The authors present alternative models using: (1) daily data, (2) daily data and lagged independent variables, (3) weekly data, and (3) weekly data and lagged independent variables. Aalborg *et al*. (2019) find that none of the considered variables can predict Bitcoin returns and the trading volume of Bitcoin can be predicted from Google searches for Bitcoin.

3.3.4 *Price Volatility*

Cryptocurrencies are highly volatile (approximately 10 times more than traditional assets), due to the intrinsic speculative characteristics of the investments, the velocity of transactions, and the unregulated environment. The group of articles under this label study some stylized facts of the volatility of returns of the cryptocurrencies. Most of the articles of this group, based on previous experience in other financial markets, apply different variations of GARCH models. This type of models are suitable for estimating the time-varying volatility. Most papers find volatility clustering, which implies that there are periods of relative calm followed by periods of swings. This fact is also known as persistence of the volatility.

Katsiampa (2017) compares different first-order GARCH-type model for the conditional variance, with an autoregressive model for the conditional mean. Particularly, the applied models are: GARCH, EGARCH, TGARCH, APARCH, CGARCH, and ACGARCH. It is found that the optimal model is the AR-CGARCH model, which suggests the importance of having both a short-run and a long-run component of conditional variance.

Ardia *et al*. (2019) is an extension of Katsiampa (2017). The model used is a Markov-switching GARCH (MSGARCH) to capture any regime changes in the Bitcoin volatility dynamics, and outperform single-regime GARCH specifications in Value-at-Risk (VaR) forecasting.

Katsiampa (2019) studies the volatility dynamics of the two major cryptocurrencies (Bitcoin and Ether), using a bivariate GARCH (BEKK model). Her results suggest that price returns of both cryptocurrencies are stationary, but exhibit volatility clustering.

Finally, Gkillas and Katsiampa (2018) use extreme value theory to investigate tail behavior in cryptocurrencies. In particular, they study the two major tail risk measures of VaR and Expected Shortfall (ES) as extreme quantiles of the Generalized Pareto distribution (GPD). They apply a parametric bootstrap bias-correction approach to the two risk measures in order to reduce any uncertainty resulting from the estimation procedure of the asymptotic extreme value distribution and the threshold selection. This study tells the different degree of riskiness of each cryptocurrency under examination.

3.3.5 *Assets Correlation and Portfolio Optimization*

This group of articles study the relationship between cryptocurrencies and the other assets. The objective of these articles is to compare the behavior of cryptocurrencies with respect to traditional assets and to evaluate the possibility of adding cryptocurrencies to current financial portfolios. In addition, some papers explore the suitability of constructing cryptocurrency-only portfolios. The rationale is that, due to the low correlation of cryptocurrencies *vis-à-vis* traditional assets, they can reduce the risk of the overall portfolio. Most of the studies suggest that cryptocurrencies can become a portfolio diversifier. However, most authors warn that it is important to evaluate the uncertainties around future regulation and the exposure of cryptocurrencies to hacking activities.

Dyhrberg (2016a) applies GARCH models to determine that bitcoin has a place on the financial markets and in portfolio management, as it can be classified as something in between gold and the U.S. dollar. Nevertheless, Baur *et al*. (2018a) replicated this study proving that Bitcoin exhibits distinctively different return, volatility, and correlation characteristics compared to other assets, including gold and the U.S. dollar. Baur *et al*. (2018a) extends Dyhrberg (2016a), adding the asymmetric GARCH model to the analysis.

In addition, Guesmi *et al*. (2019) implement various specifications of the DCC-GARCH models to investigate volatility spillovers between Bitcoin and exchange rates, stock market, and commodity series. They find that VARMA (1,1)-DCC-GJR-GARCH is the best model specification to describe the joint dynamics of Bitcoin and different financial assets. This suggests that Bitcoin may offer diversification and hedging benefits for investors.

In another vein, Liu (2019) considers different portfolio models (1/N equal weighted (EW), minimum variance (MV), risk parity (RP), Markowitz (MW), maximum Sharpe ratio (MS), and maximum utility (MU)) to examine the investability and diversification benefits of cryptocurrencies. This author shows that portfolio diversification across different cryptocurrencies can significantly improve the investment results.

Corbet *et al*. (2018c) examine the relationships between three popular cryptocurrencies (Bitcoin, Litecoin, and Ripple) and a variety of traditional financial assets. They use the generalized variance decomposition methodology by Diebold and Yilmaz (2012) to estimate the direction and intensity of spillovers across selected markets. Furthermore, they estimate unconditional connectedness relations in time–frequency domain (Barunik and Krehlik, 2016). They find evidence of the relative isolation of these assets from the financial and economic assets. Aslanidis *et al*. (2019), using a generalized dynamic conditional correlation (DCC) model (Engle, 2002), find similar results to Corbet *et al*. (2018c), and also uncovers that cross-correlation against Monero is more stable across time that other correlation pairs.

Finally, Zieba *et al*. (2019) examine the inter-relationships between 78 cryptocurrencies during the period 2015–2018 using Minimum-Spanning Trees, a methodology borrowed from econophysics. The topological properties that arise from this analysis does not change over the period of study. The paper concludes that in spite of Bitcoin's dominance, the market is heterogeneous. Thus, in order to provide an appropriate analysis of this market, it is not sufficient to study Bitcoin, but to include altcoins in empirical studies.

3.3.6 *Safe-Haven Characteristics*

Related to the previous category, articles dealing with safe-haven characteristics evaluate if bitcoin can become a substitute for gold. The rationale behind this group of articles is that both are uncorrelated with other financial assets.

Some papers in this section upholds that cryptocurrencies are not only useful portfolio diversifiers but also "wealth shields." Therefore, authors consider cryptocurrencies a commodity, rather than a medium of exchange. However, as explained in Section 3.3.5, the doubts around their regulations, the lack of security due to cyberattacks, the enormous volatility (see Section 3.3.4), and the lower liquidity (compared to traditional assets) still generate uncertainty around cryptocurrencies as safe-haven assets.

