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The resilience of cryptocurrency market efficiency to COVID-19 shock

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ABSTRACT

We examine the price disorder and informational efficiency of five cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP) before and during the COVID-19 pandemic. In this sense, we estimate the permutation entropy and Fisher information measure (FIM). We use these complexity measures to construct the Shannon–Fisher causality plane (SFCP) to map these cryptocurrencies and their respective locations in a two-dimensional plane and then apply the sliding time window approach to study the temporal evolution of informational efficiency. All cryptocurrencies exhibit high but slightly varying informational efficiency during both periods. Cardano was the most efficient cryptocurrency. These results might point to the increasing maturity and lower potential for price predictability, which matter to cryptocurrencies’ usage for liquidity risk diversification strategy.

1. Introduction

The existing finance literature suggests that market efficiency is not a stable phenomenon but rather an evolving one, often shaped by market conditions and crisis periods. It has been shown for conventional assets such as stocks, e.g., [1,2] where various markets experience contrasting levels of return predictability, suggesting an adaptive markets hypothesis. 2 With the emergence of cryptocurrencies as an appealing digital asset, many investors, traders, and bankers have become interested in such decentralized currencies and the value arising from their detachment from the global financial system, as reflected in their hedging capabilities against conventional assets [5–7]. However, it is not clear if the market efficiency of cryptocurrencies is stable during various market conditions and crisis International Monetary Fund (IMF)3 on the growing connections between Bitcoin during 2020–2021. In this regard, Kumar et al. (2022) [8] show evidence of an increase in the relationship between the cryptocurrency and US stock markets after the pandemic period.
which has implications for price predictability and thus market efficiency. Nguyen (2022) [9] reports quite similar results using weekly data and show evidence of volatility spillovers between the two markets.

Existing studies examine the efficiency of the largest cryptocurrency, Bitcoin, showing not only mixed evidence on whether Bitcoin is efficient or not, but an indication that its market efficiency is unstable yet, but it is gaining over time (see [10–12]). Furthermore, it is found to be affected by crisis periods [13–16]. Very few works exist on other cryptocurrencies such as Ethereum, XRP, BNB, and Cardano, although they have recently gained market value and proper attention from investors and crypto traders. Furthermore, some papers examine the hedging properties of cryptocurrencies during the COVID-19 pandemic.

Few works exist on other cryptocurrencies, such as Ethereum, XRP, BNB, and Cardano, although they have recently gained market value and proper attention from investors and crypto traders. Furthermore, some papers examine the hedging properties of cryptocurrencies during the COVID-19 pandemic [17,18] and raise doubt over its significance. Therefore, it is relevant to analyse the temporal evolution of market efficiency for these five cryptocurrencies, not only to add to the related literature that concentrates on Bitcoin but to extend practitioners’ knowledge on the resilience of cryptocurrency price efficiency to global events, such as COVID-19. The possible existence of price disorder and price predictability could matter to investment and trading decisions.

Against this backdrop, this study investigates the disorder, predictability, and informational efficiency of daily closing prices of five major cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP). Specifically, the entire sample period (January 01, 2018, to December 31, 2021) is divided into two periods (before and during the COVID-19 pandemic) to analyse the dynamical behaviour of cryptocurrency prices and the temporal evolution of efficiency around the pandemic.

This paper explores the price disorder and market efficiency considering the daily closing price of five relevant cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP), considering three distinct periods, before and during COVID-19. Based on our expertise [19–25], we employ the information theory quantifiers (permutation entropy and Fisher information measure) and the sliding window technique. Such a combination of methods allows us to examine the predictability of cryptocurrency prices and market efficiency as a function of time and thereby identify the potential impact of the pandemic on market efficiency in this controversial digital asset class.

