Leonardo H S Fernandes[1], Fernando Henrique Antunes de Araujo[2], José W L Silva[3], Kleber E S Sobrinho[4], and Benjamin Miranda Tabak[5]

[1]Department of Economics and Informatics, Federal Rural University of Pernambuco
[2]Affiliation not available
[3]Department of Statistics and Informatics, Federal Rural University of Pernambuco
[4]Federal Institute of Education, Science and Technology of Paraíba
[5]School of Public Policy and Government, Getulio Vargas Foundation, SGAN 602 Módulos A

November 14, 2022

# Un(punishment) of Russia-Ukraine war in the top ten digital currencies

Leonardo H. S. Fernandes[a,*], Fernando H. A. de Araujo[b], José W. L. Silva[c], Kleber E. S. Sobrinho[b], Benjamin Miranda Tabak[d]

[a]*Department of Economics and Informatics, Federal Rural University of Pernambuco, Serra Talhada, PE 56909-535 Brazil*

[b]*Federal Institute of Education, Science and Technology of Paraíba, Campus Patos, PB. Acesso rodovia PB 110, S/N Alto Tubiba - CEP: 58700-030, PB, Patos, Brazil*

[c]*Department of Statistics and Informatics, Federal Rural University of Pernambuco, Recife, PE 52171-900 Brazil*

[d]*School of Public Policy and Government, Getulio Vargas Foundation, SGAN 602 Módulos A,B,C, Asa Norte, Brasília, DF 70830-020, Brazil*

---

**Abstract**

This letter has investigated the exogenous shocks (climate change and the Russia-Ukraine war) in the top ten digital currencies' price dynamics. Therefore, we use the information theory quantifiers. We discover that the exogenous shocks have an ambiguous effect on the informational efficiency of these digital currencies. Our results shed light on the potential of altcoins to support exogenous shocks and their capability to use with portfolio selection, risk diversification and herding behaviour.

*Keywords:* Russia-Ukraine war, cryptocurrency, Altcoins, Climate change, Permutation entropy, Complexity, Inefficiency

---

*Corresponding author

*Email addresses:* `leonardo.henrique@ufrpe.br` (Leonardo H. S. Fernandes), `fernando.araujo@ifpb.edu.br` (Fernando H. A. de Araujo), `josewesley.silva@ufrpe.br` (José W. L. Silva), `kleber.enrique@academico.ifpb.edu.br` (Kleber E. S. Sobrinho), `benjaminm.tabak@gmail.com` (Benjamin Miranda Tabak)

## 1. Introduction

Cryptocurrencies have become an important asset in the world economy. These are assets that are heavily traded and have the attention of investors. The ease of trading these assets is among one of its most important features. The analysis of the efficiency of this market is at the top of the research agenda since they are relatively new markets and demand better knowledge about its dynamics. As a result, the analysis of the impact of the Ukrainian war against Russia on this market gains special relevance.

The Ukrainian war caused geopolitical tensions to increase in Eastern Europe as well as in the rest of Europe. The crisis affected the energy market, the stock market and cryptocurrencies were no exception. The increase in information asymmetry due to war can cause a drop in the efficiency of this market. We seek in this paper to contribute to this debate by evaluating the informational efficiency of the cryptocurrency market.

Khalfaoui et al. (2022) find that recent price drops in cryptocurrencies can be explained by sell-offs by significant holders, which is consistent with the hypothesis that investors in cryptocurrencies are reacting to the media spotlight on the war by seeking liquidity. Long et al. (2022) shows that not every cryptocurrency lost value as a result of the geopolitical uncertainty; in fact, several appreciated as a safe haven. Some were found to be quite sensitive, leading to a decline in price.

Using the Bandt & Pompe permutation entropy methodology and the Complexity-entropy causality plane (CECP) we show that the effect of the Ukrainian war on the information efficiency of the cryptocurrency market was ambiguous. We analyzed the top ten cryptocurrencies (largest market capitalization and higher trade volume). We found that there were changes in the efficiency ranking of these cryptocurrencies.

Several papers have employed different techniques to rank market efficiency in a variety of markets (Cajueiro & Tabak (2004), Cajueiro & Tabak (2005), Lim (2007), Kristoufek & Vosvrda (2019), Kristjanpoller et al. (2022), Fernandes et al. (2022c)). In line with these papers, our results suggest that the cryptocurrency market is constantly evolving and exogenous shocks cause changes in the dynamics of these prices. Thus, the degree of efficiency of this market changes over time.

Our results show that currencies with lower capitalization had higher efficiency before the crisis. Bitcoin and Ethereum, two with the highest capitalization, were among the most inefficient during this period. With the crisis provoked by the war, currencies with higher capitalization fell in one position (inefficiency increased). The ranking changed after the crisis and the correlation by rank is equal to 67.27%.

These changes in the degree of market efficiency can be explained by changes in the composition of investors or the strategies used to trade these assets. In times of heightened uncertainty, other assets may become more attractive, generating exits from cryptocurrency markets and flights to other markets. Our empirical results constitute a contribution to a more detailed assessment of the cryptocurrency market.

The rest of this paper is organized as follows. Section 2, describes the data set and the theoretical framework applied in this letter. Section 3 displays our findings. Section 4 presents our concluding remarks.

