Research Article

The Impact of the SARS-CoV-2 Epidemic on World Indices: The Entropy Approach

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The coronavirus disease (COVID-19) outbreak started in December 2019 in Wuhan. The virus has spread around the whole world, and it has caused a strong and serious pandemic. Symptoms such as cough, respiratory distress, diarrhea, and fatigue associated with COVID-19 are typical clinical findings. Coronavirus infection has become an important public health concern because of its increasing prevalence, serious complications, and mortality. In light of this information, we examine different entropy methods for world indices (ISE 30, FTSE 100, NIKKEI 225, SP 500, and DAX 30) in the pre-COVID-19 period (02.01.2019–17.11.2019) and the post-COVID-19 period (18.11.2019–23.11.2020) in this article. Besides, we discuss the performances of entropies such as Shannon, Renyi, Tsallis, and approximate entropy (ApEn) in detail and perform the notion of entropy for volatility measure. As a result, we present the numerical results for the data set.

1. Introduction

Entropy is a word that goes back to 1865 when Rudolf Clausius, a German physicist, granted an original noun to irreparable warmth damage termed as equivalent value. The word entropy was chosen for the fact that entropies refer to average component transformative or transformation component in Greek [1]. Tsallis [2] suggests that the concept of entropy should be widened into a notion bearing the statistical status of complicated systems. Then, Rao et al. [3] put forward the cumulative residual entropy, generalized measure of ambiguity, and applied it in reliability and picture arrangement as well as nonadditive measures of entropy. In 2008, Pincus [4] pointed out the use of approximate entropy (ApEn), a model-independent measure of consecutive disorder. Thus, through utilizing a number of varied practices for both empirical data and model-based data, he conceived cross-ApEn, concerning two-variable asynchrony measure that provides a stronger and more omnipresent measure of bivariate correspondence than correlation. In addition, he presented the following

containments to various strategies, ensured analytic statements for statistical properties of ApEn, and cross-checked ApEn with nonlinear measures, correlation, and spectral analyses as well as other entropy measures. Later, Ubriaco [5] applied the derivative to a special probability function and obtained the Shannon entropy definition which is based on probability and derivative. The information and its management can be illustrated by entropy. Most information management techniques are based on entropy. The fractional-order derivative and entropy-based binomial distribution yield a series of symmetric functions. Rompolis [6] put forward a varied method to apply the maximum entropy basis for recovering the risk neutral density of forthcoming stock, or any other entity which returns from put prices. In 2015, Sati and Gupta [7] defined a generalized cumulative remaining entropy on the basis of the nonadditive Tsallis entropy. In the same year, Sheraz et al. [8] employed an entropy for volatility markets. Then, Stosic et al. [9] investigated the effect of financial attacks on foreign exchange (FX) markets using the time-dependent block entropy technique and revealed experimental conclusions

which explain that the financial attacks are corporate with an important rise in exchange rate entropy, echoing uncertainty in FX market dynamics. The study in [10] shows every minute of the six years of entropy-dependent usage data between 1999 and 2004 based on time series and volatility, and that the entropy of the fluctuation series is based on the stock market. Khammar and Jahanshahi [11] submitted the weighted condition of this measure and named it “Weighted Cumulative Residual Tsallis Entropy (WCRTE)” and showed that it can specify the value of the survival function and Rayleigh distribution in a unique way. In 2019, Karakas [12] has attained volatility of ethereum and bitcoin, and then, the same author [13] used the world indices such as Istanbul Stock Indices (BIST 30), Brazil Index (Bovespa), Germany Index (DAX 30), Britain Index (FTSE100), South Korea (KOSPI), Japan Index (NIKKEI 225), United States Index (S&P 500), and China Index (SHANGAI) that have been examined over 8 years between 2010 and 2018, and, as a result, found the entropy notion for volatility measure to draw a comparison. Inc et al. [14] obtained approximate solutions of the nonlinear time-dependent generalized Fitzhugh–Nagumo equation with time-dependent coefficients and Sharma–Tasso–Olver equation subjected to certain initial conditions and showed that this method is efficient and convenient and, thus, it can be applied to a variety of problems. The approximate solutions are compared with the exact solutions. Then, Acay and Inc [15] proposed the temperature dynamics of a building and examined this model which has a crucial place in daily life. In 2020, Houwe et al. [16] investigated analytical solutions for the nonlinear differential-difference equations (DDEs) having fractional-order derivatives and employed the discrete tanh method in computations. As well, Akinlar et al. [17] considered an epidemic disease system by an additive fractional white noise to show that epidemic diseases may be more competently modeled in the fractional-stochastic settings than the ones modeled by deterministic differential equations, generated a new SIRS model and perturbed it to the fractional-stochastic systems, and studied chaotic behavior at disease-free and endemic steady-state points on these systems. After that, Akinlar et al. [18] considered a novel contribution because optimal control formulations, numerical solutions, and stability analysis for the fractional-order Malkus model are studied for the first time in this paper. Later, in the same year, Korpınar et al. [19] analyzed the fractional-stochastic quadratic-cubic nonlinear Schrödinger equation (QC-NLSE) describing the propagation of solitons through optical fibers and employed it to obtain stochastic solutions in the white noise space with Hermite transformation. Besides, Hashemi et al. [20] used the Adams–Bashforth–Moulton scheme (ABMS) to determine the approximate solution of a variable-order fractional three-dimensional chaotic process, demonstrating simulation results. However, Qureshi [21] examined a new time-invariant nonlinear mathematical model in fractional-(noninteger-) order settings that has been proposed under the three most frequently employed strategies of the classical Caputo. Currently, all world stock markets have been affected by the virus. The COVID-19 virus first emerged in

