Chaos, Solitons and Fractals 137 (2020) 109909

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Frontiers

Taxonomy of commodities assets via complexity-entropy causality plane

Leonardo H.S. Fernandes[a,*], Fernando H.A. Araújo[b]

[a] Department of Economics and Informatics, Federal Rural University of Pernambuco, Serra Talhada, Brazil
[b] Department of Statistics and Informatics, Federal Rural University of Pernambuco, Recife, Brazil

ARTICLE INFO

Article history:
Received 1 October 2019
Revised 2 May 2020
Accepted 17 May 2020

Keywords:
Permutation entropy
Statistical complexity
Complexity-entropy causality plane
Macrophysics policy

ABSTRACT

This paper promotes insights based on an empirical analysis of the complex dynamics of 12 significant assets of the commodity market. We applied the Complexity-entropy causality plane (CECP) to quantify the permutation entropy and appropriate statistical complexity measures consider time series of monthly spot and futures prices of these records, which made it possible to map the commodities assets and their respective locations along the CECP. The results obtained from our procedure fitting show that the price dynamics behavior varies widely along the plane from the lower-right region, characterized by high entropy and low complexity to the middle region of the plane, marked by more complex and less entropic. It suggests that the commodities that are located in the lower-right region are closer to their fundamental prices, so they are more efficient, while the commodities start pricing lies significantly farther from the right corner are more susceptible to speculative activities and present a low degree of efficiency. We also used the Bandt-Pompe permutation entropy and the Jensen-Shannon statistical complexity to elaborate the taxonomy of this market based on the complexity hierarchy, which expands the understanding inherent of the phenomenology of this important economic aggregate and can support the work of policymakers. Additionally, we proposed a novel Macrophysics policy that can be adopted as an alternative complementary of the classical fundamentals of macroeconomics used by policymakers to develop more efficient policies.

1. Introduction

In general, commodities assets, are products of primary origin [1] that are produced on a high scale with a low degree of industrialization, uniform quality standard (homogeneous products) and that play a central role in the worldwide economy.

The complex dynamics of commodities spot and futures related to the booms and busts prices [2] affect countries' balance of payments as well as their respective fiscal and monetary policies [3,4].

Thus, the relation between commodities prices shocks [5], capital flows cycles [6], fluctuations in international interest rates [7] and economic crises are widely studied in several areas [8–10].

Since, the 2000s [11,12], there has been an abrupt increase in the entry of many investors and traders in this modality of investment including institutional funds, sovereign, wealth funds, and many others [13]. This phenomenon was called as the financialization of the commodity market [14–16].

Indeed, the commodity market is characterized by a complex behavior related to the commodities spot and futures speculation presents significant sharp price spikes [17,18]. In view of this, several investors seeking to maximize their profits chose to allocate their resources in these assets and also use it as a diversification strategy [19].

In this way, the growing financialization of the global commodity market has drastically changed the dynamics of this economic aggregate. It implies rigorous fluctuations in the price, demand, supply and inventories of the commodities [12,14,17] which can lead to crises of global magnitude [20].

The shocks inherent in commodity market dynamics were predominantly analyzed as a result of fluctuations in demand from commodity price booms that led to impacts on inventories [14,21–23]. However, it is not advisable to categorically discard supply shocks related to political events that led to macro inventory fluctuations and culminated in a severe crises [17] and informational frictions [24].

By contemplating a historical perspective, the economy has already been punished as a result of some crises arising from the commodity market. We can highlight the shock due to the accu-

* Corresponding author.
E-mail addresses: leonardo.henrique@ufrpe.br (L.H.S. Fernandes), fhenrique14@gmail.com (F.H.A. Araújo).

https://doi.org/10.1016/j.chaos.2020.109909

mulation of inventories related to the end of the Korean War [25]. The oil price shocks related to Suez crises (1956–1957) [26], the oil embargo of the Organization of the Petroleum Exporting Countries (OPEC) on the USA and European countries (1973–1974) [27], the Iranian revolution (1978-1979) and Iran-Iraq war [28], the oil price spike (2007–2008) [29,30] and more recently world food crises (2007–2008) [31] and which returned in 2010 [32].

Thus, academics and policymakers have focused on the commodities price speculation [22,33], more specifically on the attitudes of speculators who buy and sell commodities in the futures market without ever taking physical possession and tend to reduce welfare[23].

So, efforts related to limits to arbitrage [33,34] have been debated to avoid anomalous failures. Professional arbitrage is usually an approach used by a very limited number of investors, but highly specialized and can lead to extreme situations in the dynamics of the commodity market, especially when prices diverge significantly from their fundamental prices[35], promoting an abrupt reduction in the degree of market efficiency and increase of risk [36].

Specifically, in addressing the issue of commodity market efficiency it is seen that it is grounded in the Efficient Market Hypothesis (EMH) [37,38]. EMH states that the market is efficient when all available information is fully reflected in market prices. In practice, based on the level of information availability, there was evidence of segregation of EMH into three distinct forms: (i) weak (historical prices), (ii) semi-strong (public information) and (iii) strong (all information even private).