## 2. Data and methodology

### *2.1. Data*

The data set employed in this research consists of financial time series of the daily closing prices inherent to the top ten cryptocurrency and altcoins, ranked by their market capitalization and trade volume. We have collected these data from the website https://coinmarketcap.com/.

Regarding the period covered in our analyses, it is essential to note that we encompass a global period for each cryptocurrency. We segregate it into two overlapping periods to examine the Ukraine war shock in these digital currencies (Global analysis and during the Russian-Ukraine war). Table 1 the details about these digital currencies.

### *2.2. Methodology*

#### *2.2.1. Bandt & Pompe permutation entropy*

The permutation entropy was proposed by Bandt & Pompe Bandt & Pompe (2002) analogous to the Shannon entropy. This approach is able to quantify the probability distribution of ordinal patterns Zunino et al. (2012) considering simultaneously three relevant attributes: the temporal causality within data set, information content and structural complexity in the underlying stochastic process. More specifically, the permutation entropy is related with a symbolic sequence to the segments of the time series under investigation (Zanin et al. (2012)), which is based on the existence of local orders by comparing neighboring values of the original series. Additionally, the complexity quantifier is measured by employing the probability distribution function (PDF) related to these symbols (Fernandes & Araújo (2020)).

Therefore, allowing time series to be represented by $x_q, q = 1, ..., Q$ and regard $Q-(d-1)$ overlapping segments $X_q = (x_q, x_{q+1}, ..., x_{q+d-1})$ of length $d$. Within each section, the values are ranked from lowest to highest in ascending order to determine which indices they correspond to $s_0, s_1, ..., s_{d-1}$ such that $x_{q+s_0} \leq x_{q+s_1} \leq ...x_{q+s_{d-1}}$. The respective $d$-tuples (or words) $\pi = (s_0, s_1, ..., s_{d-1})$ correspond to the portions in their original form. We are free to assume any of the following $d!$ possible permutations of the set $\{0, 1, ..., d-1\}$. Therefore, the entropy of permutations (order $d \geq 2$) is:

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

where $\{\pi\}$ denotes the summation over all of the $d!$ possible permutations of order $d$, where $d$ is the order of the permutation, and $p(\pi)$ is the probability of occurrences of the permutation $\pi$.

The ideal value for $d$ is intimately related to the stochastic process underneath it. On the other hand, as a general rule of thumb, the literature advocates picking a maximum $d$ to meet the requirements and encourage a better statistical fit - $n > 5d!$ (Bariviera et al. (2015)).

*2.3. Complexity-entropy causality plane (CECP)*

The (CECP) is a two-dimensional map that was suggested by Rosso et al. (2007). The abscissa axis of this map reflects the permutation entropy, while the ordinate axis of this map signifies the Jensen-Shannon statistical complexity measure (Fernandes et al. (2021e)):

$$B\left[P\right] = -\frac{K\left[P,U\right]}{K_{max}} J_z\left[P\right] \tag{2}$$

where $J_z\left[P\right] = \frac{Z[P]}{\log d!}$ is the normalized permutation entropy, $K\left[P,U\right]$ is the Jensen-Shannon divergence-based disequilibrium measure (Lamberti et al. (2004)).

$$K\left[P,U\right] = \left\{ J\left(\frac{P+U}{2}\right) - \frac{J[P]}{2} - \frac{J[U]}{2} \right\} \tag{3}$$

This complexity measure is utilized to determine the degree of dissimilarity between the BPM probability distribution of ordinal patterns, denoted by $P$, and the uniform distribution, denoted by $U$. When just one of the components of $P$ has the value one, we compute the highest possible value of $K\left[P,U\right]$. This happens when all of the other components of $P$ have the value zero.

$$K_{max} = -\frac{1}{2}\left[\frac{d!+1}{d!}\log\left(d!+1\right) - 2\log(2d!) + \log\left(d!\right)\right] \tag{4}$$

The values of the normalized permutation entropy $J_z \in [0.1]$ embraces a large number of possibilities in terms of complexity values, $B_{min} \leq B \leq B_{max}$, a standard procedure is implemented to obtain the limits of the $B_{min}$ and $B_{max}$ limits defined by Martin et al. (2006).

Both complexity measure, $J_z$ and $B_z$ denotes the fundamentals of the Information Theory. $J_z$ is a robust complexity measure to quantify the degree of randomness exhibit in a stochastic process. Given this, the lower permutation entropy shows greater predictability due to the propensity to repeat just a few ordinal patterns. This is because of the tendency to repeat only a few ordinal patterns. On the other hand, a greater amount of entropy indicates a lesser level of predictability due to the inclination to display all potential ordinal patterns.

In this approach, for a particular permutation entropy value, Jensen-Shannon statistical complexity reflects an efficient measure employed in examining the randomness of the researched system or phenomena taking into consideration its physical components (structural correlations) Crutchfield & Young (1989). The definition of statistical complexity given in Lamberti et al. (2004) assures that series that are either strictly rising or strictly decreasing (in which case $J[P] = 0$) as well as series that are entirely random (in which case $K[P,U] = 0$) have zero complexity.

When the intermediate entropy values, which are not equal to zero, are considered, it is feasible to identify the most complicated structural arrangement. In this scenario, we determine the highest complexity by determining the distribution with the most significant deviation from the uniform distribution. Given this, we measure concurrently, for a given time series, the degree of correlational structure and the randomness in the system fluctuations (Rosso et al. (2007)).