Dyhrberg (2016b) finds some relationship between bitcoin and gold. This paper uses the threshold GARCH (TGARCH) model (Glosten *et al*., 1993) to examine if bitcoin could be used as a hedge against stocks in the Financial Times Stock Exchange index (FTSE) and the U.S. dollar. The author affirms that bitcoin possess some of the same hedging abilities as gold. In the same vein, Bouri *et al*. (2017a) investigate whether bitcoin can hedge global uncertainty, measured by the first principal component of the VIXs of 14 developed and developing equity markets. They use the wavelet transform to decompose bitcoin returns into its various frequencies (or investment horizons). Their results show that hedging for bitcoin is observed at shorter investment horizons, and at both lower and upper ends of bitcoin returns and global uncertainty.

Conversely, some of the recent papers disagree with this view of bitcoin becoming a hedge or a safe-haven asset. For example, Klein *et al*. (2018) use different GARCH models (including BEKK-GARCH) to show that bitcoin does not reflect any distinctive properties of gold other than asymmetric response in variance. Moreover, they show that FIAPARCH is being the best fitting model in terms of log-likelihood and information criteria. Furthermore, Smales (2019) argues that it is unlikely to be worthwhile considering bitcoin as a safe-haven asset because is more volatile, less liquid, and costlier to transact (in terms of time and fees) than other assets (including gold), even in normal market conditions. Bouri *et al*. (2017b) show, using the Bivariate DCC model by Engle (2002), that bitcoin can usually serve as an effective diversifier but it has only hedge and safe-haven properties against Asia Pacific stocks.

3.3.7 *Bubble Formation*

Bubble behavior of cryptocurrencies easily captures media attention. This fact is one of the main drivers that made cryptocurrencies (mainly bitcoin) famous for most of the people in 2017. Therefore, in this group of articles different empirical tools are used to study the bubble behavior of cryptocurrency prices.

Cheah and Fry (2015) empirically estimate bitcoin's fundamental value. They use the Intrinsic Rate of Return and the Intrinsic Level of Risk measures. Moreover, they use the bubble models by Johansen *et al*. (2000), Andersen and Sornette (2004), and MacDonell (2014). They show that bitcoin exhibits speculative bubbles even before the big bubble of 2017. Furthermore, they find empirical evidence that the fundamental price of bitcoin is zero, which raises serious concerns upon the long-term sustainability of bitcoin.

Later, the same authors (Fry and Cheah, 2016) developed probabilistic and statistical formulation of econophysics models to test for economic bubbles and crashes. They use three estimations. First, the univariate and negative bubbles (Johansen *et al*., 2000; Yan *et al*., 2012). Second, multivariate models that describe the price of more-than-one asset simultaneously and are significant for empirical applications. Third, a bivariate bubble model, which is a method to test for the presence or absence of contagion during bubbles and negative bubbles. In addition, they also examine unpredictable market shocks. They find evidence of a negative bubble from 2014 onward in the two largest cryptocurrency markets, bitcoin and ripple. Furthermore, evidence suggests that there is a spillover from ripple to bitcoin that exacerbate price falls in bitcoin.

Finally, Bouri *et al*. (2019c) test the co-explosivity of cryptocurrencies. This paper is the first to study co-explosivity (that is, the potential interactions among bubble periods within the cryptocurrency market). The methodology used is the generalized supremum Augmented Dickey–Fuller (GSADF) test of Phillips *et al*. (2015) and a logistic regression to uncover evidence of co-explosivity across cryptocurrencies. They find evidence of a multidirectional co-explosivity behavior that is not necessarily from bigger to smaller and younger markets.

3.3.8 *Initial Coin Offering (ICO)*

ICOs or token offerings are in the cryptocurrency industry, what in stock market is an Initial Public Offering (IPO). ICOs constitute a novel mechanism to raise funds, by creating a new coin, app or service-based on blockchain. They create an alternative mechanism for funding highly innovative ventures. Investors entering into an ICO receive a cryptocurrency token that may be used either as a way of using the product the issuer is offering or be proxy for the a stake in the issuer's project. One important element is that entrepreneurs could raise capital bypassing intermediaries and thus, reducing costs. This topic is relative new, and according to Momtaz (2020) "the literature on token offerings is still in its infancy." An ICO usually includes two key elements: a white paper, and project code. A white paper is a document where the project promoter discloses information deemed necessary to attract investors. The project programming code (usually released through GitHub repositories), provides information on the technical aspects of the venture.

Papers on this matter explore the evolution of ICOs, their characteristics, and factors that influence such token sale. Adhami *et al*. (2018) find that the availability of a (good quality) source code enhances the probability of an ICO's success, but such success is unaffected by the availability of the project's white paper. Subsequently, Fisch (2019) assesses the determinants on the amount raised in 423 ICOs. In particular, the author studies if, according to Spence (1973) signaling theory, high-quality ventures are able to engage more investors. The author finds that patents do not appear as relevant to investors. However, project's technical white paper and high-quality codes are associated an increase amount of funding. In a similar vein, Zhang *et al*. (2019) find white paper quality (proxied by an index of text readability) is associated with higher ICOs first-day returns. Thus, the authors argue that better written documents could engage more investors into this sort of "blockchain crowd funding."

Felix and von Eije (2019) examine 279 ICOs between April 2013 and January 2018. Their empirical analysis reports that variables such as trading volume, issue size, and market sentiment influence ICO underpricing. Considering that ICOs have weaker legal backing, and a fuzzy regulation framework, there will be more information asymmetry between issuers and investors. Information asymmetries are particularly aggravated in innovative sectors, due to the difficulties in assessing the fair value of the investment (Pierrakis and Saridakis, 2019). In this sense, Momtaz (2020) provide evidence of systematic moral hazard in signaling. Token issuers are prone to overestimate information disclosed in white papers.

Domingo *et al*. (2020) conduct a dynamic panel data to determine variables that affect ICOs returns. The authors find that ICOs returns are highly volatile, and that investors pay attention to opinions about

ICOs posted on specialized digital forums. In addition, the paper identifies that Bitcoin spot returns or Bitcoin futures returns leads to an increase in ICOs returns.

4. Literature Gaps and Open Research Paths

According to our review, most of the papers regarding cryptocurrencies are focused on financial aspects of cryptocurrencies: informational efficiency, volatility, portfolio optimization, bubble behavior, etc.