In more detail, the weak form considers that all information on past asset prices would be incorporated into present prices. Already, the semi-strong form considers that all information publicly available would be incorporated in the present prices and the strong form considers that all kinds of information public and private would be incorporated in the present prices [39].

Something in common between these three distinct forms is the impossibility of obtaining returns above normal earnings. Therefore, no matter how heterogeneous the profile of market agents (traders, investors, banks, governments) maybe none of them can beat the market, even under normal conditions [40].

Moreover, the EMH considers that the mechanism of asset prices follows a random walk [41]. In view of this, the fundamentals of EMH were categorically questioned by factors such as long-term memory [10,42,43], fractal dimension [10,44,45] and fat-tailed [46–48]. Based on these factors was proposed the Fractals Market Hypothesis (FMH) [49].

The focus of this paper consists in to analyze the temporal evolution for the prices consider 12 representative records of commodities spot and futures assets based on the Complexity-entropy causality plane (CECP) [50]. Therefore, we used permutation entropy and corresponding statistical complexity measure which were shown to be able to map and rank these assets.

The contributions of this paper for the literature are five-fold. First, it analysis the complex dynamics of commodities spot and futures prices from the estimation of the permutation entropy combined with an intensive complexity measure. Second, the building up the CECP for this economic aggregate, which allowed us to map the commodities assets and their respective locations. Third, it shows the taxonomy of this market based on the complexity hierarchy. Fourth, it considers the inefficiency measure and presents a threshold that separates the least inefficient commodities from the most inefficient ones. Finally, it proposes a novel Macrophysics policy based on two parameters of the CECP that promote greater knowledge of the behavior of this complex market and that can collaborate in the formulation of more efficient macroeconomics policies.

The remainder of this paper is organized as follows. Section 2, presents the theoretical framework of the complexity-entropy causality plane method. Section 3, details the data set used in this paper and shows the empirical results. Section 4, discusses our empirical findings. Section 5, draws our conclusions and some concluding remarks.

2. Method

The CECP [50] depicts representation space the horizontal and vertical axes are suitable functionals of the pertinent probability distribution, more specifically the Shannon entropy of the system and an appropriate statistical complexity measure [51]. Quickly, it has become an efficient approach to analyze the physical properties of complex systems, since it allows distinguishing between stochastic noise and deterministic chaotic behavior [50].

This powerful entropy-causality approach has been applied successfully in several activities such as econophysics [40,52–54], the distinction between songs and providing a complexity hierarchy [55], in the characterization of brain development in chickens [56], in quantifier of nonstationarity effect in the vertical velocity records [57], in investigating anthropically induced effects in streamflow dynamics [51], oceanography [58] and many others [59–61].

The main idea of the CECP consists of the estimation of the permutation entropy combined with an intensive complexity measure [54,55]. It uses the Bandt & Pompe method (BPM) [62] to quantify the probability distribution considering this time causality, which takes into account a suitable partition based on ordinal patterns obtained by comparing neighboring series values.

Thus, for a given time series denoted by $x_t, t = 1, \ldots, T$ and regard $T-(d-1)$ overlapping segments $X_t = (x_t, x_{t+1}, \ldots, x_{t+d-1})$ of length d. Within each segment, the ranking of the values are performed based in increasing order to find the indices $r_0, r_1, \ldots, r_{d-1}$ such that $x_{t+r_0} \leq x_{t+r_1} \leq \ldots x_{t+r_{d-1}}$. The respective d-tuples (or words) $\pi = \left(r_0, r_1, \ldots, r_{d-1}\right)$ are symbolic corresponding the original segments, and can be assumed any of the $d!$ possible permutations of the set $\{0, 1, \ldots, d-1\}$. So, the permutation entropy of order $d \geq 2$ can be defined as

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

where $\{\pi\}$ represents the summation over all the $d!$ possible permutations of order d, and $p(\pi)$ denotes the relative frequency of occurrences of the permutation π. The optimal d strongly is related to the phenomenology of each event studied, but in order to promoted a goodness of fit statistics as a rule of thumb it is typically recommended [55] to choose maximum d such that $T > 5d!$.

The next step consists of calculating the statistical complexity measure by

$$C[P] = -\frac{J[P,U]}{J_{max}} H_S[P] \quad (2)$$

where $H_S[P] = \frac{H[P]}{\log d!}$ is normalized permutation entropy, $J[P, U]$ is the Jensen-Shannon divergence

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

it is applied to quantify the difference between the BPM probability distribution of ordinal patterns P and the uniform distribution U, and the maximum possible value of $J[P, U]$ is obtained when one of the components of P is equal to one, and all the others are equal to zero.

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

The related values of the normalized permutation entropy $H_s \in [0, 1]$ contemplate a range of possibilities in terms of complexity values, $C_{\min} \le C \le C_{\max}$, a general procedure is adopted to obtain the limits of the bounds $C_{\min}$ and $C_{\max}$ defined by ref [63].