China (Wuhan city) spreading around the world. This virus is amongst the deadliest virus known to humans all over, having deadly effect on the health care system of most of the countries. In this study, five world indices (ISE 30, FTSE 100, SP 500, NIKKEI 225, and DAX 30) were used to investigate based on the entropy approach in the pre-COVID-19 period (02.01.2019–17.11.2019) and post-COVID-19 period (18.11.2019–23.11.2020).

2. Materials and Methods

2.1. Shannon Entropy and Renyi Entropy. Shannon entropy states that a measure of the amount of information $S(p)$ containing a series of events of $p_1, p_2, \dots, p_N$ should satisfy three requirements:

S should be continuous in p_i

If all p_i are equal probably, then S should be a monotonic increasing function of N

S should be additive

Then, it proves that only S satisfying these three requirements shows

$$S(P) = -\kappa \sum_{i=1}^N p_i \ln p_i, \quad (1)$$

where κ is a positive constant. This quantity has since become known as the Shannon entropy. In the information theory applications, the asymptotic equipartition property of Shannon is given for $T \subseteq S^n$ $T \subseteq S^n$ with

$$|T| \leq e^{n(S(p)+\epsilon)}, \quad (2)$$

such that illustration n times from P yields a factor of T with probability $> 1 - \epsilon$ and $\epsilon \rightarrow 0$ as $n \rightarrow \infty$. Extensions of Shannon’s original work have resulted in many alternative measures of information or entropy. For instance, by relaxing the third point of Shannon’s requirements, that of additivity, Renyi was able to extend Shannon entropy to a continuous family of entropy measures:

$$S_q(P) = -\frac{1}{1-q} \ln \sum_{i=1}^N p_i^q. \quad (3)$$

The Renyi entropy tends to Shannon entropy as $q \rightarrow 1$. The Renyi entropy is as follows:

The scaling factor is conventional, i.e., it makes S_q nonnegative for all q and ensures $S_q(u_n) = \log n$, where u_n is the uniform distribution on an n -element set.

The main property which the Renyi entropy has in common with Shannon entropy is additivity:

$$S_q(\rho \times r) = S_q(\rho) + S_q(r). \quad (4)$$

For $\beta = 0$, acquire the min-entropy, which is the cardinality of the support of ρ : $S_0(\rho) = \log |\{i \in S | \rho(i) > 0\}|$.

For $q = 1$, acquire Shannon entropy:

TABLE 1: Statistics of world indices in the pre-COVID-19 period (02.01.2019–17.11.2019).

	ISE 30	FTSE 100	NIKKEI 225	SP 500	DAX 30
Mean	1226,0519	7262,6528	21358,17	2896,640	11998,00
Median	1237,215	7274,450	21360,09	2909,190	12034,17
Maximum	1327,420	7686,610	23520,01	3121,750	13289,46
Minimum	1045,03	6692,660	19561,96	2605,500	10416,66
Std. dev.	65,32040	186,4341	873,4083	113,5172	604,7448
Skewness	−0.674607	−0.599872	0.217312	−0.379169	−0.031424
Kurtosis	2.731324	3.472528	3,208747	2.768171	2.689980
Jarque–Bera	17.50623	15.79535	2.208500	5.973792	0.950594
Probability	0.000158	0.000372	0.033145	0.005044	0.006217

TABLE 2: Statistics of world indices in the post-COVID-19 period (18.11.2019–23.11.2020).