The cryptocurrency market, unlike traditional assets, are opened 24/7. We can find trades taken place almost every minute for the most liquid cryptocurrencies. Then, this market offers a unique opportunity to test continuous time models that can be hardly verified in traditional stock or bond markets.

As shown in Table 6, most papers are focused on daily data. Probably this is a customary use from financial economists when studying stock markets. However, it would important to explore the information gain (if it exists) in the use of high-frequency data. In addition, considering cryptocurrencies as pure speculative assets, their study at high frequency could give some hints on the behavior of traditional assets whose behavior at high frequency cannot be observed.

One topic, usually developed in engineering journals is the environmental impact of cryptocurrencies' mining. This theme is mostly not yet studied in economics journals. Even when authors may comment on the important electricity consumption of cryptocurrencies during the mining process, they fail to make a clear estimation of the environmental impact of blockchain technology as a whole. In other words, there is a need for an analysis of positive and negative externalities of the blockchain technology.

Another gap in the literature is how mining protocols could affect price. It is well known that cryptocurrencies use different protocols to maintain network consensus.[3] To the best of our knowledge, there is no paper considering the influence of consensus protocols in price formation, returns, or volatility.

Regarding ICOs there are also several unexplored paths. On the entrepreneur's side, it remains unexplored yet the motivations for the use of ICOs over other funding sources. In particular, it should be investigated the benefits and disadvantages of collecting cryptomoney instead of fiat money. Another research question is to what extent a hypothetical ICO regulation (aimed at protecting against fraud) could influence moral hazard behavior. It is also unknown if manager's gender or firm's human capital (e.g., academic background and skills of staff) influence variables such as funding size, token price behavior, and project performance. On the investor's side, it should be scrutinized the variables predispose people to provide funds to unknown individuals, to projects that are (generally) difficult to oversee. According to Fisch (2019), Ethereum-based tokens are the most common standard, and one of the factors associated to ICOs' success. It could be interesting to further explore the determinants of this preference and the potential shift toward another platforms.

In addition, we detect that there is a lack of theoretical papers that contemplate the potential impact of national (or even supranational) regulation in this market. It is remarkable the lack of an institutional economics view of these phenomena. There is an increasing interest from Central Banks to explore the introduction of digital currencies as part of their assets (De and Nelson, 2020; European Central Bank, 2020; Fernández-Villaverde *et al.*, 2020). Therefore, there is a potentially fruitful research line for experts in the fields of monetary economics regarding the impact of cryptocurrencies on financial stability.

Finally, as we highlight in this paper, most past research was focused exclusively on bitcoin, or at most in the four or five most important cryptocurrencies. Even though bitcoin represents approximately 68% of the market capitalization in January 2020, there are currently more than 5000 active cryptocurencies (Coinmarket, 2020). Zieba *et al.* (2019) reports that the cryptocurrency market is rather heterogeneous, and cannot be described by solely study Bitcoin. Extending previously used models to more cryptocurrencies can give more information about this market as a whole, putting together assets with different underlying technology, liquidity, different age, etc.

5. Conclusions

This study makes a bibliometric and literature review of the most important economic topics studied on cryptocurrencies. Bibliometric studies are a useful technique to analyze the state of the art in a specific field with large number of papers, because it could be processed by means of machine learning algorithms. However, it could hardly substitute the insight given by the specialized researcher. Consequently, our methodology is based on a combination of machine learning (for bibliometric analysis), and close reading (for literature review). The first step allows for an informed sample selection of papers, which is used in the second step. This literature review has a dual goal. First, to propose this hybrid methodology. Second, to provide an updated, useful review for new and experienced researchers in this field.

Our analysis displayed the main research lines, and some emerging paths of this novel market. We expanded previous literature, adding a comprehensive review of 107 papers, classifying them into different research topics, and identifying top papers and journals. Finally, we detected some literature gaps and propose future research paths.

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Data Availability Statement

The data that support the findings of this study are available from Web of Science/Clarivate Analytics. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Web of Science/Clarivate Analytics.

Notes

1. HCP is a metric developed by Web of Science Group, to help to identify top-performing research. HCP are papers that have received enough citations to place them in the top 1% when compared to all other papers published in the same year in the same field. For additional details of this and other metrics, see https://clarivate.libguides.com/esi.
2. Keyword-Plus are those extracted from the titles of the cited references by Thomson Reuters (the company maintaining WoS). Keyword Plus are automatically generated by a computer algorithm.
3. For example, bitcoin uses "proof of work," DASH and NEO use "proof of stake," Burstcoin uses "proof of capacity," etc. There are other alternative protocols, for example, proof of authority, proof of space. For a recent discussion of these and other technical aspects, see Belotti *et al*. (2019).

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Appendix A

Table A1. Detailed Analysis of Papers Selected in Section 2.2.