Permutation entropy and statistical complexity provide information about two distinct properties of a data set. Permutation entropy quantifies the degree of randomness inherent in a process: more predictable signals (which show a tendency to repeat only a few ordinal patterns) have lower permutation entropy than less predictable signals (which tend to exhibit all possible ordinal patterns).

For a given entropy value, statistical complexity quantifies the degree to which privileged fluctuations (ordinal patterns) exist between those accessible to the system. The definition of statistical complexity [64] ensures that both strictly increasing and decreasing series (for which $H_s[P] = 0$) and completely random series (for which $J[P, U] = 0$) have zero complexity.

For intermediate entropy values different to zero, the maximum complexity corresponds to distributions that differ more than uniform, thus exhibiting the greatest structural complexity. When calculating these quantities for a given time series, both the randomness and the degree of correlational structure in the system fluctuations can be evaluated simultaneously [50].

The time-dependent CECP analysis is based on the sliding window technique and generates a temporary evolution of complexity in the system. Given a time series $x_1, \ldots, x_N$, sliding windows $z_t = x_{1+t\Delta}, \ldots, x_{w+\Delta}, t = 0, 1, \ldots, \left[\frac{(N-w)}{\Delta}\right]$, are constructed where $w \le N$ is the window size, $\Delta \le N$ is the sliding step and [.] denotes the taking of an entire part of the argument. The time series values in each window z_t are then used to calculate the permutation entropy H_s and the statistical complexity C_s at a given time t using the methods described above. This allows us to obtain the time evolution of the window position in the CECP.

3. Data and analysis

The data employed in this study consists of the monthly spot and futures prices for 12 different commodities. For each commodity, the periods cover more than 39 years from January 1980 until March 2019 with 471 data points. The data were obtained at https://www.imf.org/en/Research/commodities-prices. A list of commodities with a price in dollar (US$) per unit of measurement and sector is presented in Table 1.

Empirical results presented in past works show that the application of the Bandt & Pompe method (BPM) is recommended when the analyzed data are not completely stationary or when changes in time are more significant than absolute values [54,65]. In this sense, it has also been shown that taking into account the normalized permutation entropy and to discriminate time series, prices provide better results than logarithmic returns [52,66,67]. The time series of commodities prices are shown in Fig. 1.

We perform the Box plot [68] to analyzed extreme situations in commodity-related to anomalous failures arising from the performance of professional arbitrators [33,35]. The Box plot is depicted in Fig. 2.

Next, we applied the CECP to map the commodities assets and their respective locations are studied along this plane. For each time series of commodities prices, the normalized permutation entropy and statistical complexity measures are calculated considering $d = 4$ to satisfy the common condition $T > 5d!$.

We also investigated the behavior dynamics of the shuffled time series of commodities prices. Therefore, we used the CECP in these series, where the shuffling procedure with 1000 x N transpositions on each series. Fig. 3 show the respective locations for each commodities assets widely varies along the CECP considering $d = 4$, as well the shuffled series.

Table 1
Description of commodities (Abbreviation) with a price in dollar (US$) per unit of measurement and sector.

Item	Commodity description	Abbreviation	Mensuration	Sector
1	Aluminum, 99.5% minimum purity, LME spot price, CIF UK ports	Aluminum	US$ per metric ton	Metal
2	Beef, Australian and New Zealand 85% lean fores, CIF U.S. import price	Beef	US$ cents per pound	Meat
3	Cocoa beans, International Cocoa Organization cash price, CIF US and European ports	Cocoa	US$ per metric ton	Agriculture
4	Coffee, Other Mild Arabicas, International Coffee Organization New York cash price, ex-dock New York	Coffee	US$ cents per pound	Agriculture
5	Cotton, Cotton Outlook 'A Index', Middling 1-3/32 inch staple, CIF Liverpool	Cotton	US$ cents per pound	Agriculture
6	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K.	Crude oil, Dated Brent	US$ per barrel	Energy
7	Crude Oil (petroleum), Dubai Fateh Fateh 32 API	Crude oil, Dubai Fateh	US$ per barrel	Energy
8	Gold, Fixing Committee of the London Bullion Market Association, London 3 PM fixed price	Gold	US$ per troy ounce	Metal
9	Nickel, melting grade, LME spot price, CIF European ports	Nickel melting, LME spot	US$ per metric ton	Metal
10	Rice, 5 percent broken milled white rice, Thailand nominal price quote	Rice percent, milled white	US$ per metric ton	Agriculture
11	Soybean Meal, Chicago Soybean Meal Futures (first contract forward) Minimum 48 percent protein	Soybean	US$ per metric ton	Agriculture
12	Sugar, U.S. import price, contract no.14 nearest futures position (Footnote: No. 14 revised to No. 16)	Sugar	US$ cents per pound	Agriculture

