The resilience of cryptocurrency market efficiency to COVID-19 shock

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Abstract

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

Keywords: Cryptocurrencies, Price time series, COVID-19, Information theory quantifiers, Economic efficiency

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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.

With the emergence of cryptocurrencies as an appealing digital asset, many investors, traders, and bankers 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 (3; 4). If these cryptocurrencies are indeed hedgers, their efficiency should remain relatively stable during various market conditional and crisis periods. Otherwise, it could jeopardize their valuable role in conventional assets.

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 (5; 6). 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 (7; 8).

Therefore, it is relevant to analyze 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 the knowledge of practitioners 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, the predictability, and the 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 analyze the dynamical behaviour of cryptocurrency prices and the temporal evolution of efficiency around the pandemic.

This paper uses the permutation entropy, Fisher information measure and the sliding window approach. Such 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.

Our main results reveal an inverse mathematical relation between the permutation entropy and Fisher information measure. From a finance point of view, the highest entropy implies the lowest predictability (highest efficiency), whereas the lowest entropy indicates the highest predictability (lowest efficiency) (9; 10). Notably, during the COVID-19 crisis, the results show that Cardano is the most efficient cryptocurrency, followed by Bitcoin. The market efficiency of these five cryptocurrencies exhibits a low level of 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 level of efficiency during the pandemic. These results provide new relevant insights into the benefits of using cryptocurrencies linked to the liquidity risk diversification strategy.

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 their coverage of both 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 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 rich 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/. Figure 1 depicts the price evolution of the five cryptocurrencies.