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Cheah and Fry (2015)	Bubble	Bitcoin	Daily	Coindesk	MacDonell (2014) test for bubbles, model in Johansen *et al*. (2000), model in Andersen and Sornette (2004)	Provide empirical evidence to address the existence of bubbles in Bitcoin markets. Determine the fundamental value of Bitcoin	Bitcoin exhibits speculative bubbles. The fundamental price of Bitcoin is zero.
Fry (2018)	Bubble	Bitcoin, Ripple, Ethereum, Bitcoin Cash	Daily	Coinmarketcap	Theoretical refinement of the model in Cheah and Fry (2015)*	Develop rational bubble models	Evidence of bubbles in Bitcoin and Ethereum. No evidence of bubbles in Ripple once we account for heavy tails and liquidity risk.
Bouri *et al*. (2019c)	Bubble	Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, Stellar	Daily	Coinmarketcap	GSADF, Logistic regression	Data-stamp price explosivity in leading cryptocurrencies	Cryptocurrencies characterized by multiple explosivity. Multidirectional coexplosivity behavior that is not necessarily from bigger to smaller and younger markets.
Geuder *et al*. (2018)	Bubble	Bitcoin	Daily	Coinmarketcap	PSY (SADF, GSADF), LPPL	Study bubble behavior in Bitcoin prices during 2016–2018	Bubble behavior is a common and reoccurring characteristic
Corbet *et al*. (2018b)	Bubble	Bitcoin, Ethereum	Daily	API	Phillips *et al*. (2011) (SADF, GSADF)	Examine the existence and dates of pricing bubbles in Bitcoin and Ethereum	There are periods of clear bubble behavior, with Bitcoin in Nov. 2017 almost certainly in a bubble phase
Cagli (2019)	Bubble	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Nem, Dash, and Monero	Daily	Coinmarketcap	Multiequation continuous time system	Investigate explosive behavior	Almost all cryptocurrencies exhibit explosive behavior and significant pairwise comovement
Fry and Cheah (2016)	Bubble	Bitcoin, Ripple	Daily	Coindesk, Coinmarketcap	Univariate and bivariate bubbles, multivariate models	Develop a suite of models for financial bubbles and crashes	Negative bubble from 2014 onward in Bitcoin and Ripple
Gkillas and Katsiampa (2018)	Bubble	Bitcoin, Ethereum, Ripple, Bitcoin Cash, Litecoin	Daily	Coindesk, Coinmarketcap	Extreme value analysis	Study the tail behavior of the returns	Bitcoin Cash is the riskiest cryptocurrency, while Bitcoin and Litecoin are the least risky.
Corbet *et al*. (2018c)	Correlation	Bitcoin, Ripple, Litecoin	Daily	Cryptocompare	GVD, BK	Analysis of crosscorrelation of crypto and traditional assets over short and long horizons	Relative isolation of cryptos from traditional assets
Aslanidis *et al*. (2019)	Correlation	Bitcoin, Ripple, Dash, Monero	Daily	Coinmarketcap	generalized DCC	Analysis of cross-correlation of crypto and traditional assets	cryptocurrencies exhibit similar mean correlation among them, and detached from traditional assets. Monero correlations are more stable

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Koutmos (2018c)	Correlation	18 cryptocurrencies	Daily	Coinmarketcap	VAR, spillover index	Measure return and volatility spillovers among cryptocurrencies	Growing interdependence among cryptocurrencies, being Bitcoin the dominant transmitter of shocks
Wei (2018a)	Correlation	Bitcoin, Tether	Daily	Coinmarketcap	ADL Granger causality, VAR	Examine the impact of cryptocurrency issuances on cryptocurrency returns	Tether grants were potentially timed to follow Bitcoin downturns and subsequent Bitcoin/Tether trading volumes increased
Tu and Xue (2019)	Correlation	Bitcoin, Litecoin	Daily	Coinmarketcap	Granger causality, BEKK-MGARCH	Study the effect of the bifurcation of Bitcoin on its interactions with Litecoin	Bifurcation weakened the market position and pricing influence of Bitcoin
Wang *et al*. (2018)	Correlation	Bitcoin	Daily	Coindesk	MVQM, Granger causality	Investigate risk spillover effect from economic policy uncertainty (EPU) to Bitcoin	Risk spillover effect from EPU to Bitcoin is negligible
Giudici and Abu-Hashish (2019)	Correlation	Bitcoin	Daily	Some exchanges	Network VAR	Understand price transmission between different crypto market exchanges, and between crypto and traditional assets	Correlation between bitcoin prices exchanges is strong, correlation of bitcoin prices with traditional assets is low
Zieba *et al*. (2019)	Correlation	78 cryptocurrencies	Daily	Coinmarketcap	Minimum Spanning Tree; VAR	Examine interdependencies between log-returns of cryptocurrencies	Changes in Bitcoin price do not affect and are not affected by changes in prices of other cryptocurrencies
Urquhart (2016)	Efficiency	Bitcoin	Daily	Bitcoinaverage	LB, runs test, Bartels, VR, AVR, WBAVR, BDS, Hurst exponent	Study the informational efficiency of Bitcoin	Bitcoin in an inefficient market but moving toward an efficient market
Nadarajah and Chu (2017)	Efficiency	Bitcoin	Daily	Bitcoinaverage	LB, runs test, Bartels, WBAVR, SST, BDS, RPT, GS	Investigate the market efficiency of Bitcoin	A power transformation of Bitcoin returns can be weakly efficient
Bariviera (2017)	Efficiency	Bitcoin	Daily	Datastream	Hurst exponent (R/S, DFA)	Study long-range dependence of Bitcoin return and volatility	Daily return time series become more efficient across time. Daily volatility exhibits long-range memory
Phillip *et al*. (2018)	Efficiency	224 cryptocurrencies	Daily	Brave New Coin (BNC)	GLM, SV, Leverage, Heavy tails	Measure and compare the varied nature of cryptocurrencies	Cryptocurrencies exhibit long memory, leverage, stochastic volatility, and heavy tailedness.
Khuntia and Pattanayak (2018)	Efficiency	Bitcoin	Daily	Coindesk	DL, GS, AMH	Evaluate the adaptive market hypothesis (AMH) in Bitcoin market	The evidence of dynamic efficiency

