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ORIGINAL - SURVEY OR EXPOSITION

# Cryptocurrency market microstructure: a systematic literature review

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**Abstract**
This study contributes to the unconsolidated cryptocurrency literature, with a systematic literature review focused on cryptocurrency market microstructure. We searched Web of Science database and focused only on journals listed on 2021 ABS list. Our final sample comprises 138 research papers. We employed a quantitative and an integrative analysis, and revealed complex network associations, and a detailed research trending analysis. Our study provides a robust and systematic contribution to cryptocurrency literature by making use of a powerful and accurate methodology—the bibliographic coupling, also by only considering ABS academic journals, using a wider keyword scope, and not enforcing any restrictions regarding areas of knowledge, thus enhancing the contribution of extant literature by allowing the insights of more high-quality peripheral studies on the subject. The conclusions of this study are of extreme importance for researchers, investors, regulators, and the academic community in general. Our study provides high structured networking and clear information for research outlets and literature strands, for future studies on cryptocurrency investment, it also presents valuable insights to better understand the cryptocurrency market microstructure and deliver helpful information for regulators to effectively regulate cryptocurrencies.

**Keywords** Cryptocurrencies · Bitcoin · Efficiency · Market microstructure · Systematic literature review · Bibliometric analysis

## 1 Introduction

To date the cryptocurrency market has experienced a rapid development, being amongst the fastest growing world financial markets (Almeida & Gonçalves, 2023a; Białkowski, 2020; Fang et al., 2021), and considered as a very popular investment asset among investors (Almeida, 2021; Li et al., 2021). Thus, attracting high attention from the media, regulators, institutional and individual investors, and also as an important and actual topic of academic research (Almeida & Gonçalves, 2022, 2023b, 2023c; Angerer et al., 2020; R. Li et al., 2021).

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Due to this increasing popularity and topicality, new empirical evidence is being produced very fast (Angerer et al., 2020; Corbet, Lucey, et al., 2019). However, this literature provides heterogeneous conclusions regarding the cryptocurrency market microstructure. Some studies indicate that the cryptocurrency market is inefficient (Akyildirim et al., 2021; Grobys et al., 2020; Sapkota & Grobys, 2021; Vidal-Tomás et al., 2019a); others, point out the opposite (Alvarez-Ramirez & Rodriguez, 2021; Burggraf & Rudolf, 2020; Caporale & Plastun, 2019; Kaiser, 2019; Lim et al., 2016); further studies, suggest the interconnectedness of the cryptocurrency market (Corbet et al., 2018; Huynh et al., 2018; Luu Duc Huynh, 2019; Shahzad et al., 2021; Tiwari et al., 2020); others the contrary (Kostika & Laopodis, 2020; Sifat et al., 2019); and others still, that the cryptocurrency market is connected to other assets (Kalyvas et al., 2021; Kurka, 2019; Luu et al., 2020; Thampanya et al., 2020); while others suggest the opposite (Corbet et al., 2018; Gil-Alana et al., 2020).

It is thus evident, the great need to synthesize, aggregate, and identify literature gaps on the existing knowledge in cryptocurrencies' literature (Angerer et al., 2020; Corbet, Lucey, et al., 2019).

Accordingly, we answer the call of Angerer et al. (2020) and Corbet et al., (2019a, 2019b), and develop a systematic literature review on cryptocurrency's market microstructure. The study's objective is threefold: 1) to consolidate and map the knowledge of the growing academic literature on cryptocurrency market microstructure; 2) to ease future research by identifying literature gaps; and 3) provide useful research outcomes for investors, academics, researchers, and regulators.

This study contributes to the unconsolidated cryptocurrency literature, with a systematic literature review focused on cryptocurrency market microstructure,[1] revealing complex network associations, and a detailed integrative analysis. We provide extended insights from previous research (Al-Amri et al., 2019; Almeida, 2021; Amsyar et al., 2020; Angerer et al., 2020; Badawi & Jourdan, 2020; Bariviera & Merediz-Solà, 2021; Corbet, Lucey, et al., 2019; Eigelshoven et al., 2021; Flori, 2019; Hairudin et al., 2020; Haq et al., 2021; Herskind et al., 2020; Huynh et al., 2020a, 2020b; Jalal et al., 2021; Kyriazis et al., 2020; Morisse, 2015; Rahardja et al., 2021; Rejeb et al., 2021; Sarpong, 2022; Silva & Silva, 2022; Sousa et al., 2022) by making use of a powerful and accurate methodology—the bibliographic coupling; also, by only considering ABS academic journals; using a wider keyword scope, and not enforcing any restrictions regarding areas of knowledge, we enhance the contribution of our literature review by allowing the insights of more peripheral studies on the subject, and thus making a more comprehensive and integrative contribution to cryptocurrency literature system than previous studies.

Our findings are of extreme importance for researchers, investors, regulators, and the academic community in general. Our findings provide researchers with structured networking and clear information for research outlets and literature strands for future studies on cryptocurrency investment. Our study also presents valuable insights for crypto investors helping them to better understand the cryptocurrency market microstructure, and thus helping them minimizing risks and maximizing returns. Additionally, it delivers insightful information for regulators to effectively regulate cryptocurrencies.

This paper is organized as follows: in Sect. 2, we present the data and the methodology used. In Sect. 3, we perform a quantitative analysis of the literature. Section 4 presents the integrative analysis of the literature and points out some future research venues. Lastly, in Sect. 5, we provide some concluding remarks.

[1] We consider market microstructure as the functioning of financial markets. Market microstructure focus on structure of exchanges and trading venues, price discovery process, determinants of spreads, intraday trading behaviour, and transaction costs (R. Kissell, 2014).

## 2 Methodology

Our paper presents a systematic review process. Our aim is to cover all cryptocurrency related literature since Satoshi Nakamoto first published his whitepaper in late 2008, up until the present day. With this goal in mind, and following the works of Almeida and Gonçalves, (2022), (2023a), (2023b); Liang, Yang and Wang (2016); Linnenluecke, Marrone and Singh (2020); Jiang, Li and Wang (2021) and Yue et al. (2021), we decided to use the Web of Science database (WoS)[2] as our main search engine, searching for academic journals between 01-01-2009 and 04-11-2021.

Using a different approach from the ones used by other authors such as Flori (2019a); Kyriazis et al. (2020); Haq et al. (2021); and Jalal, Alon and Paltrinieri (2021), we consider a wider keyword scope, not restricting our research to cryptocurrency market microstructure specific words. Also, we do not enforce any restrictions regarding areas of knowledge. Therefore, using these approaches, we enhance the contribution of our literature review by allowing the insights of more peripheral studies on the subject, and thus making a higher contribution to cryptocurrency literature than previous studies.

We considered the following keywords: “Cryptocurrency”, “Cryptocurrencies”, “Bitcoin”, “Portfolio diversification”, “Investment”, “Investor”, “investors”, “Alternative investment”. Applying the Boolean operators and the wildcard characters to the keywords, the following research equation emerges: “cryptocurrenc* OR Bitcon AND diversification AND portfolio AND invest* AND alternative”.

The quality criterions chosen for this paper follow three main guidelines: 1) the articles must be English-written academic journals; 2) they must address the topic of cryptocurrencies market microstructure from the investor/investment perspective; and 3) the journals must belong to the Academic Journal Guide ABS[3] (Association of Business Schools) list of 2021. We excluded all other research that did not meet our selection criteria, and as a result of this systematic review process our final sample included 138 articles.

In our analysis we use VOSviewer 1.6.17 software (Almeida & Gonçalves, 2022; Bartolacci et al., 2020; Ding et al., 2014; Galvao et al., 2019; Rialti et al., 2019; Sadeghi Moghadam et al., 2021; van Eck & Waltman, 2017). Different from other cryptocurrency literature analysis (Aysan et al., 2021; Bariviera & Merediz-Solà, 2021; García-Corral et al., 2022; Jalal et al., 2021; Liang et al., 2016; Merediz-Solá & Bariviera, 2019) we opted for the bibliographic coupling option, since it aggregates the articles by clusters based on the number of references they share (Bartolacci et al., 2020; Ding et al., 2014; Galvao et al., 2019; Rialti et al., 2019; Sadeghi Moghadam et al., 2021; van Eck & Waltman, 2017). This option allows for a very powerful and accurate analysis of the literature, since it is based on the number of references where relationships between the articles do not change over time, unlike other options based on the number of citations where the relationships between the articles may change (Bartolacci et al., 2020; Ding et al., 2014; Galvao et al., 2019; Rialti et al., 2019; Sadeghi Moghadam et al., 2021; van Eck & Waltman, 2017). Hence, the bibliographic coupling option in VOSviwer allows for a rigorous replication of our analysis (Bartolacci et al., 2020; Caputo et al., 2019).

Consequently, using the bibliographic coupling, a cryptocurrency market microstructure cluster naturally emerges. Which we analyze in Sect. 3 and 4 of this study.

[2] We also searched in Scopus database, however since due to the use of the ABS journal guide list as a quality criterion, the articles provided by Scopus database were significantly overlapped with WoS to be considered in this research.

[3] With the use of the ABS journal list as a quality criterion we can ensure that the studies included in the review have undergone a rigorous peer review process and are published in reputable journals.