*2.4. Sliding window technique*

We used the sliding window technique to provide a time dependent analysis of $H$ and $F$. The Sliding window technique proceeds as follow. Considering a time series $y_1, ..., y_N$, we construct the sliding windows $k_t y_{1+t\Delta}, ..., y_{w+t\Delta},\ t = 0, 1, ... \left[\frac{N-w}{\Delta}\right]$. 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 use the values inherent of the time series in each window $k_t$ to compute the Permutation entropy and the Jensen-Shannon statistical complexity, which yield the time evolution of the window position in the CECP.

## 3. Empirical Results

It is widely known that the dynamics of financial asset prices are linked to fluctuations in endogenous and exogenous variables. These fluctuations substantially impact the global economic system, covering macroeconomic variables such as interest rates, inflation, income, and employment and reducing people's welfare state.

Without any reservations, it is evident that a military conflict works as an efficient catalyst to increase the geopolitical risk that will reverberate in shocks to the financial market that are passed on to the real side of the economy.

The literature related to information theory quantifiers strongly indicates the use of price time series for financial assets to the detriment of the returns time series. Specifically, the price time series is non-stationary and allows you to visualize disorder better than the return time series, which is stationary. Figure 1 exhibits the plots of the daily closing prices of the top ten cryptocurrency and altcoins, ranked by their market capitalization and trade volume.

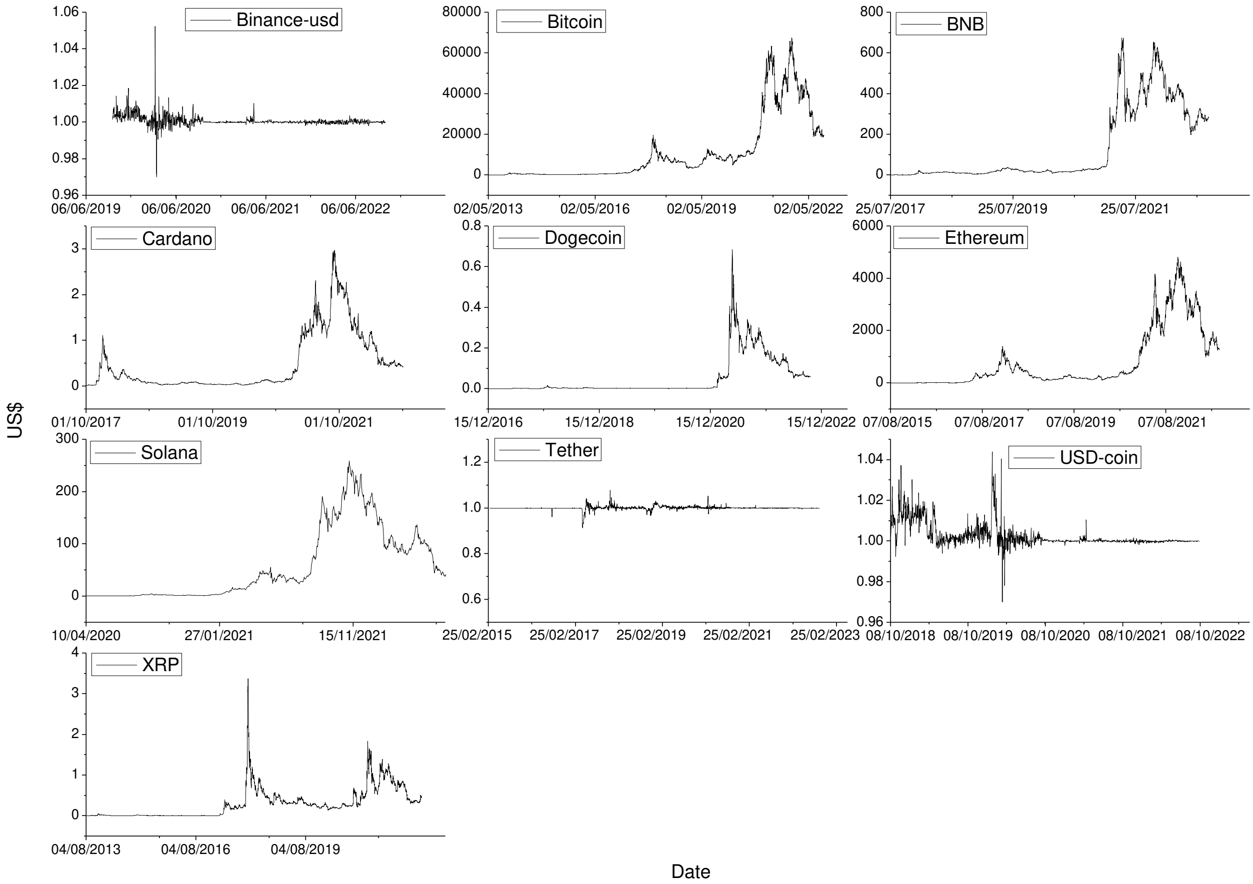


Figure 1: The timeline of the daily closing prices of the top ten digital currencies.

We employ the CECP to map these cryptocurrency and altcoins, and their respective locations are examined along this 2D map. For cryptocurrency and altcoins, both complexity measures (permutation entropy and statistical complexity) are obtained considering $d = 4$ to satisfy the common condition $T > 5d!$.