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Vliet (2018)	Efficiency	Bitcoin	Monthly	Blockchain.info	Metcalfe's Law	Present new model of the market capitalization of Bitcoin built upon Metcalfe's Law	Model fits empirical data well
Tiwari *et al*. (2018)	Efficiency	Bitcoin	Daily	Coindesk	DFA, CMA-1, CMA-2, Periodogram-LAD, Periodogram-LS, GPH, and MLE techniques	Revisit the issue of informational efficiency of Bitcoin	The market is informational efficient
Wei (2018b)	Efficiency	456 cryptocurrencies	Daily	Coinmarketcap	LB, Bartels, VR, AVR, BDS, Hurst exponent, AIR	Examine the liquidity of 456 cryptocurrencies	Return predictability diminishes as liquidity increases in cryptocurrencies
Cheah *et al*. (2018)	Efficiency	Bitcoin	Daily	Bitcoincharts	FCVAR, Log periodogram, ELW	Test whether cross-market Bitcoin markets display heterogeneous informational inefficiency	Evidence of long-memory in individual markets and the system of markets
Takaishi and Adachi (2018)	Efficiency	Bitcoin	Intraday (1-minute)	Coindesk	Autocorrelation function	Investigate the Taylor effect in Bitcoin time series	The Taylor effect is present in Bitcoin time series
Köchling *et al*. (2019b)	Efficiency	75 cryptocurrencies	Daily	Coinmarketcap	Delay measures proposed by Hou and Moskowitz (2005)	Investigate the reaction time to unexpected relevant information	Average price delay significantly decreases during the last three years. Price delay is highly correlated to market capitalization and liquidity
Thies and Molnr (2018)	Efficiency	Bitcoin	Daily	Bitstamp	Bayesian change point model	Study existence of structural breaks in the average return and volatility of the Bitcoin price	Structural breaks in average returns and volatility of Bitcoin are very frequent
Aharon and Qadan (2019)	Efficiency	Bitcoin	Daily	Bitcoincharts	OLS, GARCH, QMLE	Extend the exploration of the day-of-the-week effect to Bitcoin	Evidence about day-of-the-week effect anomaly in returns and volatility
Chevapatrakul and Mascia (2018)	Efficiency	Bitcoin	Daily	Coinmarketcap	QAR, RPT	Examine the persistence of returns on Bitcoin at different parts on the return distributions	Investors overreact during days of sharp declines in the Bitcoin price and during weeks of market rallies
Köchling *et al*. (2019a)	Efficiency	Bitcoin	Daily	Bitcoinaverage	LB, RPT, runs test, Bartels, SST, GS, WBAVR, BDS, Hurst exponent	Investigate the effect of futures in market efficiency.	There is no significant switch toward an efficient market
Al-Yahyaee *et al*. (2018)	Efficiency	Bitcoin	Daily	Coindesk	MFDFA	Assess the efficiency of Bitcoin market compared to gold, stock, and foreign exchange markets	Bitcoin is more inefficient than the gold, stock, and currency markets

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Bouri *et al*. (2019a)	Efficiency	14 cryptocurrencies	Daily	Coinmarketcap	Rolling analysis, CSAD	Examine the presence of herding behavior	Significant herding behavior varying over time
Vidal-Tomás *et al*. (2019a)	Efficiency	65 cryptocurrencies	Daily	BraveNewCoin (BNC)	Most traditional tests of efficiency	Study weak-form inefficiency of the cryptocurrency market	Extreme dispersion of returns explained by rational asset pricing models. Herding during down markets.
Vidal-Tomás *et al*. (2019b)	Efficiency	118 cryptocurrencies	Daily	BraveNewCoin (BNC)	CSSD, CSAD	Analyze the existence of herding behavior	Cryptocurrency market is weak-form inefficient due to the behavior of all the altcoins. It is more inefficient over time. Creation of new cryptocurrencies has not significantly changed the efficiency of the market.
Kaiser (2019)	Efficiency	10 cryptocurrencies	Daily	Coinmarketcap	Bid–ask spread, GARCH	Test for daily and monthly seasonality in returns, volatility, trading volume, and a spread estimator	No consistent and significant calendar effect in returns
Vidal-Tomás and Ibáñez (2018)	Efficiency	Bitcoin	Daily	Bitstamp, Mt.Gox	AR-CGARCH, AR-CGARCH-M	Examine the semistrong efficiency of Bitcoin in the Bitstamp and Mt.Gox markets	Bitcoin has no connection to measures taken by central banks
Caporale and Plastun (2018)	Efficiency	Bitcoin, Litecoin, Ripple, Dash	Daily	Coinmarketcap	Independence tests, ANOVA, OLS with dummy variables, trading simulation approach	Examine the day of the week effect	There is no conclusive evidence of inefficiency
Jiang *et al*. (2018)	Efficiency	Bitcoin	Daily	unknown	Rolling window approach	Investigate the time-varying long-term memory in the Bitcoin market	Bitcoin market is inefficient. Returns present strong persistence
Charfeddine and Maouchi (2019)	Efficiency	Bitcoin, Ethereum, Litecoin, Ripple	Daily	Coinmarketcap	LRD (Hurst exponent with various), structural breaks in the returns, splitting sample	Question the true nature of the LRD behavior observed in the returns and volatility	Evidence of LRD in returns and volatility of BTC, LTC, and XRP and the volatility of ETH
Sensoy (2019)	Efficiency	Bitcoin	Intraday (15-minute)	All exchanges	Rolling window approach, permutation entropy	Compare the time-varying weak-form efficiency of Bitcoin prices in U.S. dollars and euro at a high-frequency level	Markets have become more efficient since 2016

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Corbet and Katsiampa (2018)	Efficiency	Bitcoin	Intraday (1-minute)	unknown	EGARCH	Explore as to whether Bitcoin, exhibit similar asymmetric reverting patterns for minutely, hourly, daily, and weekly returns	Evidence of several differences in the behavior of Bitcoin price returns according to subperiods and evidence of asymmetric reverting patterns in the Bitcoin price returns
Adhami *et al*. (2018)	ICO	253 ICOs	not applicable	TokenData, Coinmarketcap, CoinSchedule, CoinDesk, IcoAlert, ICOBazaar, TokenMarket, SmithAndCrown	Logit model	Analyze the determinants of the success of token offerings	The probability of an ICOs success is higher if the code source is available, when a token presale is organized, and when tokens allow contributors to access a specific service (or to share profits)
Felix and von Eije (2019)	ICO	279 ICOs	not applicable	ICObench, Coinmarketcap	Multivariate regression analysis	Analyze underpricing in ICO	Average level of underpricing of ICOs of 123% in the USA and 97% in the other countries
Fisch (2019)	ICO	423 ICOs	not applicable	CoinSchedule	Multivariate regression analysis	Determine the factors that affect the amount of funding raised in ICOs	Technical white papers and high-quality source codes increase the amount raised, while patents are not associated with increased amounts of funding
Zhang *et al*. (2019)	ICO	244 ICOs	not applicable	Bitfinex, Binance, Huobi Global, OKEx	OLS regression	Study the association between readability of the ICO white paper and the offering's first-day return	ICO returns are affected by white paper disclosure quality
Domingo *et al*. (2020)	ICO	125 ICOs	daily	Trackico, Coinmarketcap, CBOE, StockTwits	Dynamic panel data (GMM)	Explore the influence of several key features on ICO returns	Bitcoin spot and Bitcoin futures returns exert a positive influence on ICO returns. Existence of a presale period exerts a negative influence. ICO category seems to be nonsignificant
Momtaz (2020)	ICO	495 ICOs	not applicable	ICObench; Coinmarketcap, Crunchbase, LinkedIn, Twitter, Github	Artificial intelligence (text analysis)	Provide evidence of a moral hazard in signaling in an entrepreneurial finance context	Token issuers systematically exaggerate information disclosed in white papers
Corbet *et al*. (2019)	Literature review	All cryptocurrencies	not applicable	not applicable	Systematic literature review	Provide a systematic review of the empirical literature based on the major topics that have been associated with the market for cryptocurrencies	Finds that there are numerous gaps in the cryptocurrency-related literature