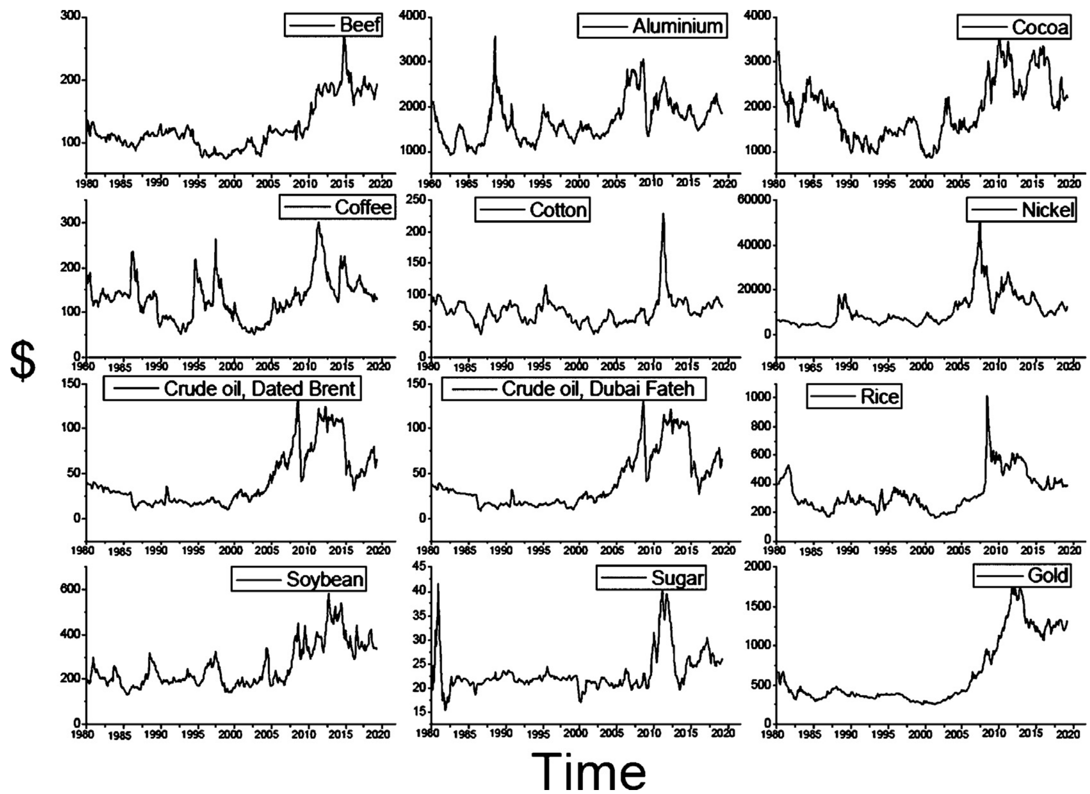

Fig. 1. The temporal evolution of the monthly spot and futures prices from January 1980 until March 2019. These time series present peculiar characteristics such as non-linear dynamics, noisy and chaotic characteristics. The temporal evolution of commodity prices to the period from 2001 to 2008 showed a common behavior related to commodity price inflation.

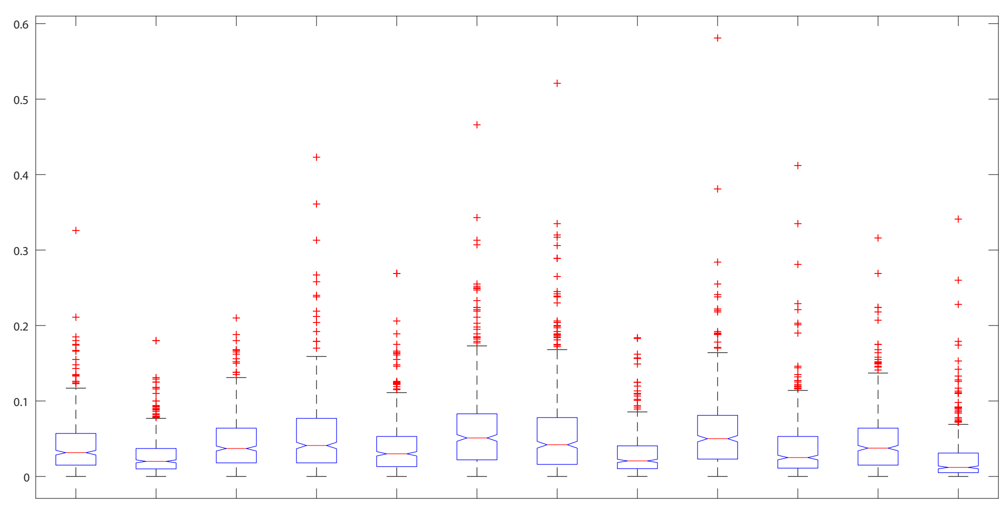

Fig. 2. The outliers represented by the red elements. The number of outliers can be an indication that anomalous failures arising from the performance of professional arbitrators' extreme events are common events of these assets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

From an economic point of view, commodities assets that are located near the lower right region of the CECP presents high entropy and low complexity means that their behavior is closer to a random walk (more efficient) [52,67,69]. Considering that the commodities assets prices were a pure random walk the variations would be a completely uncorrelated string of numbers and their associated entropy values would be maximized [40,52,54].