Our main results reveal an inverse mathematical relation between the permutation entropy and Fisher information measure. From an Econophysics point of view, the highest entropy implies the lowest predictability (highest efficiency), whereas the lowest entropy indicates the highest predictability (lowest efficiency) [26,27]. Notably, during the COVID-19 crisis, the results show that Cardano is the most efficient cryptocurrency, followed by Bitcoin. It means that Cardano and Bitcoin present an entropy increase, predictability decrease, and efficiency increase during the COVID-19 pandemic. The market efficiency of these five cryptocurrencies exhibits low fluctuations before COVID-19 and during COVID-19, suggesting their resilience to the pandemic. Specifically, the case of Ethereum shows the lowest variability in its efficiency level during the pandemic. These results provide relevant insights into the benefits of using cryptocurrencies linked to the liquidity risk diversification strategy. This paper contributed to the literature in several aspects:

(i) It promotes a higher synergy between Econophysics and Finance;
(ii) It displays that these cryptocurrencies showed significantly stable price dynamics considering the before and during the COVID-19 pandemic;
(iii) It reveals the benefits of using cryptocurrencies linked to the liquidity risk diversification strategy and risk management;
(iv) It indicates that informational efficiency is characterized by low fluctuations for both periods (before COVID-19 and during COVID-19);
(v) It suggests that cryptocurrencies analysed in this research are resilience to the COVID-19;
(vi) It draws new relevant insights for the most diverse financial agents.

The remainder of this paper is organized as follows. Section 2, describes the data and the methodology used in this letter. Section 3 presents our empirical results. Finally, Section 4 provides our concluding remarks.

2. Data and methodology

2.1. Data

Our analysis focuses on the daily closing prices of five major cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP), constituting more than 67% of the market cap of all cryptocurrencies.

The choice of these cryptocurrencies is also justified by their high liquidity and coverage of well-established (e.g., Bitcoin) and younger (BNB and Cardano) cryptocurrencies, which enriches the analysis of market efficiency. The market capitalization of each cryptocurrency relative to the total market capitalization of all cryptocurrencies is 42% (Bitcoin), 18% (Ethereum), 3.5% (BNB), 2% (XRP), and 1.5% (Cardano).

We consider three periods (global, before COVID-19, and during COVID-19) to investigate the price disorder in these cryptocurrencies. From January 01, 2018, to December 31, 2021, global data cover more than three years, with 1461

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Footnote: 4 Entropy is a significant physical quantity used in Statistical Mechanics and Thermodynamics to measure the degree of disorder in a system. We say that the greater the entropy change of a system, the greater its disorder, that is, the less energy will be available to be used. We use the permutation entropy to examine the price disorder for cryptocurrencies before and during COVID-19.
observations divided equally in two sub-periods. Before COVID-19 sub-period goes from January 01, 2018, to December 31, 2019, encompassing 730 observations.

During the COVID-19 sub-period, the other interstitial goes from January 01, 2020, until December 31, 2021, yielding 731 observations. Interestingly, the chosen sample period represents a prosperous period containing a wide variety of price actions shaped by the pandemic, facilitating the comparison between the before and after sub-period. All price data are collected from https://coinmarketcap.com/. Fig. 1 depicts the price evolution of the five cryptocurrencies.

2.2. Methodology

The Shannon–Fisher causality plane uses permutation entropy and the Fisher information measure. It allows us to quantify the disorder and inherent randomness exhibited in the temporal evolution of cryptocurrencies’ price time series. Consequently, it is crucial to properly formalize the theoretical framework of these methods.

2.2.1. Permutation entropy

We use the Bandt & Pompe method (BPM) [28] to estimate the permutation entropy. The literature shows that permutation entropy is a more suitable method to analyse non-stationary time series [29,30]. Precisely, the permutation entropy quantifies the probability distribution of ordinal patterns considering the temporal causality within the dataset. In this way, we connect the permutation entropy with the symbolic sequences of the underlying time series [31–33].