Moreover, we explore the behavior dynamics of the shuffled time series of cryptocurrency and altcoins prices. By the way, we apply the CECP in these series, where the shuffling procedure with 1000 x $N$ transpositions on each series. Fig. 2 show the respective locations for each digital currencies widely vary along the CECP considering $d = 4$ and the shuffled series.

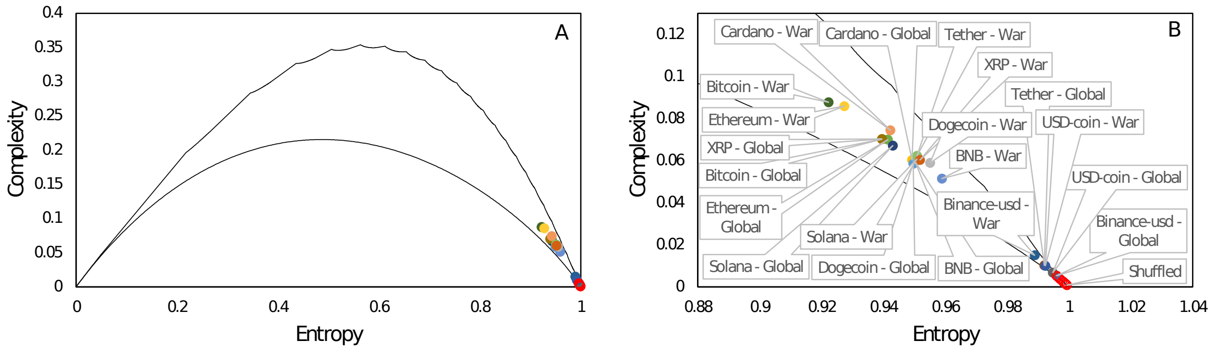


Figure 2: (A) Shows an overview of the CECP for all entire period. (B) Focus on the lower right region of the CECP, which presents high entropy and low complexity, to the mid-region of the CECP, which display low entropy and increased complexity. The red dots represent the random ideal position ($H_s = 1$, $B_s = 0$) for both plots (A) and (B).

The CECP is a powerful approach to mapping the trajectory of financial assets, mainly including extreme events such as climate change and the Russia-Ukraine war). Based on the overview of the CECP, we discover that climate change and the Russia-Ukraine war Khalfaoui et al. (2022) distinctly affected cryptocurrency and altcoins. Specifically, our findings indicate that the digital currencies that are located more distant ($H_s = 1$, $B_s = 0$) (less efficient) are characterized by high entropy and low complexity. In contrast the digital currencies that are located near to ($H_s = 1$, $B_s = 0$) are marked by more complexity and less entropy (more efficient).

The prominent compendium of the synergy between Economics Bariviera et al. (2015), Econophysics Zunino et al. (2011), Finance Fernandes et al. (2021e) and Information Theory Sigaki et al. (2018) reveals that the financial assets mapped in the lower-right region of the CECP are closer to their fundamental prices and are more efficient. Given this, it suggests that these digital currencies' behaviour is closer to a random walk).

In contrast, the financial assets mapped closer to the middle area of the CECP display low entropy and high complexity, which implies that their behaviour lying significantly farther from the right corner of the CECP is more inefficient. Thus, it indicates that these digital currencies' are more susceptible to speculative activities and present a low degree of efficiency).

Also, we apply the permutation entropy ($H_s$) and Jensen-Shannon complexity ($B_s$) to formulate the ranking of these digital currencies analogous to a complexity hierarchy. Table 1 exhibits the ranking of these digital currencies based on the complexity hierarchy ($H_s$ x $B_s$) for global analysis and during the Russia-Ukraine war.

Table 1: The ranking of these digital currencies considering two distinct periods (Global analysis and During war), values of permutation entropy ($H_s$), Jensen-Shannon complexity ($B_s$) and distance from vertex $(1, 0)$ considering $d = 5$.

| Global analysis | | | | | During war | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Ranking | cryptocurrency | Entropy | CECP | Dist. To (1,0) | Ranking | cryptocurrency | Entropy | CECP | Dist. To (1,0) |
| 1 | Binance-usd | 0.99595 | 0.00528 | 0.00664927 | 1 | USD-coin | 0.992374 | 0.010095 | 0.012651481 |
| 2 | USD-coin | 0.99479 | 0.00678 | 0.00854693 | 2 | Binance-usd | 0.988906 | 0.01504 | 0.018688814 |
| 3 | Tether | 0.99203 | 0.01025 | 0.012982143 | 3 | BNB | 0.958913 | 0.051473 | 0.065860559 |
| 4 | Dogecoin | 0.94965 | 0.05862 | 0.077277431 | 4 | Dogecoin | 0.95513 | 0.05894 | 0.074075779 |
| 5 | BNB | 0.9502 | 0.05969 | 0.077736562 | 5 | XRP | 0.951848 | 0.060317 | 0.077180153 |
| 6 | Cardano | 0.94925 | 0.06032 | 0.078830171 | 6 | Solana | 0.950846 | 0.060785 | 0.078172721 |
| 7 | Solana | 0.94304 | 0.06712 | 0.088030585 | 7 | Tether | 0.950866 | 0.062313 | 0.079354186 |
| 8 | Ethereum | 0.94145 | 0.06998 | 0.091247013 | 8 | Cardano | 0.942268 | 0.074423 | 0.094189604 |
| 9 | Bitcoin | 0.93948 | 0.0702 | 0.092685296 | 9 | Ethereum | 0.927378 | 0.085949 | 0.112522219 |
| 10 | XRP | 0.93954 | 0.0703 | 0.092725698 | 10 | Bitcoin | 0.922276 | 0.087747 | 0.117220624 |

We find a standard behaviour considering the price dynamics of these digital currencies for both periods. In particular, altcoins are more efficient than cryptocurrency. The global analysis demonstrates that three more efficient altcoins are Binance-usd followed by USD-coin and Tether. In comparison, the three more inefficient are Ethereum, Bitcoin and XRP.