## 3 Bibliometric analysis

In our first analysis, Fig. 1 presents the number of publications and citations regarding cryptocurrency market microstructure. 2019 is the year when more articles were published (46) and, also the year with the highest number of citations (1,530). On the other hand, 2017 is the year when less articles were published (2). As expected, recent years present fewer citations, given that older articles have more probabilities of having more citations. Additionally, we evidence a very low correlation (0.07) coefficient between publications and citations over time. These results highlight the novelty of this field of knowledge and, also a growing interest of the academia in the cryptocurrency market.

In Fig. 2 we evidence that Bitcoin, efficiency, market, price, and volatility are the five most frequent frequent words (both in article title and abstract) in the analyzed studies.

### 3.1 Cryptocurrency market top articles

Table 1 presents the top 10 most cited articles regarding cryptocurrency market microstruc-

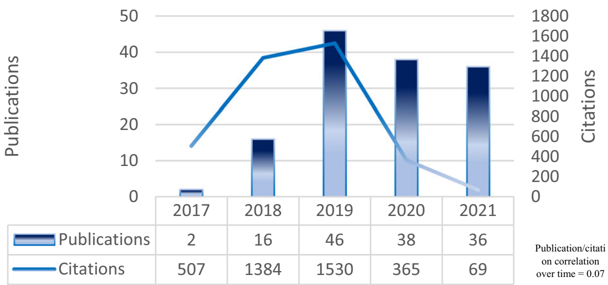


Fig. 1 Citations and publications over time


Fig. 2 Titles and Abstracts word cloud

**Table 1** Shows the top 10 articles by number of citations

| Cryptocurrency market microstructure (3855 citation and 138 publications) | | |
|---|---|---|
| Rank | Article | Citations |
| 1 | Corbet et al. (2018) | 348 |
| 2 | Katsiampa (2017) | 346 |
| 3 | Demir et al. (2018) | 173 |
| 4 | Urquhart (2017) | 161 |
| 5 | Phillip et al. (2018) | 129 |
| 6 | Brauneis and Mestel (2018) | 123 |
| 7 | Wei (2018a, 2018b) | 111 |
| 8 | Urquhart and Zhang (2019) | 107 |
| 9 | Gkillas and Katsiampa (2018) | 89 |
| 10 | Sensoy (2019) | 86 |

ture. Corbet et al. (2018) is the most cited article with 348 citations, followed by Katsiampa (2017) with 346 citations, and Demir et al. (2018) with 173 citations.

Additionally, we reveal that of the 138 analyzed studies 18.84% were solo-authored and 81.16% were co-authored. The solo-authored studies contributed with 27.76% of citations (1070) and the co-authored with 72.24% (2785). This shows evidence that solo-authored studies present a higher citations per publications ratio (41.15) compared with the co-authored studies (24.86).

### 3.2 Cryptocurrency market authors network

Table 2 presents the top 10 most cited authors regarding the cryptocurrency market microstructure literature. Paraskevi Katsiampa and Shaen Corbet are the most cited authors in our dataset with 522 and 450 citations respectively. The most productive author is Andrew

**Table 2** Shows the top 10 authors by number of citations

| Rank | Author | Publications | Citations | Citations per publications |
|---|---|---|---|---|
| 1 | Katsiampa, Paraskevi | 5 | 522 | 104.40 |
| 2 | Corbet, Shaen | 6 | 450 | 75.00 |
| 3 | Lucey, Brian | 4 | 420 | 105.00 |
| 4 | Yarovaya, Larisa | 3 | 385 | 128.33 |
| 5 | Urquhart, Andrew | 8 | 381 | 47.63 |
| 6 | Larkin, Charles | 2 | 368 | 184.00 |
| 7 | Meegan, Andrew | 1 | 348 | 348.00 |
| 8 | Gozgor, Giray | 4 | 322 | 80.50 |
| 9 | Lau, Chi Keung Marco | 4 | 322 | 80.50 |
| 10 | Demir, Ender | 3 | 317 | 105.67 |

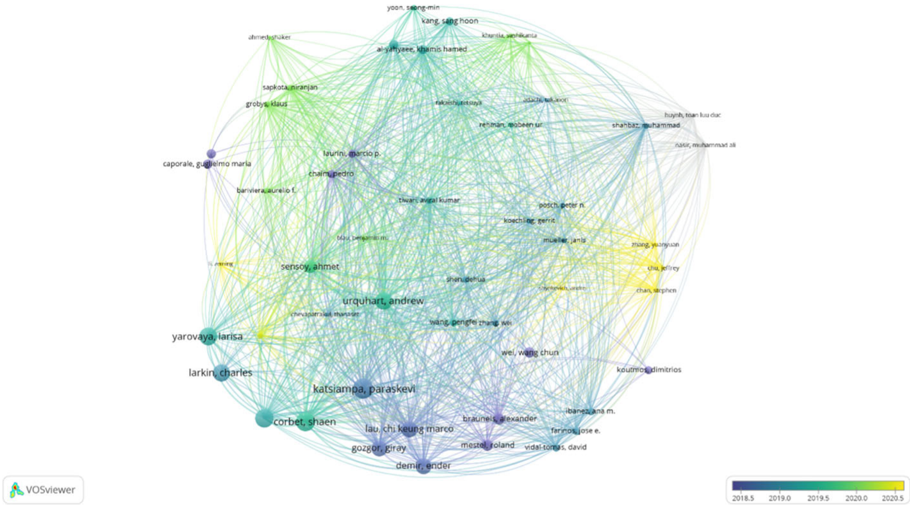


**Fig. 3** Cluster's network of the most cited authors by year (average publication per year)

Urquhart with 8 published articles. Nonetheless, Andrew Meegan is the author that presents the highest citation per publication ratio (348.00).

Figure 3 evidence a high structured and complex author's network. Where Katsiampa, Gozgore, Demir and Lau were the most cited authors in the year 2018. In the beginning of 2019 Vidal-Tomas and Larkin were the most cited authors, however in the end of the same year Urquhart and Corbet took their place as the most cited authors. Later on, in the beginning 2020 the most cited authors were Gorbys and Sapkota, by the end of the year were Chan, Chu and Zhang. Hence, revealing that the most recently cited authors are not present in the general top 10.

### 3.3 Cryptocurrency market journals network

Table 3 evidence the most productive journals regarding cryptocurrency market microstructure studies in our dataset. *Economics Letters* is the most cited journal with 1,651 citations and is also the journal that has the highest citation per publication ratio in our dataset (78.62). However, in second place with 1,222 citations appears the *Finance Research Letters*, which is by far the most productive journal in this research field with 48 publications.

In Fig. 4 we present the analysis of the most contributive research areas to our field of knowledge, and as expected finance is the research area with more contributions, followed by the economic area. With this analysis we also highlight how other areas of knowledge have contributed to the better understanding of the cryptocurrency market microstructure.

Figure 5 highlights a relatively structured network of journals. Regarding average publications per year, the *Economic Letters* is the most cited Journal around the year 2019. *Finance Research Letters* and the *Research in International Business and Finance* are the most cited journals in the year 2020, and in 2021 the journal *Annals of Operations Research* and the *Journal of Futures Markets* are the most cited journals in our research field.

**Table 3** Shows the top 10 journals by number of citations

| Rank | Journal | Publications | Citations | Citations per publications |
|---|---|---|---|---|
| 1 | Economics letters | 21 | 1651 | 78.62 |
| 2 | Finance research letters | 48 | 1222 | 25.46 |
| 3 | Research in international business and finance | 9 | 303 | 33.67 |
| 4 | International review of financial analysis | 7 | 252 | 36.00 |
| 5 | North American journal of economics and finance | 5 | 75 | 15.00 |
| 6 | Applied economics | 7 | 73 | 10.43 |
| 7 | Applied economics letters | 7 | 64 | 9.14 |
| 8 | Journal of international financial markets institutions & money | 2 | 50 | 25.00 |
| 9 | Annals of operations research | 5 | 45 | 9.00 |
| 10 | Journal of financial econometrics | 1 | 19 | 19.00 |

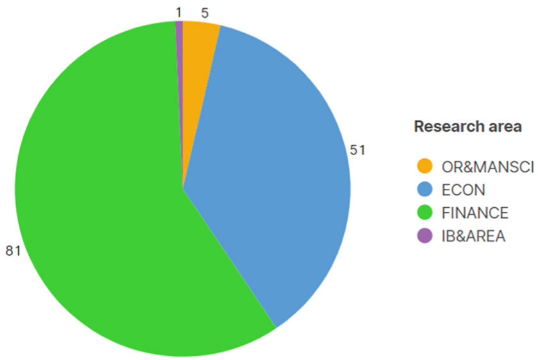


**Fig. 4** Most contributive research areas

### 3.4 Cryptocurrency market institutions network

Table 4 presents the analysis of the most productive institutions to the cryptocurrency market microstructure literature. Sheffield Hallam University is the most cited institution in our dataset with 507 citations, followed by Dublin City University (450) and Trinity College Dublin (420). University Southampton, University Reading, and Bilkent University are the institutions with more published articles in our dataset. Nonetheless, Anglia Ruskin University is the institution that presents the highest citation per publication ratio (184.00). Additionally, we find that the number of publications by university and the ranking THE (Times Higher Education) present a very low correlation of -0.082, evidencing that the number of publications is not positively correlated with the university rank.