Thus, let a time series be denoted by $Z_q, q = 1, \ldots, Q$ and regard $Q - (d - 1)$ overlapping segments $Z_q = (z_q, z_{q+1}, \ldots, z_{q+d-1})$ of length $d$. Within each segment, the ranking of values is performed based on ascending order to find the indices $s_0, s_1, \ldots, s_{d-1}$ such that $z_{q+s_0} \leq z_{q+s_1} \leq \cdots \leq z_{q+s_{d-1}}$. The $d$-tuples $\pi = (s_0, s_1, \ldots, s_{d-1})$ correspond to
Fig. 2. The cryptocurrencies' locations in the SFCP consider price time series. The red dots indicate the random ideal position ($H_s = 1, F_s = 0$). The higher distance to this random ideal position reveals a financial scenario featured by the lowest entropy, which implies high predictability and lowest efficiency. In contrast, the lower distance to this random ideal position reflects a financial scenario marked by the highest entropy, which leads to the lowest predictability and highest efficiency.

the original segments. We can assume any of the $d!$ possible permutations of the set $\{0, 1, \ldots, d - 1\}$. The permutation entropy (order $d \geq 2$) is given by:

$$H(d) = -\sum_{\pi} p(\pi) \log p(\pi)$$

where $\{\pi\}$ denotes the sum over all the $d!$ possible permutations of order $d$. The term $p(\pi)$ represents the relative frequency of occurrences of permutation $\pi$.

The optimal $d$ is directly associated with the underlying stochastic process. We follow the rule of thumb choosing a maximum $d$ that satisfies $n > 5d!$ [34].

2.3. Fisher information measure

Fisher proposed a versatile statistical measure of indeterminacy called Fisher information measure (FIM). This quantity can be understood in three different ways: (i) as an adequate measure for estimating a parameter, (ii) as a qualitative measure associated with the amount of information extracted from a set of data, and (iii) as the measure that reveals the state of disorder of a system or phenomenon. For more details, see [21]. The discrete normalized form of the Fisher's information measure ($0 \leq F \leq 1$), is:

$$F[P] = F_0 \sum_{i=1}^{N-1} \left( \sqrt{p_{i+1}} - \sqrt{p_i} \right)^2$$

where $p_i$ and $p_{i+1}$ are consecutive probabilities from discrete distribution $P$ and $F_0$ is a normalization constant ($F_0 = 1$ if $p_1 = 1$ or $p_N = 1$, and $F_0 = 1/2$ otherwise).

Then we construct the Shannon–Fisher causality plane [35] to perform a study considering simultaneously the global and local characteristics of the Bandt Pompe's probability density function (PDF). The SFCP makes possible to evaluate
Table 1
Classification of the cryptocurrencies based on the complexity hierarchy for the global period, before COVID-19 and during COVID-19.

| Ranking | Cryptocurrency | Original Entropy | Original Fisher | Dist. To (1, 0) | Original Entropy | Original Fisher | Shuffled Entropy | Shuffled Fisher |
|---------|----------------|------------------|----------------|-----------------|------------------|----------------|------------------|----------------|
| 1       | Ethereum       | 0.918084         | 0.069492       | 0.107422        | 0.993129         | 0.020548       |
| 2       | Cardano        | 0.918278         | 0.070926       | 0.108208        | 0.987115         | 0.029551       |
| 3       | XRP            | 0.918044         | 0.077240       | 0.112617        | 0.988697         | 0.025699       |
| 4       | Bitcoin        | 0.915081         | 0.076460       | 0.114269        | 0.989336         | 0.030271       |
| 5       | BNB            | 0.915411         | 0.078369       | 0.115313        | 0.994050         | 0.016461       |