In this way, entropy can be considered as a measure of predictability regarding efficiency or inefficiency for the market [40,52,70]. In pratice, the more entropic is a market, the more efficient it is, because the several agents that operate in this market will have few or any information about this asset. Thus, considering the reduced quantity and quality of disposal information, there is a tendency for a reduction in extreme speculative activities and, consequently, in extreme fluctuations. The certainty related to this statement can be only proved through an effective statistical test, but there is empirical evidence of a strong synergy among arbitrage and price fluctuations [71–76] and to neglect them would be a great mistake.

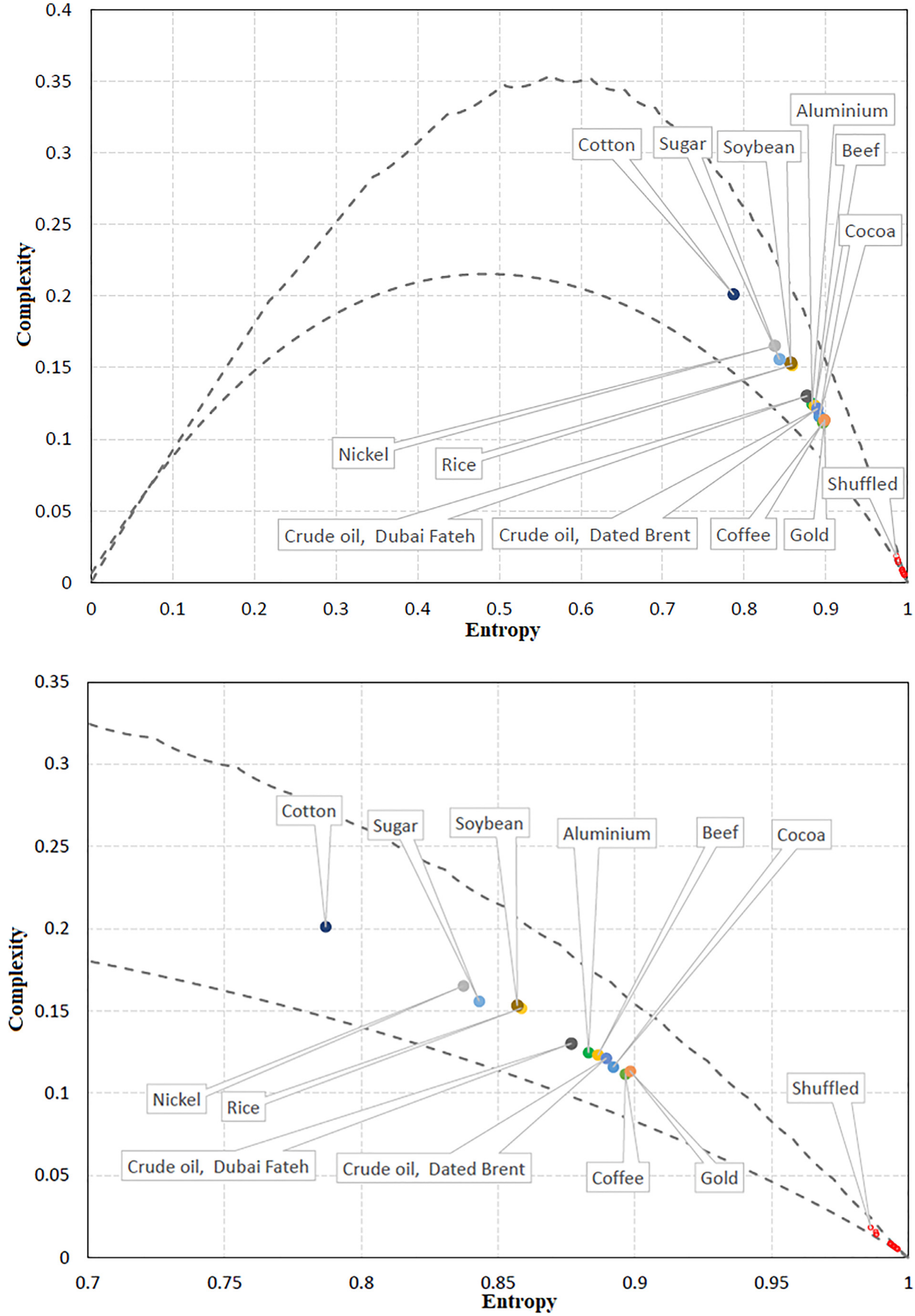

Fig. 3. Commodities assets tend to have their starting prices close to the lower-right region at the CECP, these commodities assets locations are characterized by high entropy and low complexity and goes close to the middle region of the plane, marked by more complexity and less entropic.

Table 2
Taxonomy of the commodities assets, values of permutation entropy H_s, Jensen-Shannon complexity C_s and distance from vertex (1,0) considering $d = 4$.