Figure 6 shows a highly structured and complex institutions' network. Regarding average publications per year, Sheffield Hallam University was the most cited institution by the end

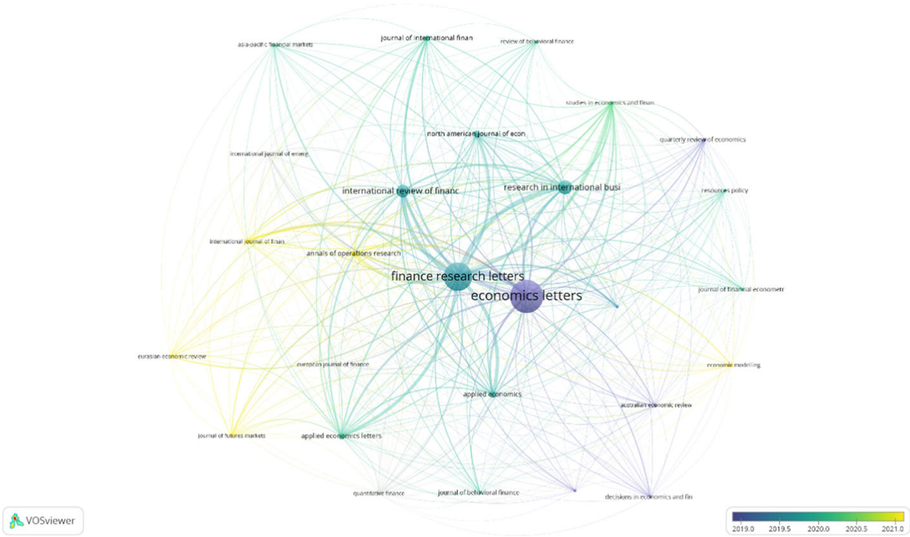


**Fig. 5** Cluster's network of the most cited journals by year (average publication per year)

**Table 4** Shows the top 10 institutions by number of citations

| Rank | Institution | Publications | Citations | Citations per publications | Times higher education ranking |
|---|---|---|---|---|---|
| 1 | Sheffield hallam university | 4 | 507 | 126.75 | 801–1000 |
| 2 | Dublin city university | 6 | 450 | 75.00 | 501–600 |
| 3 | Trinity college dublin | 4 | 420 | 105.00 | 146 |
| 4 | Anglia ruskin university | 2 | 368 | 184.00 | 301–350 |
| 5 | University of huddersfield | 5 | 323 | 64.60 | 601–800 |
| 6 | Istanbul medeniyet university | 4 | 322 | 80.50 | 801–1000 |
| 7 | University of southampton | 7 | 272 | 38.86 | 124 |
| 8 | University of sydney | 4 | 235 | 58.75 | 58 |
| 9 | University of reading | 7 | 220 | 31.43 | 201–250 |
| 10 | Bilkent university | 7 | 251 | 35.86 | 601–800 |

of 2018. In 2019 the Trinity College Dublin and the Anglia Ruskin University were the most cited institutions. In the end of 2020, the University of Economics Ho Chi Minh City and the Whu Otto Beisheim School of Management were the most cited institutions. Thus, revealing that the most recently cited institutions are not present in the general top 10.

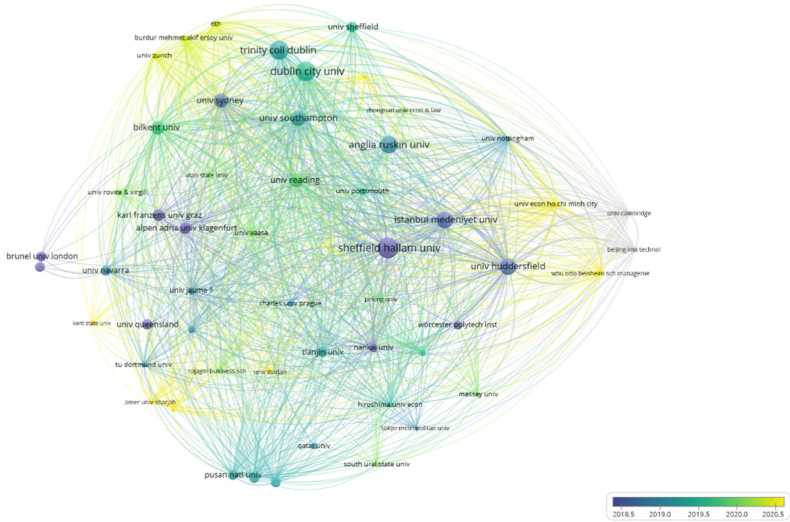


**Fig. 6** Cluster's network of the most cited institution by year (average publication per year)

### 3.5 Cryptocurrency market countries network

Table 5 and Fig. 7 show the most productive countries in our research field. England is the country that stands out as the most important country with 1,920 citations and 35 published articles. Turkey (554) is the second most cited country followed by Ireland (450). The country that has the highest citation per publication ratio in our top 10 countries is North Ireland (173.00). However, if we consider the number of citations of a country by the number of universities[4] presented in Table 6, we realize that Ireland presents the highest ratio (56.25) followed by Austria (52.75), Greece (24.00), United Kingdom (17.74), and Turkey (10.26). On the other hand, if we consider the number of publications of a country by the number of

[4] The number of universities was sourced from the THE ranking and filtered by Finance Universities.

**Table 5** shows the top 10 countries by number of citations

| Rank | Country | Publications | Citations | Citations per publications |
|---|---|---|---|---|
| 1 | England | 35 | 1920 | 54.86 |
| 2 | Turkey | 14 | 554 | 39.57 |
| 3 | Ireland | 7 | 450 | 64.29 |
| 4 | Australia | 11 | 448 | 40.73 |
| 5 | Spain | 11 | 305 | 27.73 |
| 6 | Peoples R. China | 21 | 222 | 10.57 |
| 7 | Austria | 3 | 211 | 70.33 |
| 8 | Greece | 5 | 192 | 38.40 |
| 9 | North Ireland | 1 | 173 | 173.00 |
| 10 | USA | 14 | 147 | 10.50 |

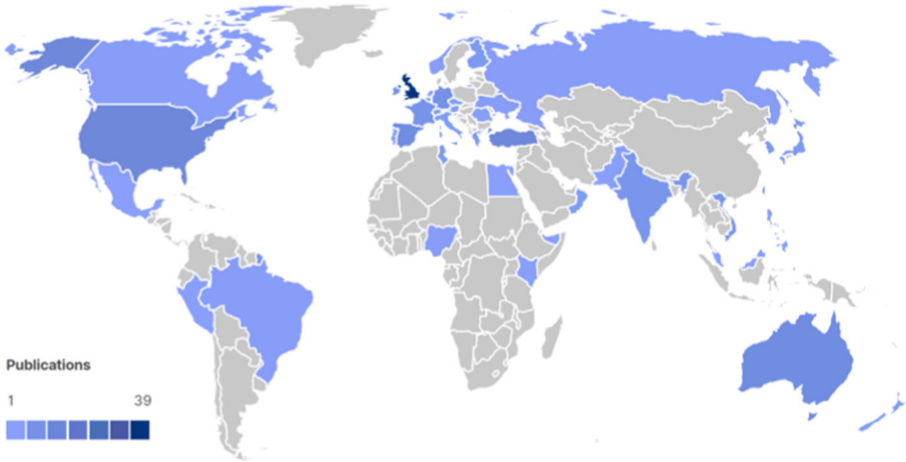


**Fig. 7** Publications by country world map

**Table 6** shows Countries' publications and citation scaled by number of universities

| Country | Publications | Citations | Number of universities | Publications per universities | Citations per universities |
|---|---|---|---|---|---|
| United Kingdom | 36 | 2093 | 118 | 0.305 | 17.74 |
| Turkey | 14 | 554 | 54 | 0.259 | 10.26 |
| Ireland | 7 | 450 | 8 | 0.875 | 56.25 |
| Australia | 11 | 448 | 37 | 0.297 | 12.11 |
| Spain | 11 | 305 | 47 | 0.234 | 6.49 |
| Peoples R. China | 21 | 222 | 77 | 0.272 | 2.88 |
| Austria | 3 | 211 | 4 | 0.750 | 52.75 |
| Greece | 5 | 192 | 8 | 0.625 | 24.00 |
| USA | 14 | 147 | 168 | 0.083 | 0.88 |

universities Ireland also present the highest ratio (0.875) followed by Austria (0.750), Greece (0.625), United Kingdom (0.305), Australia (0.297), and China (0.272). In both analysis the United States of America present the lowest ratios of the top 10 most cited countries.

Figure 8 reveals a highly structured and complex countries' network. Regarding average publications per year, Australia was the most cited country in the beginning of 2019. However, in 2020 England, Turkey and Ireland appear as the most cited countries in this research field. In the beginning of 2021, China was the most cited country, however by the end of the year, Lebanon, Pakistan, Kosovo, Kenya, and Mexico were the countries with more citations. Consequently, revealing that more recently, the most cited countries are not present in the overall top 10.