| Ranking | Cryptocurrency | Original Entropy | Original Fisher | Dist. To (1, 0) | Original Entropy | Original Fisher | Shuffled Entropy | Shuffled Fisher |
|---------|----------------|------------------|----------------|-----------------|------------------|----------------|------------------|----------------|
| 1       | Ethereum       | 0.908230         | 0.100552       | 0.136134        | 0.981839         | 0.049022       |
| 2       | Cardano        | 0.907663         | 0.104772       | 0.139654        | 0.982032         | 0.044440       |
| 3       | BNB            | 0.906297         | 0.105756       | 0.141296        | 0.980802         | 0.047989       |
| 4       | XRP            | 0.907671         | 0.108433       | 0.142416        | 0.979212         | 0.049801       |
| 5       | Bitcoin        | 0.899756         | 0.114747       | 0.152367        | 0.984035         | 0.049196       |

| Ranking | Cryptocurrency | Original Entropy | Original Fisher | Dist. To (1, 0) | Original Entropy | Original Fisher | Shuffled Entropy | Shuffled Fisher |
|---------|----------------|------------------|----------------|-----------------|------------------|----------------|------------------|----------------|
| 1       | Cardano        | 0.910083         | 0.097028       | 0.132286        | 0.979812         | 0.056503       |
| 2       | Bitcoin        | 0.912407         | 0.099796       | 0.132785        | 0.983860         | 0.041830       |
| 3       | XRP            | 0.907671         | 0.108433       | 0.142416        | 0.979212         | 0.049801       |
| 4       | Ethereum       | 0.902393         | 0.112413       | 0.145763        | 0.982381         | 0.045723       |
| 5       | BNB            | 0.904083         | 0.111000       | 0.146700        | 0.984259         | 0.044153       |

the disorder and inherent randomness exhibited in cryptocurrencies’ price time series temporal evolution. The highest entropy implies in lowest predictability (highest efficiency). Otherwise, lowest entropy implies in highest predictability (lowest efficiency).

2.4. Sliding window approach

We apply the sliding window approach to provide a time dependent analysis of both complexity measures (permutation entropy, $E_s$, and FIM, $F_s$). The sliding window approach follows this sequence. Let a time series be $x_1, \ldots, x_N$, we build the sliding windows $m_t = x_1 + t\Delta, \ldots, x_{N-w} + t\Delta$, $t = 0, 1, \ldots, \lfloor\frac{N-w}{\Delta}\rfloor$. The term $w \leq N$ is the window size, $\Delta \leq w$ is the sliding step, and $\lfloor \cdot \rfloor$ corresponds to taking the integer part of the argument. We employ the displayed time series values in each window $m_t$ to compute permutation entropy and FIM, which yield the time evolution of the window position in the SFCP.

3. Empirical results

We use the BPM to estimate the permutation entropy and the FIM. Subsequently, we apply these complexity measures to construct the SFCP. Specifically, the SFCP is a two-dimensional diagram where the x-axis reflects the permutation entropy, and the y-axis reveals the Fisher information measure. It allows us to quantify the disorder and evaluate randomness in the daily cryptocurrency closing price time series. The highest entropy implies in lowest predictability (highest efficiency). Otherwise, the lowest entropy indicates in highest predictability (lowest efficiency) [26,27].

We emphasize that our analysis encompasses three periods (the global period of our investigation, before COVID-19, and during COVID-19). Given this, for each time series of cryptocurrencies’ daily closing prices, we obtain the permutation entropy and FIM considering $d = 5$ to satisfy the condition $T > 5d!$.

Moreover, we examine the behaviour dynamics of the shuffled time series of cryptocurrencies’ daily closing prices. In this way, we employ the SFCP in these series, where we perform a shuffling procedure with $1000 \times N$ transpositions for each series. Fig. 2 shows an overview of the trajectory in the SFCP of these cryptocurrencies, for the embedding dimension $d = 5$, and the shuffled series considering the global period of our investigation, before COVID-19, and during COVID-19.

Note that the global period reveals a higher predictability scenario than other periods (before COVID-19 and during COVID-19). We must formalize that we observe a remarkable similarity in the dynamics of cryptocurrencies, considering their stability in the periods before and during COVID-19. It suggests that these cryptocurrencies are financial assets that should be regarded for liquidity risk diversification [36,37].