During the Russia-Ukraine war, there was a change in the position of the USD-coin, and Binance-usd follow by BNB. At the same time, during the Russia-Ukraine war, Cardano, Ethereum and Bitcoin are the three more inefficient ones.

We perform a dynamical analysis in these digital currencies, Given this, we employ the CECP using the sliding window approach, for embedding dimension considering $d = 4$, window size $w = 120$ days (6 months) and sliding step $\Delta = 30$ days (1 month). Fig. 3 shows the trajectory the trajectory of digital currencies in this 2D map bearing in mind both periods (Global analysis and Russia-Ukraine war).

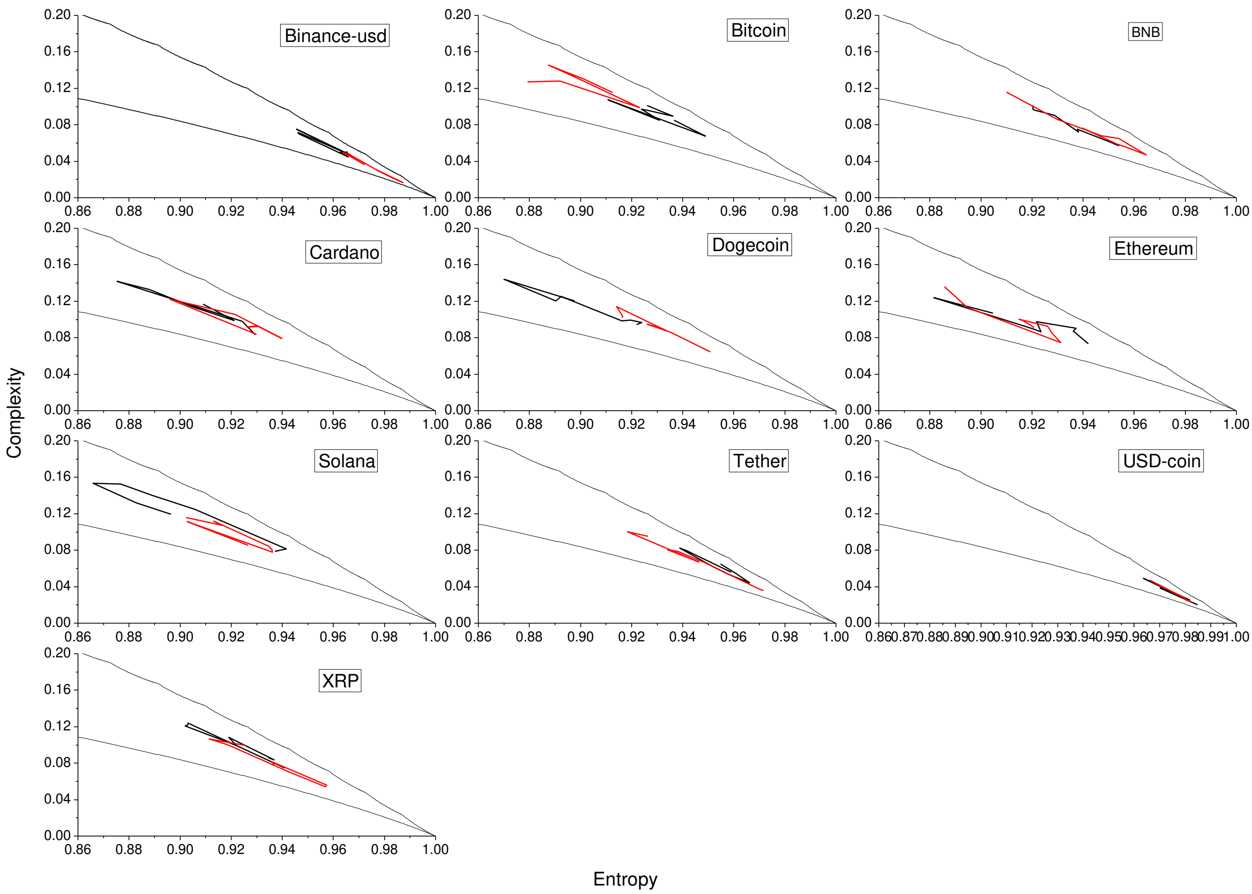


Figure 3: The digital currencies in the CECP using the sliding window technique for embedding dimension considering $d = 4$, window size $w = 120$ days (6 months) and sliding step $\Delta = 30$ days (1 month). The black line denotes the global analysis period and the red line represents the Russia-Ukraine war.

Moreover, we examine the changes suffered in inefficiency level in digital currencies. Therefore, we employ the CECP using the sliding window approach, for embedding dimension considering $d = 4$, window size $w = 120$ days (6 months) and sliding step $\Delta = 30$ days (1 month).