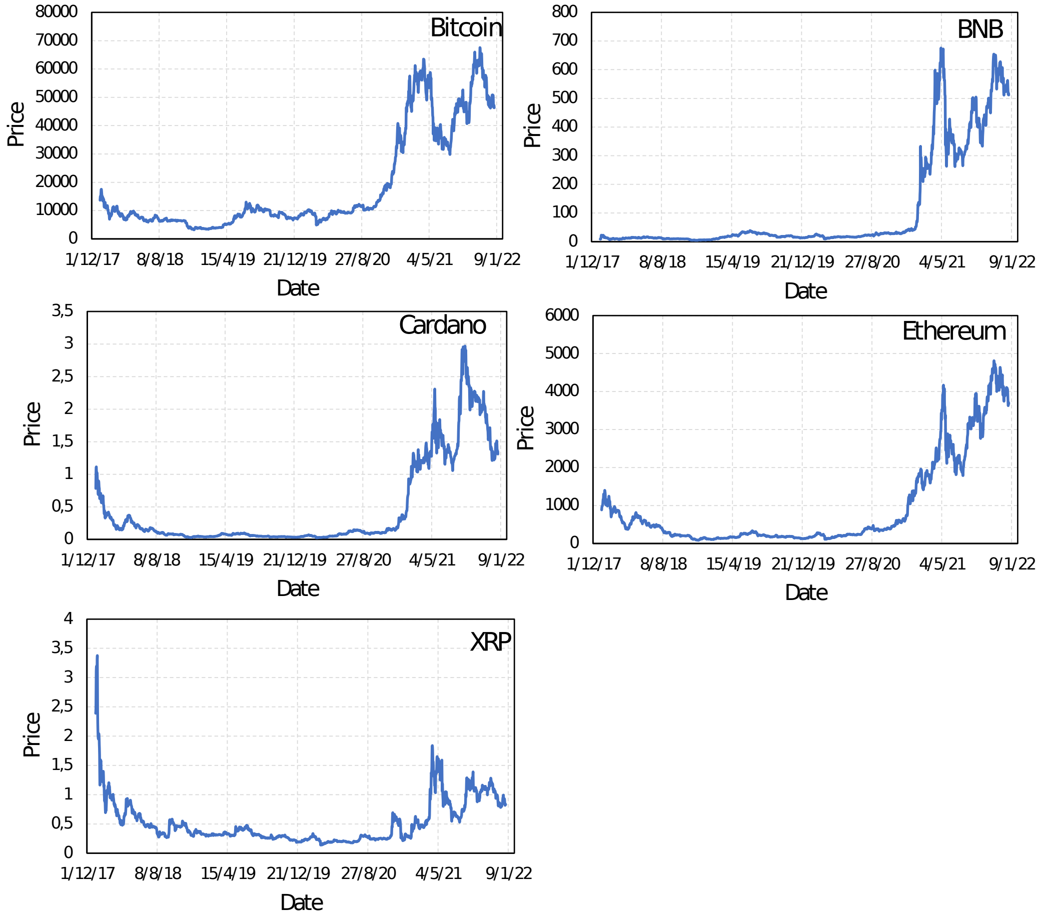

Figure 1: The timeline of daily closing prices for relevant cryptocurrency records from January 01, 2018, to December 31, 2021.

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) (11) to estimate the permutation entropy. The literature shows that permutation entropy is a more suitable method to analyze non-stationary time series (12; 13). 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 ((14), (15), (16)).

Thus, let a time series be denoted by $z_q, q = 1, ..., Q$ and regard $Q - (d - 1)$ overlapping segments $Z_q = (z_q, z_{q+1}, ..., z_{q+d-1})$ of length d. Within each segment, the ranking of values is performed based on ascending order to find the indices $s_0, s_1, ..., s_{d-1}$ such that $z_{q+s_0} \leq z_{q+s_1} \leq ... z_{q+s_{d-1}}$. The d-tuples $\pi = (s_0, s_1, ..., s_{d-1})$ correspond to the original segments. We can assume any of the $d!$ possible permutations of the set $\{0, 1, ..., d-1\}$. The permutation entropy (order $d \geq 2$) is given by:

$$H(d) = -\sum_{\pi} p(\pi) \log p(\pi) \tag{1}$$

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 π.

The optimal d is directly associated with the underlying stochastic process. We follow the rule of thumb choosing a maximum d that satisfies $n > 5d!$ (17).

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 (18). The discrete normalized form of the Fisher's information measure ($0 \leq F \leq 1$), is:

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

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 (19) 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 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 $x_1, ..., x_N$, we build the sliding windows $m_t = x_{1+t\Delta}, ..., x_{w+t\Delta}$, $t = 0, 1, ... \left[\frac{N-w}{\Delta}\right]$. The term $w \leq N$ is the window size, $\Delta \leq w$ is the sliding step, and $[\cdot]$ 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 present in the daily cryptocurrencies closing price time series. The highest entropy implies in lowest predictability (highest efficiency). Otherwise, lowest entropy implies in highest predictability (lowest efficiency) (9; 10).

We emphasize that our analysis encompass 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 x N transpositions for each series. Fig. 2 shows an overview related to 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.