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Dyhrberg *et al.* (2018)	Microstructure	Bitcoin	Intraday (twice a second)	Kraken, Gdax, Gemini	AQS	Examine transactions costs and liquidity of major Bitcoin exchanges	With low spreads and sufficient market depth for average-sized transactions, Bitcoin is investible
Koutmos (2018a)	Microstructure	Bitcoin	Daily	Bloomberg	Bivariate VAR	Examine the linkages between Bitcoin returns and transaction activity	Strong linkages between Bitcoin returns and transaction activity
Koutmos (2018b)	Microstructure	Bitcoin	Daily	Bitfinex	ARMA-GARCH, Markov-switching regime	Provide a measure of Bitcoin liquidity uncertainty and to determine market microstructure determinants	Market microstructure variables underlying Bitcoin serve as explanatory variables of Bitcoin liquidity uncertainty
Kim (2017)	Microstructure	Bitcoin	Daily	Quandl	Bid–ask spread, multivariate regression	Examine the empirical transaction costs of Bitcoin in international transactions	Transaction cost of Bitcoin is lower than foreign exchange markets
Alaoui *et al.* (2019)	Microstructure	Bitcoin	Daily	Cryptocompare	Cross-correlation test, MF-DCCA	Study the price–volume cross-correlation	Price and trading volume mutually interact in a nonlinear way, multifractality is present, Bitcoin market is not efficient
Holub and Johnson (2019)	Microstructure	Bitcoin	Daily	Bitcoincharts	Bid–ask spread	Study the global P2P market	Bitcoin bubble's impact on Bitcoin prices in the P2P market is currency and country-dependent
de la Horra *et al.* (2019)	Monetary economics	Bitcoin	Daily	Quandl	Engle–Granger two-step proceedure	Analyze the demand for Bitcoin	Bitcoin behaves as a speculative asset in the short term. In the long term, demand might be driven by expectations of Bitcoin's future utility as a medium of exchange
Gandal *et al.* (2018)	Monetary economics	Bitcoin	intraday	Bitcoincharts and Mt. Gox	Compare trading volumes in Bitcoincharts and Mt. Gox to verify impact in trading prices	Explore if suspicious trades are linked to movements of bitcoin price	A single trader could excercise significant influence on bitcoin price. Cryptocurrency market is vulnerable to manipulation.

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Böhme *et al*. (2015)	Overview	no applicable	not applicable	not applicable	Overview of cryptocurrency topic	Discuss bitcoin benefits and costs	Present an overview for a nontechnical audience. Point out risks, regulatory issues, and interactions with the conventional financial system and the real economy.
Platanakis *et al*. (2018)	Portfolio	Bitcoin, Litecoin, Ripple, Dash	Weekly	Coinmarketcap	MVPO, SR	Examine the diversification benefits of cryptocurrencies	Little difference between naïve and optimal diversification
Symitsi and Chalvatzis (2018)	Portfolio	Bitcoin	Daily	Datastream	VAR conditional mean process, VAR-BEKK-AGARCH, multivariate LB	Study spillover effects between Bitcoin and energy and technology companies	Evidence of unilateral return and volatility spillovers and bidirectional shock influences. Portfolio management implications and benefits.
Platanakis and Urquhart (2019)	Portfolio	Bitcoin, Litecoin, Ripple, Dash	Weekly	Coinmarketcap	MVPO, BL(VBCs), SR	Compare different portfolio construction methods using cryptocurrencies	Sophisticated portfolio techniques (Black-Litterman model with VBCs) are preferred when managing cryptocurrency portfolios
Dyhrberg (2016a)	Portfolio	Bitcoin	Daily	Coindesk	GARCH, EGARCH	Explore the financial characteristics of bitcoin using GARCH models	Bitcoin can be classified as something in between gold and the American dollar
Baumohll (2019)	Portfolio	Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens, NEM	Daily	unknown	Quantile cross-spectral approach, standard Pearson's correlations, DMCA	Analyze the connectedness between forex and cryptocurrencies using the quantile	Significant negative dependencies between forex and cryptocurrencies
Liu (2019)	Portfolio	10 cryptocurrencies	Daily	Coinmarketcap	SR	Examine the investablitiy and role of diversification in cryptocurrency market	Portfolio diversification across different cryptocurrencies can significantly improve investment results
Brauneis and Mestel (2019)	Portfolio	500 cryptocurrencies	Daily	Coinmarketcap	MVPO	Assess risk-return benefits of cryptocurrency-portfolios	Combining cryptocurrencies enriches the set of low-risk cryptocurrency investment opportunities
Ji *et al*. (2019)	Portfolio	6 cryptocurrencies	Daily	Coinmarketcap	VAR, FEVD	Examine connectedness via return and volatility spillovers	Litecoin and Bitcoin are at the center of the connected network of returns
Guesmi *et al*. (2019)	Portfolio	Bitcoin	Daily	Datastream	DCC-GARCH	Explore the conditional cross effects and volatility spillover between Bitcoin and financial indicators	Bitcoin market allow hedging the risk investment