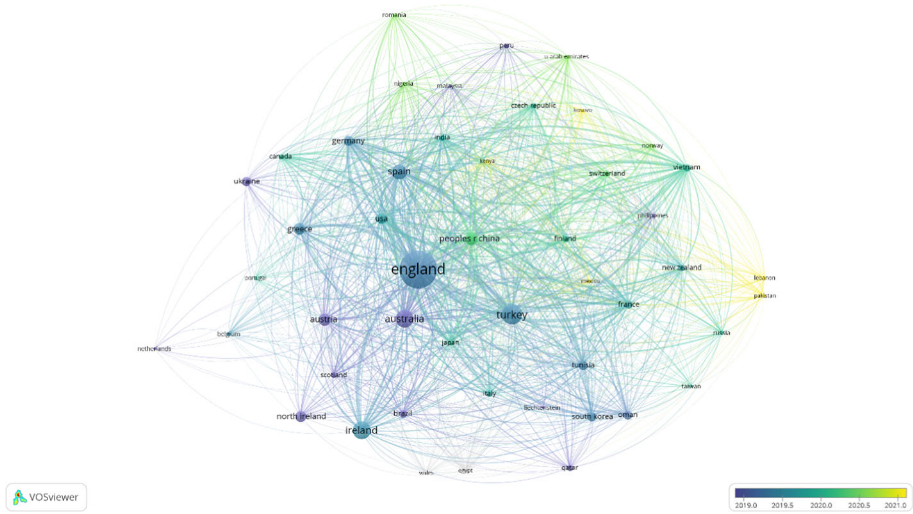


**Fig. 8** Cluster's network of the most cited country by year (average publication per year)

## 4 Literature findings on cryptocurrency market microstructure

### 4.1 Is the cryptocurrency market efficient?

#### 4.1.1 Cryptocurrency market efficiency

This literature review addresses the efficiency in the cryptocurrency market. We found evidence supporting the existence of efficiency in the cryptocurrency market. For instance, evidence reveals a significant low volatility premium, indicating that the cryptocurrency market is more efficient than expected (Burggraf & Rudolf, 2020), and becoming more efficient over the years (Alvarez-Ramirez & Rodriguez, 2021). Evidence also shows that the average price delay tends to decrease, implying that the efficiency in the cryptocurrency market is improving (Köchling et al., 2019b).

Nonetheless, evidence also reports that there are heterogeneous patterns of efficiency in the cryptocurrency market (Brauneis & Mestel, 2018), that there are seasonality patterns in cryptocurrency returns supporting a weak-form efficient market hypothesis (Caporale & Plastun, 2019; Kaiser, 2019; Lim et al., 2016). Additionally, it is revealed that there are no significant momentum payoffs in the cryptocurrency market, that the cross-sectional momentum even present negative payoffs, thus supporting the hypothesis that the cryptomarket presents some efficiency (Grobys & Sapkota, 2019). It is also found that the turnover ratio as a measure of liquidity positively affects efficiency, evidencing that cryptocurrencies become more efficient as liquidity decreases (Brauneis & Mestel, 2018).

Regarding the Bitcoin market in specific, we found that it presents signs of efficiency (Wei, 2018a). In fact, there is evidence that Bitcoin is the most efficient cryptocurrency (Brauneis & Mestel, 2018). Future Bitcoin values are unpredictable, fact that is suggested by the presence of a random walk in the returns of cryptocurrencies, which supports the efficient market hypothesis (EMH) (Yaya et al., 2021). Furthermore, evidence shows that the multifractal degree in Bitcoin time series is related to market efficiency in a non-linear manner (Takaishi &

Adachi, 2020). Moreover, making use of the Strongly Typed Genetic Programming (STGP)-based learning algorithm, evidence reveals that Bitcoin market populated with high frequency traders (HFTs) at one-minute frequency is efficient (Manahov & Urquhart, 2021).

Further evidence on Bitcoin efficiency reveals that after the introduction of Bitcoin futures, Bitcoin spot market became more efficient (Kim et al., 2020; Köchling et al., 2019a). Thus, Bitcoin futures seem to have affected the informational efficiency in Bitcoin spot market, turning them more informational efficient after the introduction of Bitcoin futures (Shynkevich, 2021). Both Bitcoin spot and future markets have responded to substantial regulatory and fraudulent events, presenting therefore evidence of market efficiency. In addition, it is revealed that information flows and price discovery suffered a reversion, and now they are transmitted from future market to spot markets, possibly by the influx of sophisticated and institutional investors (Akyildirim, Corbet, Katsiampa, et al., 2020).

The evaluation of Bitcoin efficiency during times of market stress highlights that Bitcoin market kept efficient during the COVID-19 pandemic (Wu et al., 2021). The comparison of these results with other assets revealed that during the pandemic Bitcoin was more efficient than Ethereum, Binance Coin, and S&P500; and presented similar efficiency with spot Gold market (Wu et al., 2021). These results highlight that Bitcoin seem to be efficient during times of market stress (Wu et al., 2021).

Additional evidence reports that specific transactions registered on the Bitcoin blockchain are able to predict short-term Bitcoin returns (Ante & Fiedler, 2021). Therefore, evidencing that the Bitcoin market reacts to certain large Bitcoin transfers, pricing in the new information. Thus, these specific large Bitcoin transfers can be considered as relevant aspects in the informational efficiency of Bitcoin, as well as in its market structure (Ante & Fiedler, 2021).

#### 4.1.2 Cryptocurrency market inefficiency

In our literature review we also documented evidence that supports the inefficiency of the cryptocurrency market (Aggarwal et al., 2020; Akyildirim et al., 2021; Caporale et al., 2018; Grobys et al., 2020; Sapkota & Grobys, 2021; Takaishi & Adachi, 2018; Vidal-Tomás et al., 2019a). For instance, evidence suggests that after an event, the information is not immediately fully reflected in the price, thus implying inefficiency (Hashemi Joo et al., 2020). Furthermore, it is highlighted that simple announcements of any type of plan related to a cryptocurrency increases dramatically companies shares value, thus evidencing a new form of information asymmetry, such as the example of KODAKCoin on Kodak stocks (Corbet et al., 2020).

Further evidence reveals presence of a cross-section dependence amongst the most popular cryptocurrencies; evidencing that the cryptomarket is inefficient, specially the top ranked cryptocurrencies (Hu et al., 2019a). It is also revealed that reversal effects are more evident among cryptocurrencies with less liquidity and smaller market capitalization (Kozlowski et al., 2021). Nonetheless, these effects are also evidenced for cryptocurrencies with larger market capitalization and more liquidity; however, at shorter holding periods (Kozlowski et al., 2021). These effects are driven by market inefficiency as well as a compensation for liquidity (Kozlowski et al., 2021). Consequently, it is evident the presence of reversal effects in the cryptocurrency market for daily, weekly, and monthly holding periods (Kozlowski et al., 2021).

In addition, investigating the efficiency in the cryptocurrency market from a structural break perspective, and volatility spillovers, evidence reveals that the cryptocurrency market systematically present structural breaks (Canh et al., 2019). Additionally, it reveals causality effects among large cryptocurrencies, especially in Bitcoin, Litecoin, Ripple, Stellar, Monero, Dash, Bytecoin. Furthermore, it is shown that cryptocurrencies are correlated in a whole with higher volatility spillover among them (Canh et al., 2019).

Further evidence reveals that even after controlling for past volatility and skewness, size and volume, there is evidence of a strong presence of small price bias in cryptocurrency investors. Thus, indicating the presence of inefficiency in the cryptocurrency market (Aloosh & Ouzan, 2020). It is also shown that the cryptocurrency market is weak-form inefficient, and that its inefficiency seems to increase over time (Vidal-Tomás et al., 2019b).

There is also evidence highlighting inefficiency in the specific case of Bitcoin (Aggarwal et al., 2020; Chevapatrakul & Mascia, 2019) For instance, it is revealed that there is presence of dual long memory and structural changes in Bitcoin and Ethereum, suggesting that these markets are inefficient (Mensi, Al-Yahyaee, et al., 2019). Furthermore, it is revealed a delayed response of Bitcoin's volatility to a volatility shock in Ethereum returns, hence, indicating that the Bitcoin market is inefficient (Beneki et al., 2019).

Additionally, evidence reveals that there are large arbitrage opportunities during Bitcoin market crashes, between the Bitcoin spot and futures market (Hattori & Ishida, 2020). Further evidence reveals that Bitcoin presents information inefficiency, for 115- and 60-min returns. Therefore, evidencing that it is possible to generate abnormal profits for these cryptocurrencies with the use of algorithmic trading strategies at 1 min or 60 min trading (Aslan & Sensoy, 2020). In addition, evidence also reveals that a Bitcoin market populated with high frequency traders (HFTs) at five-minute frequency, reveals to be inefficient (Manahov & Urquhart, 2021). Hence, the higher the frequencies, the lower the pricing efficiency of Bitcoin is (Guégan & Renault, 2021).

In addition, evidence reveals that the daily returns of Bitcoin Investment Trust fund (BIT), whose shares have been trading at a significant premium over its net asset value (NAV), reveal significant positive autocorrelation in shorter lags, thus evidencing that the market for Bitcoin Investment Trust fund (BIT) seem to be inefficient (Shynkevich, 2020).