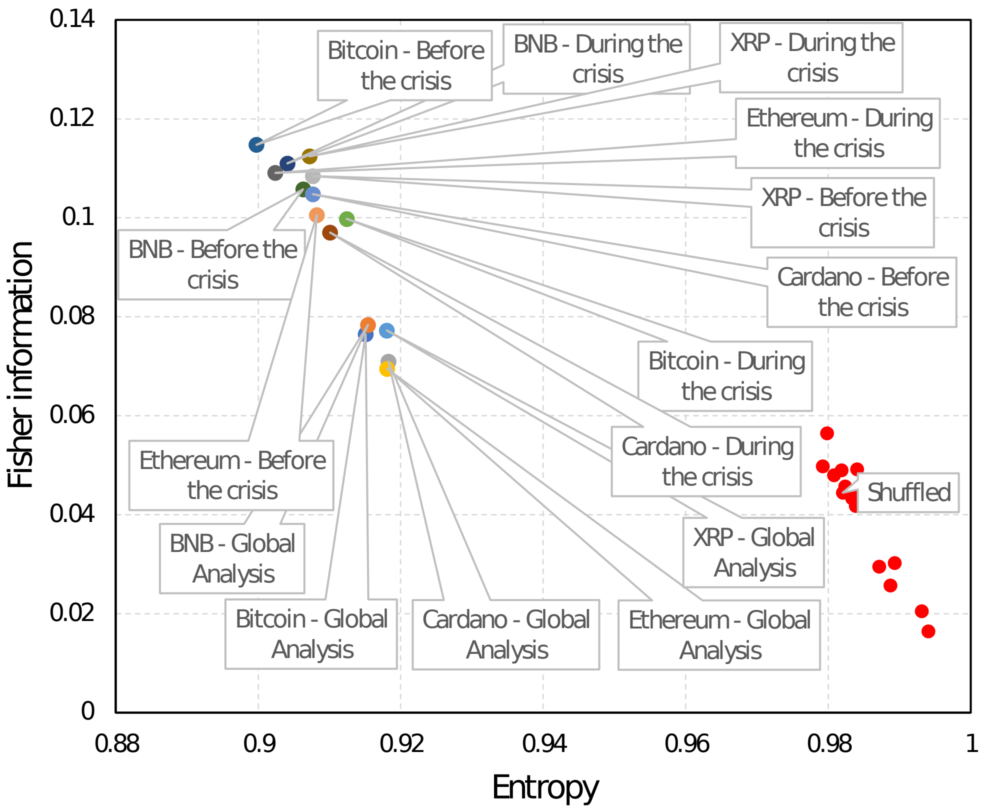

Figure 2: The cryptocurrencies' locations in the SFCP considering price time series. The red dots indicate the random ideal position ($H_s = 1$, $F_s = 0$). The higher distance to this random ideal position reveals a financial scenario featured by the lowest entropy, which implies high predictability 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.

Note that the global period reveals higher predictability scenario than other periods (before COVID-19 and during COVID-19). It is essential to 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 considered for liquidity risk diversification (20; 21).

Also, we use the permutation entropy and FIM to classify the cryptocurrencies based on the complexity hierarchy for global period, before COVID-19, and during COVID-19. Table 1 shows the classification of the crytpocurrencies 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 of these cryptocurrencies for both periods, before COVID-19, and during COVID-19. In this sense, we employ the sliding window approach to explore the dynamical interplay between permutation entropy and FIM concerning an embedding dimension $d = 4$, windows size $= 180$ (6 months), and sliding window $= 30$ days (1 month). Fig. 3 displays the temporal evolution of efficiency for all

Table 1: Classification of the cryptocurrencies based on the complexity hierarchy for global period, before COVID-19, and during COVID-19.

	Global Analysis	Original			Shuffled	
Ranking	Cryptocurrency	Entropy	Fisher	Dist. To (1,0)	Entropy	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

	Before the crisis	Original			Shuffled	
Ranking	Cryptocurrency	Entropy	Fisher	Dist. To (1,0)	Entropy	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

	During the crisis	Original			Shuffled	
Ranking	Cryptocurrency	Entropy	Fisher	Dist. To (1,0)	Entropy	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	0.907210	0.112413	0.145763	0.982381	0.045723
4	Ethereum	0.902393	0.109070	0.146367	0.983355	0.043365
5	BNB	0.904083	0.111000	0.146700	0.984259	0.044153

cryptocurrencies considering before COVID-19 and during COVID-19.