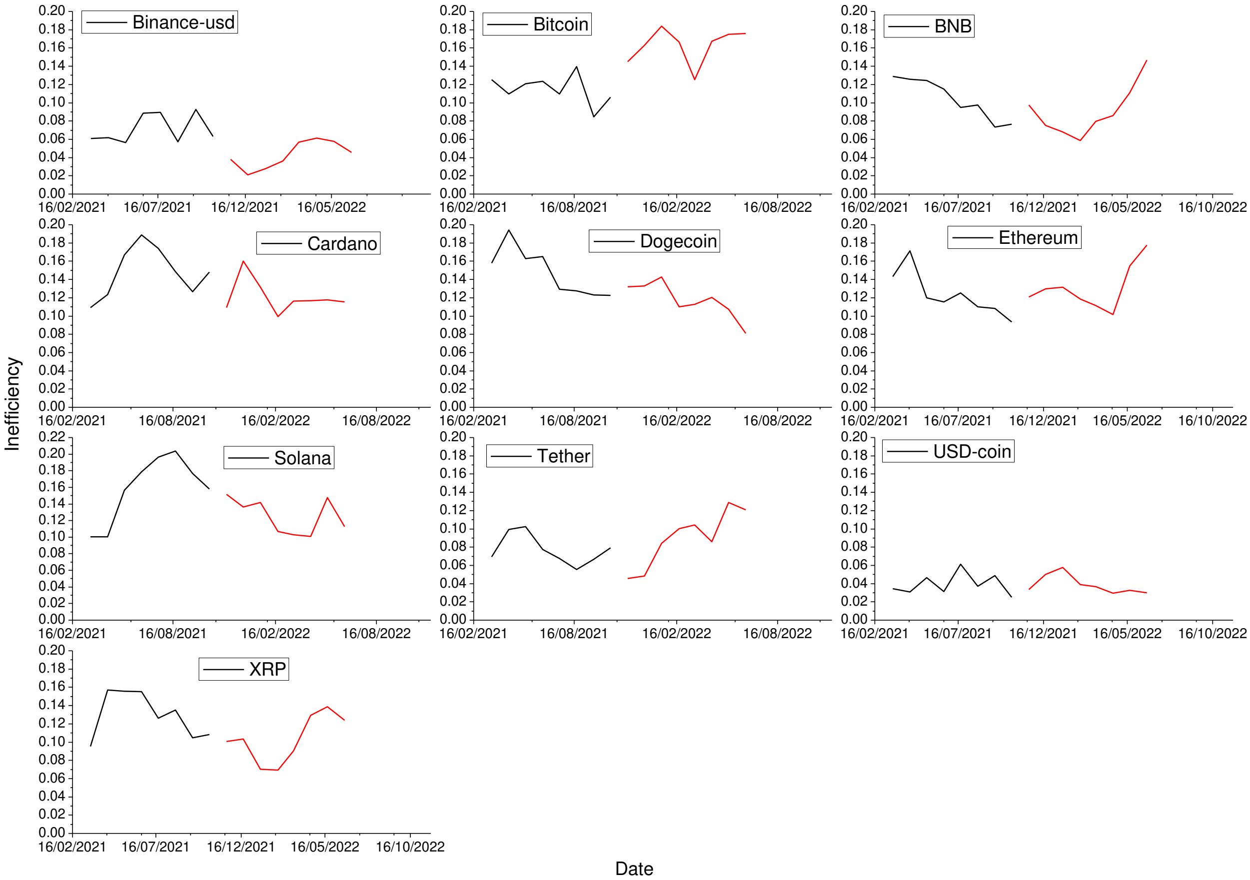


Figure 4: The complex dynamics related to the changes suffered in inefficiency level in digital currencies for both periods. The black line denotes the global analysis period and the red line represents the Russia-Ukraine war.

We have observed an ambiguous effect of climate change and the Russia-Ukraine war on these digital currencies. Specifically, digital currencies notably showed a decrease in informational inefficiency (USD-coin, Binance-usd, BNB, Dogecoin, and XRP). At the same time, the digital currencies with more expressiveness for the financial market, considering the volume traded and the capitalized market, were strongly impacted, presenting an increase in informational inefficiency (Tether, Cardano, Ethereum, and Bitcoin). Table 2 summarizes the changes suffered in inefficiency level in digital currencies for both periods.

The mean and standard deviation value, calculating the percentage change in inefficiency values, period before the war compared to the period during the war. Positive values indicate that the value of inefficiency increased during the war. Otherwise, negative values indicate that the inefficiency decreased during the war.

Table 2: Evaluating the changes suffered in inefficiency level in digital currencies for both periods.

| Digital currencies | %Changes in the inefficiency informational Mean | Standard deviation |
|---|---|---|
| Binance-usd | -39.6128164 | -6.7259937 |
| Bitcoin | 41.6194273 | 16.1056294 |
| BNB | -13.5885881 | 26.6355781 |
| Cardano | -18.4797131 | -33.2687663 |
| Dogecoin | -20.5476409 | -26.1440825 |
| Ethereum | 5.9703171 | 1.8597356 |
| Solana | -21.2620079 | -46.1128037 |
| Tether | 16.2092715 | 86.5083376 |
| USD-coin | -2.1988412 | -13.840566 |
| XRP | -20.4145685 | 3.9775733 |

## 4. Concluding remarks

We have examined the complex price dynamics of the top ten digital currencies ranked by their trade volume and market capitalization using the CECP and considering the impacts of extreme events such as climate changes and the Russia-Ukraine war.