#### 4.1.3 Adaptive market hypothesis

Other studies evidenced that the inefficiency/efficiency of the cryptocurrency market is time varying (Caporale et al., 2018; Keshari Jena et al., 2020). They reveal that there are still periods of inefficiency that alternate with periods of efficiency, thus supporting the Adaptive Market Hypothesis (AMH) (Chu et al., 2019; Duan et al., 2021; López-Martín et al., 2021; Mensi et al., 2019a, 2019b, 2019c; Noda, 2021; Tran & Leirvik, 2020; Vidal-Tomás et al., 2019b). For instance, evidence reveals that the cryptocurrency market presents multifractality and long-memory properties, thus evidencing inefficiency; however it is revealed that this inefficiency varies across time (Al-Yahyaee et al., 2020; Charfeddine & Maouchi, 2019; Khuntia & Pattanayak, 2020). Moreover, the calendar effects in the cryptocurrency market are also time varying. For instance, Bytecoin appears to be the more inefficient in case of Monday anomalies; Bitcoin presents the January anomalies; Monero the turn-of-the-month (TOTM) effects; and Verge for the Saturday and Sunday (S&S) anomalies (Khuntia & Pattanayak, 2021). Additionally, evidence highlights that when the cryptocurrency market faces a downturn, the inefficiency seems to be higher; however, when the market is upwards the inefficiency level seems to decrease. This fact highlights that the level of inefficiency is time varying (Mensi et al., 2019a, 2019b, 2019c), thus supporting the adaptive market hypothesis (AMH).

### 4.2 The role of liquidity in the cryptocurrency market

This strand of literature also addresses the liquidity issues in the cryptocurrency market. We found evidence revealing the important role of liquidity in cryptocurrency market efficiency (Wei, 2018a), which is highlighted when in liquid markets, volatility is lower and efficiency is higher, since traders arbitraged away the return predictability (Al-Yahyaee et al., 2020; Wei, 2018a).

Further evidence shows that the liquidity in the cryptocurrency market decreases after negative news announcements, whereas increases after positive news announcements (Yue et al., 2021). Yet, regarding Bitcoin intraday dynamics, evidence highlights that liquidity is highest during the opening times of major global exchanges, and that the markets seem to be more illiquid during the early morning (Eross et al., 2019). Furthermore, liquidity presents a positive and significant effect on Bitcoin informational efficiency, unlike volatility that presents a negative effect (Sensoy, 2019).

It is also shown that Bitcoin returns and volatility present significant positive relationship with liquidity uncertainty. However, on the other hand, trade volume, market capitalization and transaction fees, present a significant negative relationship (Koutmos, 2018b). It is also highlighted that as intraday volatility rises, liquidity uncertainty also rises. Conversely, when trade volume and market capitalization rise, liquidity uncertainty will tend to decrease (Koutmos, 2018b). Nonetheless, the period where liquidity was highest for Bitcoin investors was around 2013 and 2014 (Koutmos, 2018b).

In addition, the reviewed literature present evidence showing that reversal effects are more evident among cryptocurrencies with less liquidity and smaller market capitalization (Kozlowski et al., 2021). These effects are driven by market inefficiency as well as a compensation for liquidity (Kozlowski et al., 2021). It is also evidenced that liquidity factors, contribute to the explanation of excess returns (Lim et al., 2016). Furthermore, the existence of a weak positive correlation between returns and volume suggests that a misinterpretation among investors may cause extreme price movements, and illiquidity in the cryptocurrency markets (Chan et al., 2022).

Other studies reveal that the turnover ratio as a measure of liquidity positively affects efficiency, similarly as size (market capitalization) (Brauneis & Mestel, 2018); that there is a high correlation between delays, liquidity and size (Köchling et al., 2019b); and that returns and liquidity also seem to have some impact on the size effect (Li et al., 2020a, 2020b).

### 4.3 Are the cryptocurrency markets volatile?

Volatility is also another important feature of the cryptocurrency market. The findings in this literature review shows that the cryptocurrency market dynamic presents two different states (stable and volatile) which differ from one cryptocurrency to another in volatility, mean return, and interstate dynamics (Bejaoui et al., 2020). It also shows that cryptocurrencies have several unique characteristics such as the long memory, leverage effects, heavy tails and stochastic volatility (Phillip et al., 2018).

Reviewing the literature we further understand that cryptocurrencies are correlated in a whole, with higher volatility spillovers among them (Canh et al., 2019), and also that they present volatility clustering (W. Zhang et al., 2018). We also understand that the volatility component seems to be driven by the level of popular interest in cryptocurrencies and major market developments (Chaim & Laurini, 2019).

Additional evidence further reveals that there is higher volatility exposure in the Crypto-Index 20 than in the FTSE 100, FTSE MIB, IBEX 35, CAC 40, DAX and MDAX European equity indexes (Aliu et al., 2021). Thus, evidencing the high volatility of the cryptocurrency market, compared to the equity markets.

Regarding the specific case of Bitcoin, our literature review reveals, that it suffers from extreme volatility (Wu et al., 2021), with its highest level during US market trading hours (Dyhrberg et al., 2018). Nonetheless, it is evidenced that Bitcoin and Litecoin are least risky cryptocurrencies compared to other cryptocurrencies, such as Bitcoin cash (Gkillas & Katsiampa, 2018). Further evidence indicates that Bitcoin volatility responds to the major news, highlighting for instance, that Bitcoin and Ethereum conditional covariance is significantly affected by cross-products of previous news or shocks, and also by previous covariance terms (Katsiampa, 2019). Additional evidence demonstrates that the price volatility is positively related to the geopolitical risk (Aysan et al., 2019), indicating that geopolitical risks present a predictive power on Bitcoin returns and volatility (Aysan et al., 2019).

In addition, evidence proves that decentralized Bitcoin exchanges (LocalBitcoins) present higher volatility when compared with the centralized exchanges (GDAX, Kraken, Bitcoin.de, Bitstamp, Rock Trading, and Coinfloor). Albeit, centralized exchanges present volatility increases as prices jump; in decentralized exchanges the same does not occur (Matkovskyy, 2019).

Several other studies contribute to this strand of literature with some related findings on cryptocurrency volatility modelling. For instance, evidence reveals that allowing for stochastic volatility and a heavy tailed distribution, will provide more accurate forecasts in cryptocurrencies returns and volatilities (Cross et al., 2021); that attention measures such as the SVI Google index, significantly affect the conditional mean and the conditional variance of Bitcoin returns (Figá-Talamanca & Patacca, 2019); that Bitcoin display discontinuous return jumps and varying average volatility that need to be properly captured (Chaim & Laurini, 2018); that the use of close prices when conducting a forecast of Bitcoin volatility will result in higher forecasting errors (Vidal-Tomás, 2021); that the existence of multifractality in Bitcoin's volatility, evidences the need to include it in a unified model along with the volatility roughness (Takaishi, 2020). In addition, this literature review reveals several model specifications that are found to be appropriate to measure cryptocurrency's volatility. For instance, when analyzing cryptocurrency prices, the stochastic volatility (SV) models seem to outperform the generalized autoregressive conditional heteroskedasticity (GARCH) models (Tiwari et al., 2019). The SV models appear to be more robust to misspecifications as well as to radical changes in the time-series (Tiwari et al., 2019). Furthermore, to explain Bitcoin price volatility the AR-CGARCH model seems to be an optimal model in terms of goodness-of-fit, suggesting that it is important to consider the short and the long run components of the conditional variance (Katsiampa, 2017). Moreover, the generalized autoregressive score (GAS) models specifications with heavy-tailed distributions seem to improve the goodness-of-fit as well as the forecast performance for Bitcoin risk and returns (Troster et al., 2019). Other study developed a model to analyze the default risk in cryptocurrencies. The developed model is based on a linear discriminant analysis to predict cryptocurrency defaults (Grobys & Sapkota, 2020). The model has the ability to serve as a screening tool for investors since it can explain 87% of bankruptcies in the cryptomarket, after only one month of trading (Grobys & Sapkota, 2020).

### 4.4 Does uncertainty affect the cryptocurrency market?

In this strand of literature, we also found evidence that uncertainty affects the cryptocurrency market. For instance, there is evidence that indicates that Chinas' EPU is able to predict Bitcoin returns (Cheng & Yen, 2020); there is also evidence that Bitcoin returns are negatively associated with the changes in the United States EPU, thus, revealing that United States EPU present a predictive power over Bitcoin returns (Demir et al., 2018). Moreover, Bitcoin seems to react to uncertainty shocks in the traditional markets, indexed by the CBOE—DJIA Volatility Index (CBOE/VXD) (Panagiotidis et al., 2019).

Additionally, evidence shows a strong connectedness among cryptocurrencies in periods of high market uncertainty, whereas in periods of low market uncertainty it indicates a weak connectedness (Antonakakis et al., 2019). Moreover, changes in domestic regulation produce large international spillovers across cryptocurrency markets (Borri & Shakhnov, 2020).

### 4.5 Cryptocurrency's prices behavior

Cryptocurrency price behavior is also addressed in this literature review. Evidence reveals that in the cryptocurrency market approximately four-fifth of the mid-price changes seem to be established within the market itself (Mark et al., 2020). In addition, it is shown that the price movements of Bitcoin are linked to its transaction activity, albeit the returns seem to explain more of the variation in transaction activity than the transaction activity in the returns (Koutmos, 2018a).