Ranking	Commodities	Entropy (H_s)	Complexity (C_s)	Dist. to (1,0)
1	Coffee	0.896504	0.111636	0.1522
2	Gold	0.898277	0.113425	0.1524
3	Cocoa	0.89208	0.11594	0.1584
4	Crude oil, Dated Brent	0.889552	0.121246	0.1640
5	Beef	0.886498	0.123249	0.1676
6	Aluminium	0.883023	0.124727	0.1710
7	Crude oil, Dubai Fateh	0.876741	0.130219	0.1793
8	Rice	0.858482	0.151657	0.2074
9	Soybean	0.856965	0.153307	0.2097
10	Sugar	0.843068	0.155936	0.2212
11	Nickel	0.837317	0.165314	0.2319
12	Cotton	0.786897	0.201213	0.2931

On the other hand, commodities assets that are located near the middle region of the CECP presents low entropy and high complexity which implies that their behavior is lying significantly farther from the right corner of CECP (more inefficient). Considering that the commodities assets prices somewhat correlated, then their entropy would not attain its maximal value [40].

The permutation entropy H_s and Jensen-Shannon complexity C_s are used to quantify commodity assets according to their efficiency. For each commodity, the time evolution is characterized by a temporal pattern derives in deviations from the ideal position to a stochastic process inherent a random walk. From an economic point of view, the higher distance to this random ideal position reflects a lower level of efficiency. Table 2 presents the taxonomy of the commodities assets based on the complexity hierarchy.

Our results show that Coffee, Gold, Cocoa and Crude oil, Dated Brent are near to the lower boundary of the CECP, which implies that their behavior is closer to a random walk. In view of this, they can be considered more efficient commodities assets [40,52,54,67,69]. Moreover, the Euclidian distance presents a high similarity in the behavior of Coffee and Gold. It suggests that these commodities assets are less complex per entropy value. While, the commodities assets such as Rice, Soybean, Sugar, Nickel, and Cotton are lying significantly farther from the right corner, which implies these commodities assets are less efficient [52,54] and show long-term correlated.

Besides, we checked the changes suffered by commodities in terms of inefficiency over time. Given this, we used the CECP analysis in sliding windows of size of 120 data (around ten business years) width a step of 12 data (around one business year), and in each window, we calculated the distance of CECP position from the right vertex (1,0). We chose the size of the windows described above to obtain a sufficiently long time series for permutation entropy calculations. In order to obtain good statistics as a rule of thumb it is tipically recommended [55] to choose maximum d such that $T > 5!$. Fig. 4 present the temporal evolution of inefficiency measure based on the right vertex (1,0).

For the entire period covered in this analysis, it is possible to verify that the value 0.4 related to the measure of inefficiency is a threshold that separates the least inefficient commodities from the most inefficient ones. The evolutionary dynamics of less inefficient commodities showed constant or low variability around this threshold. On the other hand, the evolutionary dynamics of the most inefficient commodities such as cotton, nickel, sugar, soybean remained above this threshold for almost every period analyzed with brief moments of variability around this value.

4. Discussion

Based on the results presents in Table 2 and Fig. 4, we carry out individual studies to understand the conditioning factors inherent in 3 significant records of the most efficient commodities. Coffee is the most widely consumed beverage, second only to water [77], so it is an agricultural commodity that has a decisive role from an economic standpoint [78].

According to the International Coffee Organization (ICO), during 2015 (153,987) - 2018 (170,561), there was an increase in world production measured in thousand 60 kg bags of 10.76%. For the same period 2015 (155,491) - 2018 (165,345) the world coffee consumption increased 6.34%. Thus, the gap between world production in the coffee year 2018 and the world coffee consumption in the same period reveals it created a surplus of 5.216 million bags.

The analysis of production by country in a thousand 60 kg bags for the 2018 harvest shows that Brazil (62,925) remained the main producer, but it should be noted that production in Vietnam (31,174), Colombia (13,858) Indonesia (9418), Ethiopia (7776) and Honduras (7328) are also significant worldwide.

Thus, in the event of an increase in the price of coffee due to inventory control or a reduction in the quantity produced in the harvest in Brazil, the impact will be mitigated by the production of these other players.

Also, this evident increase in the surplus of coffee for this respective period put downward prices for all groups (Brazilian Naturals, Colombian Milds, Robustas, and Others Milds), which composite the ICO indicator, which implied in a decrease of volatility and arbitrage for the ICO composite indicator.

Moreover, the use of technological innovations [79] and a greater knowledge of the ecophysiology of coffee [80] were conditioning factors that provided that led to an increase in production, as well as improvements in crop quality and greater sustainability [81].

Gold is a typical commodity in the metal sector which, due to its physical and chemical properties [82], presents high economic importance. Specifically, we can highlight good chemical stability and conduction properties are the main grounds of using gold in several applications by the electronic industry [83]. Moreover, this commodity asset widely used by other economic segments such as aerospace, communications, biotechnology, and jewelry.

For medical and biological purposes, the gold nanoparticles have a large number of applications including photoablation, diagnostic imaging, radiosensitization, vaccine development, antioxidant, and multifunctional drug-delivery vehicles [84].