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Kajtazi and Moro (2019)	Portfolio	Bitcoin	Daily	Bitcoinity	Mean-CVaR	Explore the effects of adding bitcoin to an optimal portfolio	Bitcoin may help in diversification although it has speculative characteristics
Urquhart (2017)	Price clustering	Bitcoin	Daily	Bitcoincharts	Clustering test, conditional effects, standard probit model	Study the price clustering in Bitcoin	There is significant evidence of price clustering at round numbers but there is no significant pattern of returns after the round number. Price and volume have significant positive relationship with price clustering at whole numbers.
Li *et al*. (2020)	Price clustering	Bitcoin	Intraday (1-minute)	Bitcoincharts	Chi-squared test, Herfindahl–Hirschman index, OLS	Extend the current literature on price clustering in Bitcoin market	Evidence of clustering for open, high, and low prices
Hu *et al*. (2019)	Price clustering	Bitcoin, Litecoin, Ripple	Intraday	Bitstamp	Transaction frequency	Investigate intraday price behavior	There is evidence supporting the negotiation and strategic trading hypotheses, but no support for attraction hypothesis
Akcora *et al*. (2018)	Price discovery	Bitcoin	Daily	Coinbase	HFG, GARCH	Model the network with a high fidelity graph to characterize the flow of information	Identification of certain subgraphs with predictive influence on Bitcoin price and volatility
Brauneis and Mestel (2018)	Price discovery	73 cryptocurrencies	Daily	Coinmarketcap	KS, GARCH, (LB, VR, BDS, Hurst exponent), MOE, TR	Investigate efficiency/predictability and brk to asses liquidity of cryptocurrencies	Efficiency is positively related to liquidity
Urquhart (2018)	Price discovery	Bitcoin	Intraday (5-minute)	Bitcoincharts	RV, VAR	Study the attention of Bitcoin by employing Google Trends data	Attention of Bitcoin is influenced by the previous day's high realized volatility and volume
Kapar and Olmo (2019)	Price discovery	Bitcoin	Daily	Coindesk	IS, CS	Analyze the Bitcoin price discovery process	The Bitcoin futures market dominates the price discovery process
Shen *et al*. (2019)	Price discovery	Bitcoin	Intraday (5-minute)	Bitcoincharts	VAR, Granger causality test	Examine the link between investor attention and Bitcoin returns, trading volume and realized volatility	The number of tweets is a significant driver of next day trading volume and realized volatility
Sun *et al*. (2020)	Price discovery	42 cryptocurrencies	Daily	Investing	LightGBM (GBDT), SVM, RF	Forecast the price trend	LightGBM algorithm outperforms other methods
Troster *et al*. (2019)	Price discovery	Bitcoin	Daily	Coindesk	GARCH, GAS, VaR	Model and forecast bitcoin returns and risk	Heavy-tailed GAS models improve goodness-of-fit and forecast performance of bitcoin returns and risk

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Demir *et al*. (2018)	Price discovery	Bitcoin	Daily	Coindesk	VAR, OLS	Analyze the prediction power of the economic policy uncertainty (EPU) index on the daily Bitcoin returns	EPU has a predictive power on Bitcoin returns, serving as a hedging tool against uncertainty
Feng *et al*. (2018)	Price discovery	Bitcoin	Daily	Bitcoincharts	OSI	Propose a novel indicator to assess informed trades ahead of cryptocurrency-related events	Evidence of informed trading in the Bitcoin market prior to both positive and negative large events
Panagiotidis *et al*. (2018)	Price discovery	Bitcoin	Daily	Coindesk	LASSO	Examine the significance of 21 potential drivers of bitcoin returns	Search intensity and gold returns are the most important variables for bitcoin returns
Bouri *et al*. (2019b)	Price discovery	Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, Stellar	Daily	Coinmarketcap	Granger causality	Extend the understanding on the Granger causality from trading volume to the returns and volatility	Evidence of Granger causality from trading volume to the returns
Aalborg *et al*. (2019)	Price discovery	Bitcoin	Intraday (10-minute)	Bitcoincharts	Heterogeneous AR, HAR-RV	Study which variables can explain and predict the return, volatility and trading volume of Bitcoin	Trading volume can be predicted from Google searches, but none of the considered variables can predict returns
Dastgir *et al*. (2019)	Price discovery	Bitcoin	Weekly	Investing	Granger Causality	Examines the causal relationship between Bitcoin attention (measured by the Google Trends search queries) and Bitcoin returns	Bidirectional causality mainly exists in both tails
Panagiotidis *et al*. (2019)	Price discovery	Bitcoin	Daily	Coindesk	VAR, FAVAR, PCA	Examine the effects of shocks on bitcoin returns	Evidence of a significant interaction between bitcoin and traditional stock markets, weak interaction with FX markets and the macroeconomy
Bleher and Dimpfl (2019)	Price discovery	12 cryptocurrencies	Intraday (hourly)	Cryptocompare	VAR, Granger-causality	Evaluate the usefulness of Google search volume to predict returns and volatility of multiple cryptocurrencies	Returns are not predictable, volatility is partly predictable
Dyhrberg (2016b)	Safe-haven	Bitcoin	Daily	Coindesk	Asymmetric GARCH	Explore the hedging capabilities of bitcoin	Bitcoin possess some of the same hedging abilities as gold
Bouri *et al*. (2017a)	Safe-haven	Bitcoin	Daily	Coindesk	OLS, Wavelet decomposition	Examine whether Bitcoin can hedge global uncertainty	Bitcoin does act as a hedge against uncertainty in the short horizon
Bouri *et al*. (2017b)	Safe-haven	Bitcoin	Daily	Thomson Reuters	DCC	Examine whether Bitcoin can act as a hedge and safe-haven for major world stock indices, bonds, oil, gold, the general commodity index, and the U.S. dollar index	Bitcoin is a poor hedge and is suitable for diversification purposes only