Additional evidence supports the negotiation hypothesis regarding the price behavior of cryptocurrencies (Hu et al., 2019b; Urquhart, 2017). Evidence reports that Bitcoin prices cluster around round numbers (Hu et al., 2019b; Mbanga, 2019), showing no significant pattern of returns after the round numbers (Urquhart, 2017). The negotiation hypothesis is further supported since the price and volume present positive relationships with price clusters (Urquhart, 2017). There is also evidence in support of the strategic trading hypothesis, but at high frequencies (Hu et al., 2019b), and also supporting the psychological barrier hypothesis, since high and low prices reveal patterns of clustering that are affected by the time frame (Li et al., 2020a, 2020b). Further evidence reveals a strong and positive association between sentiment and price clustering. The microstructure patterns of price clustering presented in Bitcoin market seemed to be similar to the equity markets (Baig et al., 2019).

Additionally, evidence highlights positive serial correlation in cryptocurrency prices (Corbet & Katsiampa, 2020). However, this serial correlation decreases with prior negative price returns. Therefore, evidencing asymmetric reverting patterns in the Bitcoin price returns (Corbet & Katsiampa, 2020). It was also found a higher persistence of positive returns compared to negative ones, further supporting the existence of asymmetric reverting behavior in the Bitcoin price returns (Corbet & Katsiampa, 2020).

Evidence shows that factors such as the market factor, equity-based factors, volatility factors, and liquidity factors, contribute to the explanation of excess returns. On the other hand, factor such as the risk-free rate, hash rate and the number of projects seem not to be able to explain the excess returns (Lim et al., 2016). Additionally, it is revealed that the interest rates in Bitcoin lending are related to the loan-to-value ratio (S. Zhang et al., 2021). More specifically, when the price of Bitcoin increases by \$10,000, the interest rate decreases by 10.7%, fact that encourages borrowers to buy more money, leading to pro-cyclical speculation (S. Zhang et al., 2021).

Further evidence reveals that the size and the reversal factors are better in explaining cryptocurrency returns than the traditional CAPM model (Shen et al., 2020). It is also evidenced that two price factors that are able to better forecast future cryptocurrency returns are the closing price of the last day, and the maximum price during last week (Yang & Zhao, 2021).

Other studies reveal that bifurcations in the cryptocurrency market also pose a risk, since it weakens the market position and the pricing influence of cryptocurrencies (Tu & Xue, 2019). Also, Bitcoin shows the strongest bubble behavior. This may be explained by the fact that Bitcoin is the cryptocurrency that has the widest media coverage and therefore, attracts more general public awareness (Hafner, 2020).

### 4.6 Cryptocurrency market behavior and connectedness

#### 4.6.1 Cryptocurrency market behavior

Subsequently, we also analyze studies that address the cryptocurrency market behavior. For instance, evidence on cryptocurrencies' dynamic behavior reveals that the cryptocurrency market presents different degrees of long range dependence, and follow different stochastic processes (Bariviera, 2021). Largest cryptocurrencies appear to follow monofractal processes. Conversely, the other cryptocurrencies exhibit strong multifractality (Bariviera, 2021). In addition, cryptocurrencies' dynamic conditional correlations seem to indicate that they were susceptible to market events and to speculative attacks (Kostika & Laopodis, 2020).

Evidence reveals a significant tail dependence between investor attention and the returns of cryptocurrencies, mainly in the low frequencies domain (Su et al., 2021). There are also indications that in the median quantiles there is no directional predictability from investor attention to cryptocurrency returns. Hence, suggesting that long-term components seem to be important sources of dependence (Su et al., 2021).

It is further revealed that there is no prominent external driver for cryptocurrencies, meaning that each cryptocurrency appears to be affected by a specific external driver, this may suggest that the underlying mining objective is the main determinant (Erzurumlu et al., 2020).

#### 4.6.2 Cryptocurrency market interconnectedness

From the analyses of studies regarding cryptocurrencies interconnectedness we found evidence of spillover effects within this market (Tiwari et al., 2020), evidencing a high interconnection in the cryptocurrency market (Corbet et al., 2018). It is also shown that bad contagion affects the entire cryptocurrency market (Shahzad et al., 2021). The reviewed literature mentions that Bitcoin and Ethereum conditional covariance is significantly affected by cross-products of previous news or shocks, and by previous covariance terms. Therefore, suggesting that they are interconnected (Katsiampa, 2019). There is also evidence of a long run cointegration between the value at risks of several altcoins and Bitcoin (Tan et al., 2021); and also a significant bilateral co-explosive relationship above the 10% level between Bitcoin—Dash, Ethereum–Dash, Ethereum–Monero, Ethereum–Litecoin, and Ripple–Stellar (Cagli, 2019). The explosive behavior in the returns of Bitcoin, Ripple, and Stellar is originated in the upper tails of the returns distributions (Cai et al., 2021). In addition, there are also indications of co-movements in the time frequency space where Bitcoin leads the relationship with Dash, Monero and Ripple (Mensi et al., 2019a, 2019b, 2019c). Yet, Ethereum seems to lead on the relationship with Bitcoin (Mensi et al., 2019a, 2019b, 2019c).

Additionally, there is also evidence reporting weak or no interconnectedness in the cryptocurrency market. For instance, it is revealed that cryptocurrencies' correlations with each other are weak and do not present a common long run path (Kostika & Laopodis, 2020), highlighting a very low connectedness amongst the top six cryptocurrencies (Bitcoin, Ethereum, Litecoin, Stellar, Ripple and Tether) (Gil-Alana et al., 2020). Evidence also shows no clear indication of a lead-lag relationship between Bitcoin and Ethereum (Sifat et al., 2019). Furthermore, in an analysis of the impact of cryptocurrency issuances on their subsequent returns, it is revealed that Tether issuances seem not to impact subsequent Bitcoin returns (Wei, 2018b).

On the other hand, there is also evidence suggesting that the interconnectedness in the cryptocurrency market is time varying (Aslanidis et al., 2019). It is revealed that total dynamic connectedness of cryptocurrencies ranges between 25 and 75% (Antonakakis et al., 2019). In periods of high uncertainty, the cryptomarket seem to have strong connectedness, whereas in periods of low uncertainty it presents weak connectedness (Antonakakis et al., 2019). Additional evidence reveals that Ethereum is getting more relevance as a main net transmitter in the cryptocurrency market (Antonakakis et al., 2019), and that Monero presents the more stable correlations (Aslanidis et al., 2019).

### 4.6.3 Cryptocurrency market connectedness to other markets

With regard to cryptocurrencies connectedness to other markets, we found evidence of a significant and positive relationship between the sensitivities of technology, clean energy industry indices, and Bitcoin returns, when stronger sentiment appears (Kalyvas et al., 2021). Consequently, revealing the importance of the technology and clean energy sectors for the production and operation of cryptocurrencies (Kalyvas et al., 2021).

In addition, evidence also reveals a connectedness with traditional assets (Kurka, 2019), and a small risk spillover from cryptocurrencies into non-digital assets (Milunovich, 2018). Albeit, different cryptocurrencies present different reactions to traditional assets (Kostika & Laopodis, 2020). It is shown that in the case of Bitcoin, shocks that are transmitted to other assets such as commodities and stocks (Kurka, 2019). For instance, there is evidence of a spillover effect from Bitcoin to precious metals (Rehman, 2020), implying that changes in the returns of either the markets have the potential to affect extreme returns in the other market (Rehman, 2020); also that the Chinese Yuan can significantly affect cryptocurrency prices, more specifically Bitcoin's and Litecoin's prices (Elsayed et al., 2020). Furthermore, the US oil index is a receiver of informational flows from the cryptocurrency market, while the European crude oil index is a source of informational flows to the cryptocurrency market (Huynh, Shahbaz, et al., 2020).

Additionally, it is highlighted that there are hedge and diversification properties in Bitcoin that hold unconditionally (Rehman, 2020), nonetheless are challenged by the high levels of idiosyncratic shocks to Bitcoin (Rehman, 2020). Consequently, cryptocurrencies may be seen as diversifiers against other non-digital asset classes in general (Milunovich, 2018), and against commodities in particular (Huynh et al., 2021).

Nonetheless, there is also evidence suggesting that cryptocurrencies are somehow decoupled from the main financial assets. For instance, it is evidenced that the correlations between cryptocurrencies and other traditional financial assets (bonds, stocks, indices and Gold) seem to be insignificant (Aslanidis et al., 2019). Other studies reveal no cointegration between cryptocurrencies and traditional assets (Corbet et al., 2018; Gil-Alana et al., 2020). These findings also highlight cryptocurrencies ability as a diversification tool (Corbet et al., 2018; Gil-Alana et al., 2020; Giudici & Abu-Hashish, 2019).

### 4.7 Investment properties of the cryptocurrency market

#### 4.7.1 Characterization of cryptocurrency properties

Literature on the investment properties of the cryptocurrency market reveals that cryptocurrencies present diversification abilities against traditional assets (Corbet et al., 2018; Gil-Alana et al., 2020; Giudici & Abu-Hashish, 2019; Kurka, 2019). In portfolios composed only by cryptocurrencies, Bitcoin and Ripple present the largest diversification effect (EhlerS & Gauer, 2019). In a mixed portfolio, a combination of Bitcoin with other cryptocurrencies (Ethereum and DASH) provides better diversification benefits (EhlerS & Gauer, 2019; Mensi et al., 2019a, 2019b, 2019c). However, when analyzing the performance of naïve and optimal cryptocurrency portfolio diversification, evidence shows that the naïve diversification is comparatively equally as good as the optimal diversification (Platanakis et al., 2018).