Our findings reveal that digital currencies, notably marked with the highest trade volumes and market capitalization, were the hardest hit by the Russia-Ukraine war. It suggests that these digital currencies became more susceptible to arbitrage during this extreme event.

In contrast, the digital currencies with the lowest trade volumes and market capitalization presented an opposite situation regarding this issue. It reveals that digital currencies became more efficient during this extreme event.

Our empirical evidence suggests the real potential of the altcoins to support exogenous shocks Fernandes et al. (2022c) and their capability to use with portfolio selection Kim (2022), risk diversification Tzouvanas et al. (2020), and herding behaviour Yousaf & Yarovaya (2022) for the most diversified agents profile in the financial market.

Other articles by the authors, see:de Araujo et al. (2019); Fernandes et al. (2020b,a); de Araujo et al. (2020); Fernandes et al. (2021b,a,c); De Araujo & Fernandes (2021); De Araujo et al. (2021); Fernandes et al. (2021d); Araujo & Fernandes (2022); Fernandes et al. (2022e,f,a,d,b,h); Fernandes & Araujo (2022); Fernandes et al. (2022i,g)

## 5. Declaration of Competing Interest

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

## References

de Araujo, F. H. A., Bejan, L., Rosso, O. A., & Stosic, T. (2019). Permutation entropy and statistical complexity analysis of brazilian agricultural commodities. *Entropy*, *21*, 1220.

de Araujo, F. H. A., Bejan, L., Stosic, B., & Stosic, T. (2020). An analysis of brazilian agricultural commodities using permutation–information theory quantifiers: The influence of food crisis. *Chaos, Solitons & Fractals*, *139*, 110081.

Araujo, F. H. A. d., & Fernandes, L. H. (2022). Lighting the populational impact of covid-19 vaccines in brazil. *Fractals*, *30*, 2250066.

Bandt, C., & Pompe, B. (2002). Permutation entropy: a natural complexity measure for time series. *Physical review letters*, *88*, 174102.

Bariviera, A. F., Guercio, M. B., Martinez, L. B., & Rosso, O. A. (2015). A permutation information theory tour through different interest rate maturities: the libor case. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *373*, 20150119.

Cajueiro, D. O., & Tabak, B. M. (2004). Ranking efficiency for emerging markets. *Chaos, Solitons Fractals*, *22*, 349–352.

Cajueiro, D. O., & Tabak, B. M. (2005). Ranking efficiency for emerging equity markets ii. *Chaos, Solitons Fractals*, *23*, 671–675.

Crutchfield, J. P., & Young, K. (1989). Inferring statistical complexity. *Physical review letters*, *63*, 105.

De Araujo, F. H., Fernandes, L. H., & Tabak, B. M. (2021). Effects of covid-19 on chinese sectoral indices: A multifractal analysis. *Fractals*, *29*, 2150198.

De Araujo, F. H. A., & Fernandes, L. H. S. (2021). Multifractal detrended fluctuations analysis for ibovespa assets. *Fractals*, *29*, 2150183.

Fernandes, L. H., de Araújo, F. H., & Silva, I. E. (2020a). The (in) efficiency of nymex energy futures: A multifractal analysis. *Physica A: Statistical Mechanics and its Applications*, *556*, 124783.

Fernandes, L. H., Araújo, F. H., Silva, I. E., Leite, U. P., de Lima, N. F., Stosic, T., & Ferreira, T. A. (2020b). Multifractal behavior in the dynamics of brazilian inflation indices. *Physica A: Statistical Mechanics and its Applications*, *550*, 124158.

Fernandes, L. H., de Araújo, F. H., Silva, I. E., & Neto, J. S. (2021a). Macroeconophysics indicator of economic efficiency. *Physica A: Statistical Mechanics and its Applications*, *573*, 125946.

Fernandes, L. H., de Araujo, F. H., Silva, J. W., & Tabak, B. M. (2022a). Booms in commodities price: Assessing disorder and similarity over economic cycles. *Resources Policy*, *79*, 103020.

Fernandes, L. H., de Araújo, F. H., Silva, M. A., & Acioli-Santos, B. (2021b). Covid-19 lethality in brazilian states using information theory quantifiers. *Physica Scripta*, *96*, 035003.

Fernandes, L. H., Araujo, F. H., Silva, M. A., & Acioli-Santos, B. (2021c). Predictability of covid-19 worldwide lethality using permutation-information theory quantifiers. *Results in Physics*, *26*, 104306.

Fernandes, L. H., & Araujo, F. H. A. d. (2022). Multifractal dynamics of covid-19 vaccines in europe. *Available at SSRN 4195154*, .

Fernandes, L. H., Araujo, F. H. A. d., Silva, J. W., Silva, I. E., & Tabak, B. M. (2022b). Evaluating the efficiency of brazilian stock market indices: The case of covid-19. *Fractals*, *30*, 2250014.

Fernandes, L. H., & Araújo, F. H. (2020). Taxonomy of commodities assets via complexity-entropy causality plane. *Chaos, Solitons Fractals*, *137*, 109909.