Analysis of world economic history in terms of price stability and accessibility suggests that gold is the most effective commodity investment. In chronological terms, gold was considered for a long time the ultimate storage of value [85] and due to its ability to hedge periods of market stress inherent to high volatility in stock market indices it can be considered a safe asset [86].

Recently, it was found that gold remains the only safe asset for investors and traders operating in developed markets, but in de-

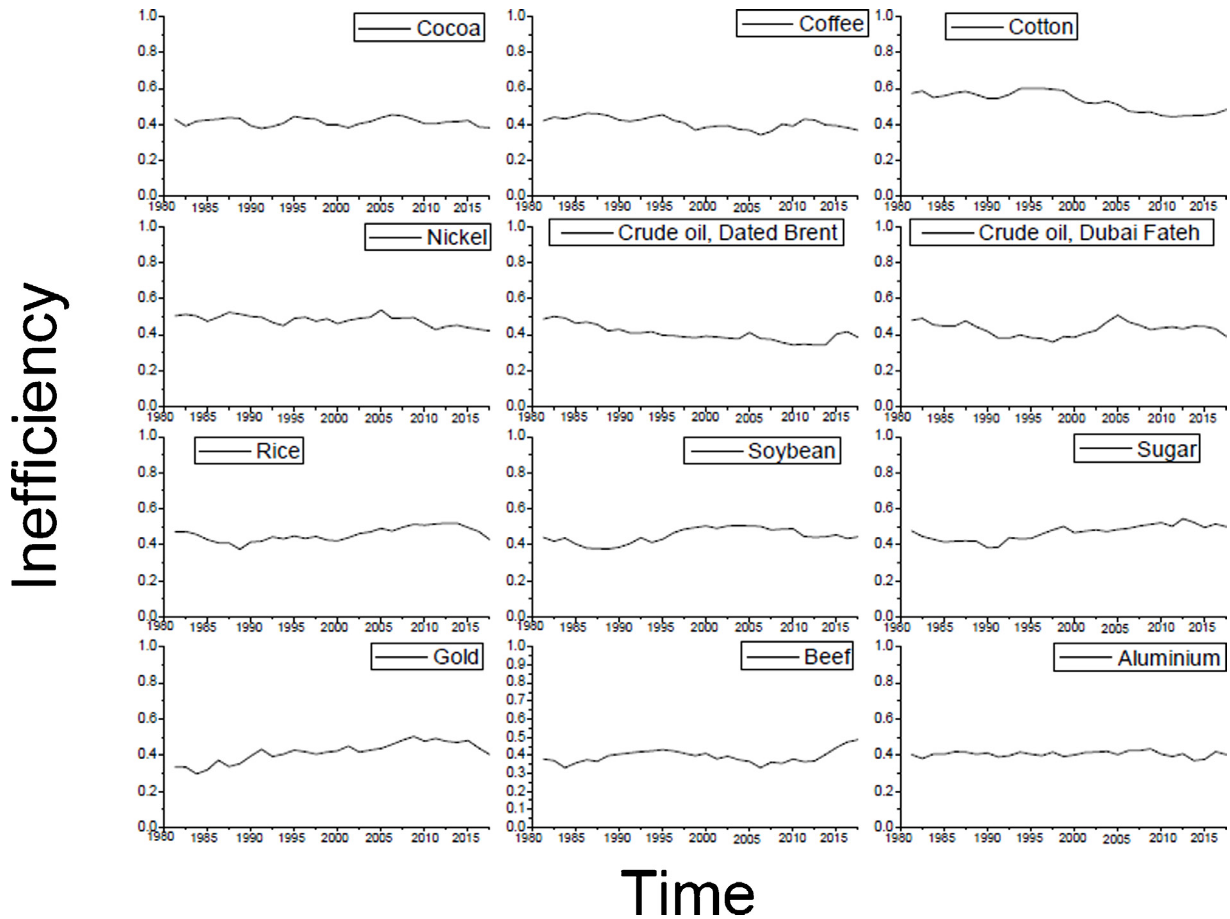

Fig. 4. Timeline of inefficiency measure distance from CECP considering ($H_s = 1$, $C_s = 0.$).

veloping markets like the Chinese stock market, there is already another option besides gold [87].

Probably gold occupies only the second position in our ranking due to the abrupt increase in global demand provided by the purchase of 145.5*t* of gold, the largest *Q*1 increase in global reserves since 2013. This sharp increase in the global demand for gold by central banks is closely associated with the desire of investors and traders to diversify their investments with safe and liquid assets in their portfolios. This led to more complex movements in the price of this asset, which suggests higher volatility and speculative activities [88].

Crude oil plays an excessively important role in the world economy. This commodity is the main source of energy for global economic activity [89] and is notoriously one of the most demanded commodities in the world. Thus, it also is clear that complex movements in crude oil price have significant effects on macroeconomic variables such as economic growth rate [90], exchange rate [91], economic stability [92], inflation [93], and political / religious events [94]. In this sense, the crude oil price dynamics can be used as indicative of global economic activity.