The safe haven ability of cryptocurrencies is more present in cryptocurrencies that have a larger market capitalization and higher liquidity (Wang et al., 2019). In the case of Bitcoin, the safe-haven ability can be considered against CAD, CHF and GBP at intraday levels (Urquhart & Zhang, 2019).

There is also evidence highlighting positive interrelationships between the conditional correlations of financial market stress and cryptocurrencies (Akyildirim, Corbet, Lucey, et al., 2020). However, the hedging ability of cryptocurrencies is more evident in Bitcoin, against global geopolitical risks (Aysan et al., 2019; Kurka, 2019), and also against expected inflation (Blau et al., 2021). It is also highlighted that Bitcoin's main worth comes from being a short position on modern expansionary monetary policies (Morillon, 2021).

Additionally, literature also reveals that momentum portfolios of cryptocurrencies present diversification, hedge and safe haven properties against traditional assets (Tzouvanas et al., 2020).

#### 4.7.2 Traders and investors of the cryptocurrency market

Literature addressing cryptocurrency traders and investors reveals that despite of the existence of different groups of age, gender, and trading patterns in the cryptocurrency trading, men are the dominant gender. They trade more frequently, hold positions shorter and realize lower returns (Hasso et al., 2019). Crypto-investors seem to pay frequent attention to news and high ranked cryptos such as Bitcoin and Ethereum during all market phases (Subramaniam & Chakraborty, 2020). Further evidence reveals the existence of psychological barriers in cryptocurrencies such as Bitcoin, Dash, Litecoin and Ripple. Bitcoin presents the strongest signs of psychological barriers (Fonseca et al., 2020). Moreover, it is also revealed that high readability of the whitepapers captures more interest from investors (S. Zhang et al., 2019).

In addition, evidence reveal bidirectional causal relationship between Bitcoin attention (measured by google trends search queries) and Bitcoin returns (Dastgir et al., 2019). It also reveals that higher investors' crisis sentiment, measured by the FEARS index, increases the price crash risk of cryptocurrencies (Anastasiou et al., 2021).

#### 4.7.3 Trading strategies in the cryptocurrency market

Investment and trading strategies are also addressed in the reviewed literature. We found evidence suggesting that naïve portfolios tend to outperform optimized portfolios (Brauneis & Mestel, 2019; Kajtazi & Moro, 2019; Liu, 2019). It is also revealed that technical analysis

(TA) is suitable to help investors navigate in the cryptocurrency markets (Anghel, 2021). Moreover, comparatively to the fixed length MA (FMA) or to the trading range break-out (TRB), the variable length MA (VMA) trading strategy seems to be the best trading strategy when trading Bitcoin (Corbet et al., 2019a, 2019b). Additionally, the technical trading rules present high risk-adjusted returns compared to simple buy and-hold strategy (Hudson & Urquhart, 2021). Conversely, there is also evidence suggesting that on an aggregated level, it seems that simple trading rules such as the variable moving average strategy aren't able to generate excess positive returns of a buy-and-hold strategy (Ahmed et al., 2020).

Further evidence reveals that in order to allow for a significant reduction of the variability of crypto-portfolio returns, it is important to develop asset-specific stop-loss rules, since these rules survival rate is just up to 35% (Białkowski, 2020).

### 4.8 Cryptocurrency's market future research venues

Literature reveals several literature gaps that future research needs to properly address. For instance, to explore the presence of dynamic patterns of calendar effects such the Turn-of-the-Year effect, the Halloween effect, the weather effect, and the Month-of-the-Year effects (Khuntia & Pattanayak, 2021). Also, to further investigate the time varying efficiency of the cryptocurrency markets (Charfeddine & Maouchi, 2019; Shahzad et al., 2021; Yang & Zhao, 2021), and what are the factors affecting it (Ahmed et al., 2020; Ante & Fiedler, 2021; Chu et al., 2019; Kajtazi & Moro, 2019; Keshari Jena et al., 2020).

Other highlighted future lines of research are the need to further understand cryptocurrencies role against expansionary policies (Morillon, 2021); analyse momentum profitability in cryptocurrency markets (Grobys & Sapkota, 2019), and other alternative factors such as size and value (Burggraf & Rudolf, 2020); further investigate cryptocurrencies diversification and hedging effects on investment portfolios (Aliu et al., 2021; Antonakakis et al., 2019; Cagli, 2019; Kajtazi & Moro, 2019; Yang & Zhao, 2021), as well as to analyse crypto-indices such as the CRIX10 and the WorldCoinIndex on optimal portfolios (Kajtazi & Moro, 2019); further understand, investors' preferences of cryptocurrencies (Huynh, Shahbaz, et al., 2020), and the Bitcoin lending rates and defaults (S. Zhang et al., 2021); analyse the differences in the risk-return relation between different cryptocurrencies during stressed and normal market periods (Tan et al., 2021), as well as to investigate the characteristics of cryptocurrencies in terms of liquidity, volatility, and transaction volume (Cross et al., 2021; Fonseca et al., 2020; Su et al., 2021).

Literature finds the necessity to further explore and understand cryptocurrencies behavior with regard to other variables such as: stocks, bonds, gold (Aliu et al., 2021), WTI index and derivatives on energy commodities (Grobys et al., 2020; Huynh et al., 2021; Yang & Zhao, 2021). Also, to further understand their relations using other uncertainty measures (Demir et al., 2018) such as global risk factors, monetary policy, (Corbet et al., 2018; Hashemi Joo et al., 2020; Huynh et al., 2021), domestic political risk indicators (Aysan et al., 2019), as well as to consider news, and exchange rates effects (Elsayed et al., 2020).

Regarding datasets and data frequency, future research should also consider datasets that cover more cryptocurrencies (Corbet et al., 2019a, 2019b; Elsayed et al., 2020; Fonseca et al., 2020; Matkovskyy, 2019), more granular and longer datasets (Sifat et al., 2019), high frequency data (hourly) (Chu et al., 2019; Giudici & Abu-Hashish, 2019; Matkovskyy, 2019; Vidal-Tomás, 2021), and intra-day data (Aysan et al., 2019; Elsayed et al., 2020; Li et al., 2020a, 2020b).

Future research should also consider the application of copulas (Gil-Alana et al., 2020), different dynamic models such as the generalized autoregressive score (GAS) framework (Matkovskyy, 2019), more advanced Machine learning tools (Anghel, 2021), and correlation network models (Giudici & Abu-Hashish, 2019). It should also consider alternative measure of risk such as value at risk and maximum drawdown (Burggraf & Rudolf, 2020), and apply more complicated technical trading rules such as pairs trading (Canh et al., 2019; Corbet et al., 2019a, 2019b; Shynkevich, 2020). Overall it is highlighted that research on cryptocurrencies is at an experimental stage, and hence requires more rigorous econometric techniques to establish the stylized facts in the market (Gil-Alana et al., 2020).

Table 7 summarizes the literature review; we highlight the main conclusion and future research by literature topic.

## 5 Conclusion

Our study adds to cryptocurrency's current literature, a systematic literature review on cryptocurrency market microstructure. We searched on WoS database and focused only on journals listed on 2021 ABS list. We employed a quantitative and an integrative analysis.

Our quantitative analysis results reveal a growing interest in this field of knowledge over the past few years. We also highlight high structured and complex networks of authors, countries, and institutions. Unlike in the studies by Almeida and Gonçalves (2022), Almeida and Gonçalves (2023a) Almeida and Gonçalves (2023b), and Aysan et al. (2021) we found that the most cited journal is the E*conomics* Letters. Europe, hosts the most contributive institutions in this literature strand as in Almeida and Gonçalves (2022), Almeida and Gonçalves (2023a), Jiang, Li and Wang (2021), Yue et al. (2021), and García-Corral et al. (2022), however contradicting Almeida and Gonçalves (2023b) results, where China is the most contributive country. Additionally, as expected, the most contributive areas of knowledge are Finance and Economics.