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Smales (2019)	Safe-haven	Bitcoin	Daily	Data.bitcoinity, Blockchain.com	Correlation with other assets	Study whether Bitcoin characteristics in a period of relative calm (2011–2017) is coherent with a safe-haven asset	Bitcoin is not currently a safe-haven, although its low correlation with traditional assets
Baur *et al*. (2018a)	Safe-haven	Bitcoin	Daily	Coindesk	GARCH, EGARCH, TGARCH	Analyze the relationship between Bitcoin, gold, and the U.S. dollar	Bitcoin exhibits distinctively different return, volatility, and correlation characteristics compared to other assets
Klein *et al*. (2018)	Safe-haven	Bitcoin	Daily	Coindesk	APARCH, FIAPARCH, BEKK-GARCH	Compares Gold and Bitcoin from an econometric perspective	Bitcoin and Gold feature fundamentally different properties as assets and linkages to equity markets
Urquhart and Zhang (2019)	Safe-haven	Bitcoin	Intraday (hourly)	Bitcoincharts	DCC, ADCC, GARCH, GJRGARCH, EGARCH	Investigate whether Bitcoin can act as a hedge or safe-haven against world currencies	Bitcoin can be considered as hedge and diversifier for currency investors
Katsiampa (2017)	Volatility	Bitcoin	Daily	Coindesk	AR, EGARCH, TGARCH, APARCH, CGARCH, ACGARCH	Study the ability of several GARCH models to explain Bitcoin price volatility	The optimal model in terms of goodness-of-fit to the data is the AR-CGARCH
Baur and Dimpfl (2018)	Volatility	20 cryptocurrencies	Daily	Coinmarketcap	TGARCH, AR, QAR	Analyze asymmetric volatility effects for the 20 largest cryptocurrencies	Volatility increases more in response to positive shocks than to negative shocks
Corbet *et al*. (2018a)	Volatility	Bitcoin	Intraday (1-minute)	Thomson Reuters	Mood statistic, Lepage statistic, OLS, IS, CS, ILS	Investigate the effect of the introduction of Bitcoin futures	The introduction of Bitcoin futures has increased the spot volatility of Bitcoin
Chaim and Laurini (2018)	Volatility	Bitcoin	Daily	unknown	SV, Qu and Perron (2013) and Laurini *et al*. (2016)	Estimate stochastic volatility models with jumps to volatility and returns	Jumps to volatility are permanent, jumps to returns are contemporaneous, volatility was highest in late 2013 and during 2014, big jumps to mean returns are negative and related to hacks and forks
Khuntia and Pattanayak (2020)	Volatility	Bitcoin	Hourly	Bitcoincharts	MFDFA	Evaluate the adaptive pattern of long memory in the volatility of intraday bitcoin returns and to test the impact of the trading volume on time-varying long memory	Long memory exists and fluctuates over time, the time-varying pattern of long memory is coherent with AMH

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Table A1. (Continued).

Paper	Group	Cryptocurrencies studied	Data Frequency	Source of data	Methodology	Aim of the paper	Results
Phillip *et al*. (2019)	Volatility	149 cryptocurrencies	Daily	Brave New Coin (BNC)	JBAR-SV-GLR	Study some stylized facts about the variance measures of Cryptocurrencies	Volatility of Cryptocurrencies can be measured with fast moving autocorrelation functions, as opposed to smoothly decaying functions for fiat currencies
Tan *et al*. (2020)	Volatility	102 cryptocurrencies	Daily	Coinmarketcap	GK, ABL-CARR	Measure and model volatilities	There is evidence of volatility persistence and leverage effects improving predictability of volatility, reducing risk, and diminishing the level of speculation in cryptocurrency market
Ardia *et al*. (2019)	Volatility	Bitcoin	Daily	Datastream	MSGARCH, VaR	Test the presence of regime changes in the GARCH volatility dynamics	Daily log-returns exhibit regime changes in their volatility dynamics
Mensi *et al*. (2019)	Volatility	Bitcoin, Ethereum	Daily	Coindesk	GARCH, FIGARCH, FIAPARCH, HYGARCH, Markov-switching dynamic regression	Explore the impacts of structural breaks on the dual long memory levels of Bitcoin and Ethereum price returns	Evidence of dual long memory property of Bitcoin and Ethereum
Katsiampa (2019)	Volatility	Bitcoin, Ethereum	Daily	Coinmarketcap	Bivariate Diagonal BEKK	Investigate the volatility dynamics of the two major cryptocurrencies	Evidence of interdependency in the cryptocurrency market. Conditional volatility and correlation are responsive to major news
Yi *et al*. (2018)	Volatility	52 cryptocurrencies	Daily	Coinmarketcap	Volatility spillover index (GVD), LASSO-VAR	Examine both static and dynamic volatility connectedness	Connectedness fluctuates cyclically and has shown a rise trend since the end of 2016
Fang *et al*. (2019)	Volatility	Bitcoin	Daily	Coindesk	GARCH-MIDAS, DCC-MIDAS	Assess whether the long-run volatilities of Bitcoin, global equities, commodities, and bonds are affected by global economic policy uncertainty	The long-term volatility of Bitcoin, equities, and commodities are significantly affected by economic policy uncertainty, although the effect on the volatility of Bitcoin is different from the other assets
Gillaizeau *et al*. (2019)	Volatility	Bitcoin	Daily	Bitcoincharts	GVD	Identify and characterize the givers and the receivers of volatility in cross-market Bitcoin prices and to discuss diversification strategies	Bitcoin prices depict strong dynamic spillover in volatility, especially during episodes of high uncertainty

Table A2. List of Acronyms Used in Table A1.

Acronym	Name
ABL-CARR	Asymmetric bilinear Conditional autoregressive range
ACGARCH	Asymmetric component GARCH
BL(VBCs)	Black–Litterman portfolio optimization with variance-based constraints
CGARCH	Component GARCH
CSAD	Cross-sectional absolute standard deviations
CSSD	Cross-sectional standard deviation of returns
DCC	Dynamic conditional correlation
DFA	Detrended fluctuation analysis
DMCA	Detrended moving-average cross-correlation analysis
ELW	Exact local Whittle
FCVAR	Fractionally cointegrated VAR
FIAPARCH	Fractionally integrated asymmetric power ARCH
FIGARCH	Fractionally integrated GARCH
GAS	Generalized autoregressive score
GK	Garman and Klass volatility measures
GLR	Gegenbauer Log Range
HYGARCH	Hyperbolic GARCH
JBAR	Jump buffered autoregressive model
LASSO	Least absolute shrinkage and selection operator
LB	Ljung–Box test
LightGBM	Light gradient boosting machine
LRD	Long range dependence
MF-DCCA	Multifractal detrended cross-correlations analysis
MSGARCH	Markov-switching GARCH
MVPO	Mean–variance portfolio optimization
RPT	Robustified portmanteau test
SR	Sharpe ratio
VAR	Vector autoregression
VaR	Value-at-risk test
VAR-BEKK-AGARCH	Asymmetric BEKK generalized autoregressive conditional heteroskedasticity
VR	Variance ratio test
WBAVR	Wild bootstrapped automatic VR test