According to the monthly oil market report, March 2019 that was prepared by the Organization of Petroleum Exporting Countries (OPEC), considering the period from 2015 to 1Q19 the world oil demand and supply balance, mb/d presented an increase of 5.16%. This growth in global demand for oil during this period was driven by increased demand from emerging Asia [95] as well the strong growth presented by the worldwide petrochemical demand, particularly in the United States and China.

The strong growth in world petrochemical demand for oil is a key factor for global economic growth. Currently, oil is an indispensable input to the manufacture of many products that satisfy this rising demand such as plastic, artificial fertilizers, solvents, lubricants for automotive, food preservatives, personal care items, furnishings and many others that are indispensable to modern life.

Moreover, it is necessary to emphasize the increased use of crude oil as an asset of financial speculation [89]. Empirical evidence indicates that financial speculation affected directly the sharp increase in the real price of oil in 2007/08 [95] and that the limits to arbitrage which is one of the most recurrent themes for policymakers did not prevent the increase in the real price of oil in the physical market [21].

Although there has been an increase in the global demand for crude oil some factors such as excessive speculative activities [96,97] and volatility spillover [88] in the crude oil price have contributed to this important commodity, occupying only the fourth position in our ranking.

Overall, commodities prices show significant volatility resulting from low supply price elastic. Thus, in the face of economic fluctuations, the response of producers of these goods considering a short-term time horizon occurs via prices and not via quantities.

Other factors, such as the expansion of biofuel, fluctuations in the exchange rate, economic growth, the sharp increase in energy prices and the financialization of the commodities market, also reflect the complexity inherent in the global economic environment of the last decade.

It is clear that the combination of all these factors has drastically changed the dynamics of the commodity market and consequently the behavior of the world economy. Because of this, the implementation of regulatory models by an international regulatory agency can collaborate to reduce the ailments of this market and enhance the positive effects of commodities concerning the formation of the Gross Domestic Product (GDP), the reduction of the poverty rate and social disparities, especially in developing economies.

The regulation of the commodity market can be obtained by controlling the entropy of commodity prices, bearing in mind that entropy should have an optimal value, that is, that it allows access to little or no information by economic agents, but without compromising the complexity of economy [98,99]. In our Macropysics policy, the optimum economic level will occur at the point of convergence between the permutation entropy and Jensen-Shannon's complexity.

5. Conclusions

In summary, this paper presents an empirical analysis of the temporal evolution of the monthly frequency of spot and futures prices for 12 records of commodities assets. We applied the CECP to investigate the disorder and quantify an appropriate statistical complexity measure of these commodities assets over more than 39 years.

Based on the CECP, we estimated the 2 parameters of this method, more specifically, the normalized permutation entropy H_S and Jensen-Shannon's statistical complexity C_S, which made it possible to map the behavior dynamics of these commodities assets and their respective locations are studied along the CECP. We found that commodities assets tend to have their starting prices close to the lower-right region at the CECP and go close to the middle region of the plane.

In our investigations related to the taxonomy of the commodities assets, we found that Coffee, Gold, Cocoa and Crude oil, Dated Brent are located near the lower right region of the CECP. This region of the CECP presents high entropy and low complexity means that their behavior is closer to a random walk (more efficient). Otherwise, the commodities assets such as Rice, Soybean, Sugar, Nickel, and Cotton have lie significantly farther from the right corner. This region of the CECP presents less entropic and high complexity (more inefficient). Therefore, the entropy can be considered as a measure of the market's (in)efficiency. In this sense, the higher entropy of the market, the lower is its predictability and the higher is its efficiency level [40,52,70]. We also concluded that their prices show long-term memory. Thus, the market trend of these assets has continued for years and has not been eliminated by arbitration, as described by the Efficient Market Hypothesis (EMH).

In addition to excessive speculative activities, the combination of events such as financialization of the commodities market, economic growth, fluctuations in exchange rates, expansion of biofuels and inflation of energy prices has severely impacted the dynamics of the commodities market, consequently, the global economic scenario of the last decade became more complex and unfavorable, resulting in reduced welfare and possibly the destruction of great economic value. These harmful effects caused to the economy must not be combated only through fiscal, monetary and exchange rate policies. The empirical results of our analysis shed new light on the development of more efficient macroeconomic policies for the commodities market, linked to the perception of the economy as a complex system.

An efficient macroeconomic policy that addresses the complex dynamics of the commodities market must be based on the understanding that a higher level of entropy leads to a higher level of disorder [39] and that the more complex the structure of a country's production network is, the greater the economic development of that country [98,99]. Given this, we suggest a macrophysics policy that contemplates the problem inherent to the economic balance through the convergence of these two parameters. The adoption of macrophysics as a complement to classic macroeconomic policies will provide a greater level of knowledge of complex economic and social phenomena and will contribute to more stable economic systems.

Declaration of Competing Interest

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

CRediT authorship contribution statement

Leonardo H.S. Fernandes: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Fernando H.A. Araújo:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization.

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