Fernandes, L. H., Bouri, E., Silva, J. W., Bejan, L., & de Araujo, F. H. (2022c). The resilience of cryptocurrency market efficiency to covid-19 shock. *Physica A: Statistical Mechanics and its Applications*, (p. 128218).

Fernandes, L. H., De Araujo, F. H., & SILVA, J. W. (2022d). An analysis of the predictability of brazilian inflation indexes by information theory quantifiers. *Fractals*, (p. 2250097).

Fernandes, L. H., De Araujo, F. H., Silva, J. W., & Silva, M. A. (2021d). Insights into the predictability and similarity of covid-19 worldwide lethality. *Fractals*, *29*, 2150221.

Fernandes, L. H., de Araujo, F. H., & Tabak, B. M. (2021e). Insights from the (in)efficiency of chinese sectoral indices during covid-19. *Physica A: Statistical Mechanics and its Applications*, *578*, 126063.

Fernandes, L. H., Silva, J. W., & de Araujo, F. H. (2022e). Multifractal risk measures by macroeconophysics perspective: The case of brazilian inflation dynamics. *Chaos, Solitons & Fractals*, *158*, 112052.

Fernandes, L. H., Silva, J. W., de Araujo, F. H., Ferreira, P., Aslam, F., & Tabak, B. M. (2022f). Interplay multifractal dynamics among metal commodities and us-epu. *Physica A: Statistical Mechanics and its*

*Applications*, *606*, 128126.
Fernandes, L. H., Silva, J. W., Quintino, D., Santos, A. L., Ferreira, T. A., & Araujo, F. H. A. d. (2022g). Comparing the efficiency and similarity between wti, fiat currencies and foreign exchange rates. *Fluctuation and Noise Letters*, .
Fernandes, L. H., Silva, J. W., QUINTINO, D. D., DE ARAUJO, F. H., & TABAK, B. M. (2022h). Multifractal cross-correlations risk among wti and financial assets. *Fractals*, (p. 2250191).
Fernandes, L. S., Silva, J. W., Antunes de Araujo, F. H., & Tabak, B. M. (2022i). Multifractal cross-correlations between green bonds and financial assets. *Available at SSRN 4227059*, .
Khalfaoui, R., Gozgor, G., & Goodell, J. W. (2022). Impact of russia-ukraine war attention on cryptocurrency: Evidence from quantile dependence analysis. *Finance Research Letters*, (p. 103365).
Kim, J. H. (2022). Analyzing diversification benefits of cryptocurrencies through backfill simulation. *Finance Research Letters*, *50*, 103238.
Kristjanpoller, W., Fernandes, L. H., & Tabak, B. M. (2022). Examining the fractal market hypothesis considering daily and high frequency for cryptocurrency assets. *Fractals*, *30*, 2250070–417.
Kristoufek, L., & Vosvrda, M. (2019). Cryptocurrencies market efficiency ranking: Not so straightforward. *Physica A: Statistical Mechanics and its Applications*, *531*, 120853.
Lamberti, P., Martin, M., Plastino, A., & Rosso, O. (2004). Intensive entropic non-triviality measure. *Physica A: Statistical Mechanics and its Applications*, *334*, 119–131.
Lim, K.-P. (2007). Ranking market efficiency for stock markets: A nonlinear perspective. *Physica A: Statistical Mechanics and its Applications*, *376*, 445–454.
Long, H., Demir, E., Będowska-Sójka, B., Zaremba, A., & Shahzad, S. J. H. (2022). Is geopolitical risk priced in the cross-section of cryptocurrency returns? *Finance Research Letters*, *49*, 103131.
Martin, M., Plastino, A., & Rosso, O. (2006). Generalized statistical complexity measures: Geometrical and analytical properties. *Physica A: Statistical Mechanics and its Applications*, *369*, 439–462.
Rosso, O., Larrondo, H., Martin, M., Plastino, A., & Fuentes, M. (2007). Distinguishing noise from chaos. *Physical review letters*, *99*, 154102.
Sigaki, H. Y., Perc, M., & Ribeiro, H. V. (2018). History of art paintings through the lens of entropy and complexity. *Proceedings of the National Academy of Sciences*, *115*, E8585–E8594.
Tzouvanas, P., Kizys, R., & Tsend-Ayush, B. (2020). Momentum trading in cryptocurrencies: Short-term returns and diversification benefits. *Economics Letters*, *191*, 108728.
Yousaf, I., & Yarovaya, L. (2022). Herding behavior in conventional cryptocurrency market, non-fungible tokens, and defi assets. *Finance Research Letters*, *50*, 103299.
Zanin, M., Zunino, L., Rosso, O. A., & Papo, D. (2012). Permutation entropy and its main biomedical and econophysics applications: a review. *Entropy*, *14*, 1553–1577.
Zunino, L., Fernández Bariviera, A., Guercio, M. B., Martinez, L. B., & Rosso, O. A. (2012). On the efficiency of sovereign bond markets. *Physica A: Statistical Mechanics and its Applications*, *391*, 4342–4349.
Zunino, L., Tabak, B. M., Serinaldi, F., Zanin, M., Pérez, D. G., & Rosso, O. A. (2011). Commodity predictability analysis with a permutation information theory approach. *Physica A: Statistical Mechanics and its Applications*, *390*, 876–890.