	ISE 30	FTSE 100	NIKKEI 225	SP 500	DAX 30
Mean	1287,1338	6379,9955	22412,79	3165,256	12329,73
Median	1297,285	6123,820	23112,88	3232,250	12822,26
Maximum	1496,790	7674,560	26014,62	3623,000	13789,00
Minimum	1014,100	4993,890	16552,83	2220,500	8441,710
Std. dev.	106,5718	699,3948	1827,824	279,4826	1209,913
Skewness	−0.250346	0.617331	−1.175042	−0.974508	−1.297747
Kurtosis	2.706596	2.110804	3,951717	3,539609	3.795668
Jarque–Bera	3.592315	24.79044	68.84024	43.79541	78.91692
Probability	0.016593	0.000004	0.000000	0.000000	0.000000

TABLE 3: Different entropy measures of ISE 30, FTSE 100, NIKKEI 225, SP 500, and DAX 30 in the pre-COVID-19 period (02.01.2019–17.11.2019).

	Shannon		Tsallis		Renyi	Approximate entropy
Method	Value	q	Value	r	Value	Value
ISE 30						
ML	5.396743	0	220.0000000	0	5.398163	0.7846485
MM	5.397149	0.2	92.5761790	0.25	5.397804	
Jefferys	5.396744	0.4	40.8280410	0.5	5.397448	
Laplace	5.396745	0.6	19.1544962	1	5.396743	
SG	5.396743	0.8	9.7146361	2	5.395365	
Minimax	5.396749	1	5.3967431	4	5.392732	
CS	5.396743	1.2	3.3008212	8	5.387939	
Shrink	5.39745	1.4	2.2112471	16	5.380020	
		1.6	1.6012332	32	5.368983	
		1.8	1.2333170	64	5.356709	
2		0.9954624	Infinite	5.319076		
FTSE 100						
ML	5.424631	0	226.0000000	0	5.424950	0.7947985
MM	5.424699	0.2	94.6256717	0.25	5.424870	
Jefferys	5.424631	0.4	41.5280750	0.5	5.424790	
Laplace	5.424631	0.6	19.3935912	1	5.424631	
SG	5.424631	0.8	9.7962946	2	5.424315	
Minimax	5.424631	1	5.4246308	4	5.423694	
CS	5.424631	1.2	3.3103449	8	5.422489	
Shrink	5.424754	1.4	2.2144993	16	5.420221	
		1.6	1.6023437	32	5.416139	
		1.8	1.2336962	64	5.409257	
2		0.9955919	Infinite	5.368548		
NIKKEI 225						
ML	5.424339	0	226.0000000	0	5.424950	0.689666
MM	5.424363	0.2	94.6212737	0.25	5.424798	
Jefferys	5.424339	0.4	41.5250909	0.5	5.424646	

TABLE 3: Continued.

Method	Shannon		Tsallis		Renyi Value	Approximate entropy Value
	Value	q	Value	r		
Laplace	5.424339	0.6	19.3920726	1	5.424339	
SG	5.424339	0.8	9.7956076	2	5.423721	
Minimax	5.42434	1	5.4243394	4	5.422458	
CS	5.424339	1.2	3.3102262	8	5.419834	
Shrink	5.424384	1.4	2.2144524	16	5.414208	
		1.6	1.6023255	32	5.402104	
		1.8	1.2336893	64	5.381751	
		2	0.9955893	Infinite	5.333581	
SP 500						
ML	5.424201	0	226.0000000	0	5.424950	0.6455126
MM	5.424373	0.2	94.6190516	0.25	5.424762	
Jefferys	5.424202	0.4	41.5236068	0.5	5.424575	
Laplace	5.424202	0.6	19.3913293	1	5.424201	
SG	5.424201	0.8	9.7952767	2	5.423462	
Minimax	5.424203	1	5.4242014	4	5.422009	
CS	5.424201	1.2	3.3101709	8	5.419211	
Shrink	5.424507	1.4	2.2144308	16	5.414035	
		1.6	1.6023173	32	5.405173	
		1.8	1.2336862	64	5.391980	
		2	0.9955882	Infinite	5.350668	
DAX 30						
ML	5.42371	0	226.0000000	0	5.424950	0.5535031
MM	5.423752	0.2	94.6115378	0.25	5.424640	
Jefferys	5.42371	0.4	41.5185260	0.5	5.424329	
Laplace	5.42371	0.6	19.3887524	1	5.423710	
SG	5.42371	0.8	9.7941149	2	5.422476	
Minimax	5.423712	1	5.4237103	4	5.420029	
CS	5.42371	1.2	3.3099716	8	5.415223	
Shrink	5.423792	1.4	2.2143522	16	5.406039	
		1.6	1.6022869	32	5.389845	
		1.8	1.2336746	64	5.367814	
		2	0.9955838	Infinite	5.323234	

TABLE 4: Different entropy measures of ISE 30, FTSE 100, NIKKEI 225, SP 500, and DAX 30 in the post-COVID-19 period (18.11.2019–23.11.2020).