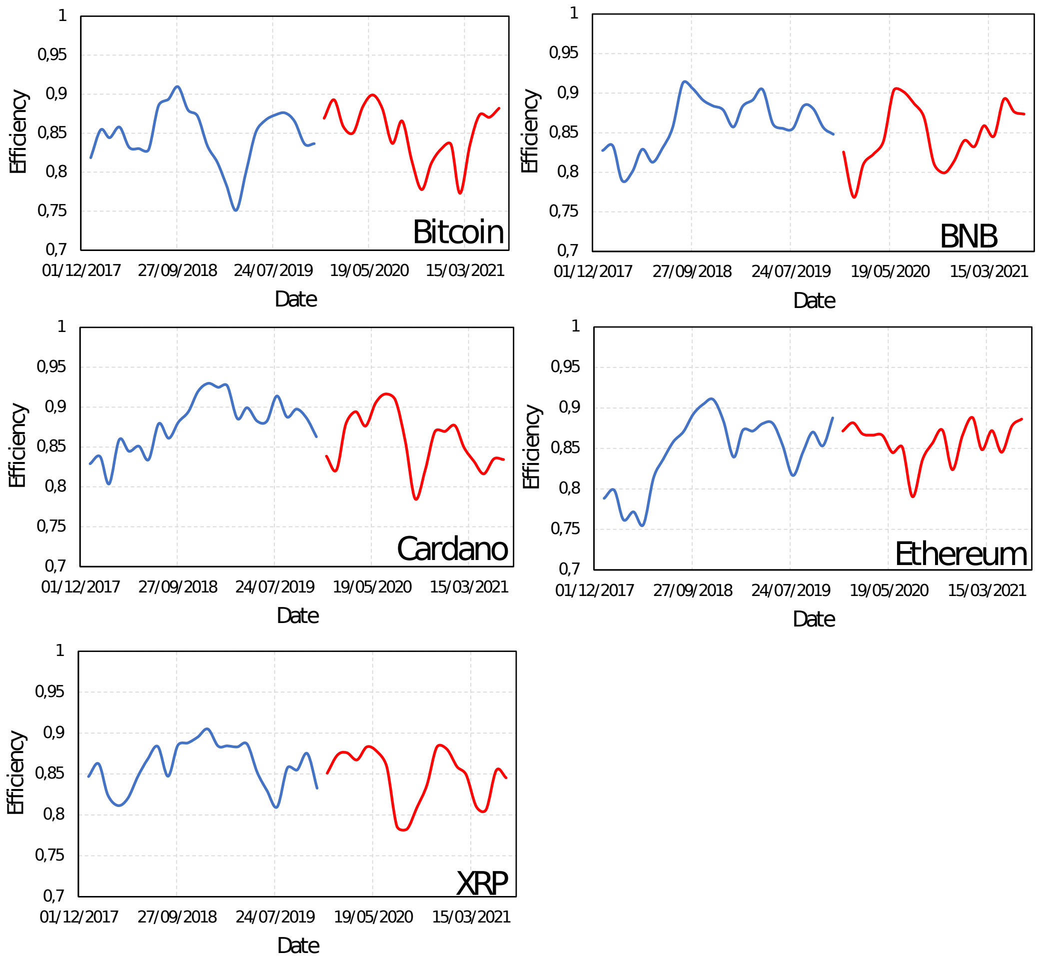

Figure 3: Temporal evolution of efficiency for all cryptocurrencies using sliding window approach for both periods (before COVID-19 and during COVID-19). Note that the blue line represents the dynamical investigation using sliding window for all cryptocurrencies from January 01, 2018, to December 31, 2019 (before COVID-19), and encompasses 730 observations. The red line displays the dynamical investigation using 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 a low level of 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., (5; 6). The resemblances in the temporal evolution of efficiency between younger and older (and between smaller and larger) cryptocurrencies suggest that the cryptocurrency markets have gained maturity, which makes them comparable to well established conventional assets.

4. Concluding remarks

The finance literature highlights the peculiarity of Bitcoin regarding hedge and safe haven properties (3) for other conventional assets. Recent evidence shows that Ethereum and XRP can also be used in this sense (7; 8; 4). However, less evidence exists on the temporal evolution of efficiency of these cryptocurrencies, including BNB and Cardano, during the pandemic.

In this paper, we provide the first empirical proof that the efficiency of cryptocurrencies (Bitcoin, BNB, Cardano, Ethereum, and XRP) have weathered the shocks of the COVID-19 outbreak. During the COVID-19 crisis, Cardano is the most efficient cryptocurrency, followed by Bitcoin. The efficiency displays 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 pre-pandemic and pandemic periods from an information theory perspective. It is counterintuitive, with confirmation from the stock markets, that investors should view each market condition independently for the sake of price predictability (2).

Notably, young and small cryptocurrencies adhere to the efficient market hypothesis, increasing maturity and lowering the potential for price predictability. Therefore, an extrapolation of past efficiency evolution might be enough to predict efficiency dynamics during crisis periods. Thus, our findings shed light on the benefits of using cryptocurrencies linked to the liquidity risk diversification strategy and risk management.

Other articles by the authors, see (22; 23**?** ; 24; 25; 26; 27; 28; 29; 30; 31; 32; 33; 34; 35; 36; 37; 38; 39; 40; 41)

5. Declaration of Competing Interest

The authors declare that this work has no conflicting personal or financial influences.

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