Our integrative analysis main findings reveal several important features. Firstly, the inefficiency/efficiency of the cryptocurrency market is time varying, thus supporting the adaptive market hypothesis (AMH). Secondly, the liquidity in the cryptocurrency market decreases after negative news announcements and increases after positive news announcements; Bitcoin liquidity is highest during the opening times of major global exchanges, and more illiquid during the early morning. Thirdly, there are high volatility spillovers among cryptocurrencies; however, decentralized Bitcoin exchanges present higher volatility than the centralized exchanges. We also found that there is a strong connectedness among cryptocurrencies in periods of high market uncertainty, and weak connectedness in periods of low market uncertainty. Other main findings are that the price behavior of cryptocurrencies supports the negotiation hypothesis, that Bitcoin prices cluster around round numbers, and reveal a strong and positive association between sentiment and price clustering. Another important highlight shows that cryptocurrencies' dynamic behavior reveals different degrees of long-range dependence and follow different stochastic processes. Our literature review main findings also show that the interconnectedness in the cryptocurrency market is time varying, and the cryptocurrency market presents connectedness with traditional assets; however, different cryptocurrencies present different reactions to traditional assets. We also found that cryptocurrencies present diversification, safe-haven and hedging abilities. Another important finding shows that men are the dominant gender in cryptocurrency investments, trading more frequently, holding positions shorter and realizing lower returns. Finally, our main findings highlight that naïve

**Table 7** Summary of main literature findings and future research by literature topic

| Literature topic | Main findings | Future research |
|---|---|---|
| Cryptocurrency market efficiency | No significant momentum payoffs in the cryptocurrency market;<br>Bitcoin spot market is becoming more efficient;<br>Bitcoin market prices in the new information;<br>Bitcoin market kept efficient during the COVID-19 pandemic | Topics and objectives<br>Explore the dynamic patterns of calendar effects such the Turn-of-the-Year effect, the Halloween effect, the weather effect, and the Month-of-the-Year effects;<br>Further explore the time varying efficiency of the cryptocurrency markets, and what are the factors affecting it;<br>Cryptocurrencies relationships with other variables such: stocks, bonds, gold, energy commodities, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>Datasets that cover more cryptocurrencies;<br>High frequency data;<br>Longer datasets |
| Cryptocurrency market inefficiency | Information is not immediately fully reflected in the prices;<br>Reversal effects in the cryptocurrency market for daily, weekly, and monthly holding periods;<br>Large arbitrage opportunities during Bitcoin market crashes;<br>Presence of dual long memory and structural changes in Bitcoin and Ethereum | |
| Adaptive market hypothesis (AMH) | The inefficiency/efficiency of the cryptocurrency market is time varying;<br>Calendar effects in the cryptocurrency market are time varying;<br>When the cryptocurrency market faces a downturn, the inefficiency seems to be higher; when the market is upwards the inefficiency level seems to decrease | |
| Liquidity in the cryptocurrency market | Decreases after negative news announcements, and increases after positive news announcements;<br>Bitcoin liquidity is highest during the opening times of major global exchanges, and more illiquid during the early morning;<br>Presents positive and significant effect on Bitcoin informational efficiency | Topics and objectives<br>Investigate cryptocurrencies' liquidity characteristics;<br>Cryptocurrencies relationships with other variables such: global risk factors, trade policy uncertainty, monetary policy, geopolitical risk, domestic political risk indicators, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>Intra-day data;<br>Longer datasets |

**Table 7** (continued)

| Literature topic | Main findings | Future research |
|---|---|---|
| Cryptocurrency market volatility | High volatility spillovers among cryptocurrencies,<br>Decentralized Bitcoin exchanges present higher volatility then the centralized exchanges;<br>Seems to be driven by the level of popular interest in cryptocurrencies and major market developments;<br>Is positively related to the geopolitical risk;<br>Cryptomarkets are more volatile than equity markets;<br>Stochastic volatility (SV) models outperform the generalized autoregressive conditional heteroskedasticity (GARCH) models | Topics and objectives<br>Further investigate cryptocurrencies' volatility characteristics<br>Data Coverage and frequency<br>Datasets that cover more cryptocurrencies;<br>High frequency data<br>Research methodologies<br>Use different dynamic models such the generalized autoregressive score (GAS) framework;<br>Consider alternative measures of risk such as value at risk and maximum drawdown |
| Uncertainty in the cryptocurrency market | Uncertainty affects the cryptocurrency market;<br>EPU's of China and US have predictive power over Bitcoin returns;<br>Strong connectedness among cryptocurrencies in periods of high market uncertainty, and weak connectedness in periods of low market uncertainty | Topics and objectives<br>Understand cryptocurrency's role against expansionary policies;<br>Cryptocurrencies relationships with other variables such: global risk factors, trade policy uncertainty, monetary policy, geopolitical risk, climate policy uncertainty, domestic political risk indicators, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>Intra-day data;<br>Longer datasets |
| Cryptocurrency's prices behavior | Approximately four-fifths of the mid-price changes seem to be established within the market itself;<br>Supports the negotiation hypothesis;<br>Bitcoin price movements are linked to its transaction activity;<br>Bitcoin prices, cluster around round numbers;<br>Strong and positive association between sentiment and price clustering | Topics and objectives<br>Cryptocurrencies relationships with other variables such: global risk factors, monetary policy, domestic political risk indicators, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>Datasets that cover more cryptocurrencies;<br>Intra-day data;<br>Longer datasets |

**Table 7** (continued)

| Literature topic | Main findings | Future research |
| --- | --- | --- |
| Cryptomarket behavior | Presents different degrees of long-range dependence;<br>Follows different stochastic processes;<br>Largest cryptocurrencies follow a monofractal process, the others exhibit strong multifractality;<br>Each cryptocurrency appears to be affected by a specific external driver | Topics and objectives<br>Analyze the differences in the risk-return relation between different cryptocurrencies during stressed and normal market periods;<br>Cryptocurrencies relationships with other variables such: stocks, bonds, gold, WTI index, energy commodities;<br>Data Coverage and frequency<br>Datasets that cover more cryptocurrencies;<br>Intra-day data;<br>Longer datasets |
| Cryptomarket interconnectedness | Spillover effects within the market;<br>Interconnectedness is time varying;<br>Co-movements in the time frequency space among cryptocurrencies | |
| Cryptomarket connectedness to other markets | Connectedness with traditional assets;<br>Different cryptocurrencies present different reactions to traditional assets;<br>Bitcoin reveals relationships with commodities, stocks, and technology and clean energy sectors | |
| Characterization of cryptocurrency properties | Diversification against traditional assets;<br>Safe haven ability of cryptocurrencies is more present in cryptocurrencies that have a larger market capitalization and higher liquidity;<br>Hedging against global geopolitical risks and expected inflation | Topics and objectives<br>Cryptocurrencies relations with other variables such: stocks, bonds, gold, WTI index, energy commodities, global risk factors, trade policy uncertainty, monetary policy, geopolitical risk, climate policy uncertainty, domestic political risk indicators, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>High frequency data;<br>Longer datasets<br>Research methodologies<br>More correlation models |

**Table 7** (continued)

| Literature topic | Main findings | Future research |
|---|---|---|
| Traders and investors of the cryptomarket | Men are the dominant gender in cryptocurrency investment;<br>Men trade more frequently, hold positions shorter and realize lower returns;<br>Psychological barriers in cryptocurrencies | Topics and objectives<br>Further understand, investors' preferences of cryptocurrencies<br>Data Coverage and frequency<br>Longer datasets;<br>High frequency data |
| Trading strategies in the cryptomarket | Naïve portfolios tend to outperform optimized portfolios;<br>Technical analysis (TA) is suitable to help investors in the cryptocurrency markets;<br>Define asset-specific stop-loss rules | Topics and objectives<br>Cryptocurrencies diversification and hedging effects on investment portfolios;<br>Cryptocurrencies relations with other variables such: stocks, bonds, gold, WTI index, energy commodities, global risk factors, trade policy uncertainty, monetary policy, geopolitical risk, climate policy uncertainty, domestic political risk indicators, and consider news, and exchange rates effects<br>Data Coverage and frequency<br>Datasets that cover more cryptocurrencies<br>Intra-day data;<br>longer datasets<br>Research methodologies<br>More advanced Machine learning tools;<br>More complicated technical trading rules such as pairs trading |

portfolios tend to outperform optimized portfolios, and technical analysis (TA) are suitable to help investors navigate in the cryptocurrency markets.

Differently from previous literature reviews (Al-Amri et al., 2019; Almeida, 2021; Amsyar et al., 2020; Angerer et al., 2020; Badawi & Jourdan, 2020; Bariviera & Merediz-Solà, 2021; Corbet, Lucey, et al., 2019; Eigelshoven et al., 2021; Flori, 2019; Hairudin et al., 2020; Haq et al., 2021; Herskind et al., 2020; Jalal et al., 2021; Kyriazis et al., 2020; Morisse, 2015; Rahardja et al., 2021; Rejeb et al., 2021; Sarpong, 2022; Silva & Silva, 2022; Sousa et al., 2022), our study adds to current cryptocurrency literature, a focused systematic literature review on cryptocurrency market microstructure; revealing complex network associations, and a detailed integrative analysis. Our study differentiates itself from previous ones by making use of the bibliographic coupling. Furthermore, by only considering ABS academic journals; using a wider keyword scope, and not enforcing any restrictions regarding areas of knowledge, we enhance the contribution of our literature review by allowing the insights of more peripheral studies on the subject, and thus making a more comprehensive and integrative contribution to cryptocurrency literature system than previous studies.

A study with these contributions is of extreme importance for researchers, investors, regulators, and the academic community in general. Our findings provide researchers with structured networking and clear information for research outlets and literature strands, with time trended information relevant for future studies on cryptocurrency investment. Our study also presents valuable insights for crypto investors helping them to better understand the cryptocurrency market, and thus helping them minimizing risks and maximizing returns. Additionally, it delivers insightful information for regulators to effectively regulate cryptocurrencies.

While it is true that using only one database (WoS) may be seen as a limitation of the research, it should be noted that the ABS journal guide list was used as a quality criterion, and therefore the marginal articles provided by Scopus database were not deemed significant. Future important venues of research in the cryptocurrency literature should also understand the behavior of cryptoinvestors in various contexts (Burggraf et al., 2020), including the Terra-Luna stablecoin meltdown and the FTX Scandal, and more specifically, to assess the stability of stable coins (Almeida & Gonçalves, 2023b; Grobys & Huynh, 2022; Huynh, 2022).

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## Declarations

**Conflict of interest** The authors declare that there are no conflict of interest regarding the publication of this paper.

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