Also, we use the permutation entropy and FIM to classify the cryptocurrencies based on the complexity hierarchy for the global period before COVID-19 and during COVID-19. Table 1 shows the classification of the cryptocurrencies for these periods.

Before the crisis, Ethereum was the most efficient cryptocurrency, followed by Cardano. Cardano is the most efficient cryptocurrency during the crisis, following Bitcoin. We apply the permutation entropy and FIM to examine the efficiency...
Fig. 3. Temporal evolution of efficiency for all cryptocurrencies using sliding window approach for both periods (before COVID-19 and during COVID-19). Note that the blue line represents the dynamical investigation using the sliding window for all cryptocurrencies from January 01, 2018, to December 31, 2019 (before COVID-19), and encompasses 730 observations. The red line displays the dynamical investigation using the sliding window for all cryptocurrencies from January 01, 2020, until December 31, 2021 (during COVID-19) and includes 731 observations.

As shown in Fig. 3, all cryptocurrencies for both periods (before COVID-19 and during COVID-19) exhibit low fluctuations. It suggests that in times of crisis, the market efficiency of cryptocurrencies exhibits some resiliency. It is especially the case of Ethereum, which indicates the lowest variability in efficiency during the pandemic. This evidence is in line with previous studies on the Bitcoin market, e.g., [10,11]. The temporal evolution of efficiency between younger and older (and between smaller and larger) cryptocurrencies suggest that the cryptocurrency markets have gained maturity, making them comparable to well-established conventional assets.

Also, we quantify the fluctuations for both periods. Table 2 presents the size of these fluctuations for both periods. We observe that the absolute difference in the size of fluctuations for both periods showed a very low discrepancy. It is a strong indication of crypto’s resilience to the COVID-19 pandemic.

4. Concluding remarks

The finance literature highlights the peculiarity of Bitcoin regarding hedge and safe haven properties [5] for other conventional assets. Recent evidence shows that Ethereum and XRP can also be used in this sense [7,17,18]. However,
Table 2
Evaluating the fluctuations for both periods.

| Periods       | Bitcoin | BNB  | Cardano | Ethereum | XRP  |
|---------------|---------|------|---------|----------|------|
|               | Mean    | Std  | Mean    | Std      | Mean  | Std  |
| Before COVID-19 | 0.84536 | 0.036304 | 0.859552 | 0.033481 | 0.878118 | 0.033506 |
| During COVID-19 | 0.849498 | 0.037238 | 0.845905 | 0.037708 | 0.857079 | 0.035686 |
| Absolute difference | 0.004062 | 0.000933 | 0.013646 | 0.004227 | 0.021038 | 0.002180 |

less evidence exists on the temporal evolution of the efficiency of these cryptocurrencies, including BNB and Cardano, during the pandemic.

In this paper, we provide the first empirical proof that the informational efficiency of cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum and XRP) has successfully withstood the shocks of the COVID-19 outbreak. During the COVID-19 crisis, Cardano was the cryptocurrency that presented the highest information efficiency, followed by Bitcoin. Information efficiency generally showed low fluctuations for both periods (before COVID-19 and during COVID-19).

Our results reveal that these cryptocurrencies presented significantly stable price dynamics considering the before and during COVID-19 periods. With confirmation from the stock markets, it is counterintuitive that investors should view each market condition independently for the sake of price predictability [2].

Notably, young and small cryptocurrencies showed an increase in entropy. It suggests an increase in the disorder in the price series of this asset, which implies a decrease related to the predictability of the prices of these assets. Thus, our findings shed light on the benefits of using cryptocurrencies linked to liquidity risk diversification and risk management strategy. Also, we evaluate the size of fluctuations for both periods, which allows us to verify that both periods display a very low discrepancy. It indicates that cryptos were resilient to the COVID-19 pandemic.

5. Dedication
To the Immaculate Heart of the Virgin Mary and to the Sacred Heart of Jesus.

Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability
Data will be made available on request.

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