Method	Shannon		Tsallis		Renyi Value	Approximate entropy Value
	Value	q	Value	r		
ISE 30						
ML	5.557801	0	254.0000000	0	5.541264	0.605173
MM	5.558188	0.2	103.9217249	0.25	5.540389	
Jefferys	5.557804	0.4	44.6150090	0.5	5.539521	
Laplace	5.557806	0.6	20.4188729	1	5.537801	
SG	5.557801	0.8	10.1368950	2	5.534431	
Minimax	5.557813	1	5.5378010	4	5.527964	
CS	5.557801	1.2	3.3479548	8	5.516089	
Shrink	5.558543	1.4	2.2270007	16	5.496175	
		1.6	1.6064999	32	5.468754	

TABLE 4: Continued.

Method	Shannon	q	Tsallis		Renyi	Approximate entropy Value
	Value		Value	r	Value	
		1.8	1.2350782	64	5.442340	
		2	0.9960515	Infinite	5.390417	
FTSE 100						
ML	5.539317	0	255.0000000	0	5.545177	0.4216846
MM	5.539395	0.2	104.2128898	0.25	5.543729	
Jefferys	5.539318	0.4	44.6980209	0.5	5.542269	
Laplace	5.539319	0.6	20.4418658	1	5.539317	
SG	5.539317	0.8	10.1430007	2	5.533302	
Minimax	5.539326	1	5.5393168	4	5.520987	
CS	5.539317	1.2	3.3482870	8	5.496723	
Shrink	5.539468	1.4	2.2270537	16	5.458418	
		1.6	1.6064983	32	5.421958	
		1.8	1.2350713	64	5.398850	
NIKKEI 225						
ML	5.541764	0	255.0000000	0	5.545177	0.4849035
MM	5.541786	0.2	104.251176	0.25	5.544299	
Jefferys	5.541764	0.4	44.723779	0.5	5.543437	
Laplace	5.541764	0.6	20.454859	1	5.541764	
SG	5.541764	0.8	10.148825	2	5.538606	
Minimax	5.541767	1	5.541764	4	5.532970	
CS	5.541764	1.2	3.349274	8	5.523834	
Shrink	5.541811	1.4	2.227440	16	5.510553	
		1.6	1.606647	32	5.490232	
		1.8	1.235127	64	5.457949	
		2	0.996068	Infinite	5.394338	
SP 500						
ML		0	255.0000000	0	5.545177	0.484537
MM	5.541305	0.2	104.240513	0.25	5.544141	
Jefferys	5.541149	0.4	44.7167917	0.5	5.543124	
Laplace	5.54115	0.6	20.4514234	1	5.541148	
SG	5.541148	0.8	10.1473229	2	5.537413	
Minimax	5.541157	1	5.5411479	4	5.530728	
CS	5.541148	1.2	3.3490311	8	5.519871	
Shrink	5.541472	1.4	2.2273475	16	5.504498	
		1.6	1.6066119	32	5.485190	
		1.8	1.2351145	64	5.463312	
		2	0.9960633	Infinite	5.410064	
DAX 30						
ML	5.42371	0	226.0000000	0	5.424950	0.5196777
MM	5.540173	0.2	104.2217368	0.25	5.543865	
Jefferys	5.540133	0.4	44.7046841	0.5	5.542587	
Laplace	5.540133	0.6	20.4455670	1	5.540132	
SG	5.540132	0.8	10.1448044	2	5.535607	
Minimax	5.540138	1	5.5401324	4	5.527909	
CS	5.540132	1.2	3.3486380	8	5.516591	
Shrink	5.540219	1.4	2.2271995	16	5.503120	
		1.6	1.6065573	32	5.489558	
		1.8	1.2350947	64	5.475649	
		2	0.9960562	Infinite	5.432999

FIGURE 1: Data of world indices graphs and quantile graphs in the pre-COVID-19 period (02.01.2019–17.11.2019).

FIGURE 2: Data of world indices graphs and quantile graphs in the post-COVID-19 period (18.11.2019–23.11.2020).

$$S_1(\rho) = \lim_{q \rightarrow 1} S_q(\rho),$$

$$\frac{d}{dq} \left(\frac{1}{1-q} \log \left(\sum_i \rho(i)^q \right) \right)_{q=1} = - \sum_i \rho(i) \log \rho(i). \quad (5)$$

For $q = \infty$, acquire the min-entropy:

$$S_\infty(\rho) = -\log \max_i \rho(i) = \log \min_i \frac{1}{\rho(i)}. \quad (6)$$

2.2. Tsallis Entropy. For any positive real number α , the entropy of order α of probability measure p on finite set X is defined as

$$S_\alpha(p) = \begin{cases} \frac{1}{\alpha-1} \left(1 - \sum_{i \in X} p_i^\alpha \right), & \text{if } \alpha \neq 1, \\ - \sum_{i \in X} p_i \ln p_i, & \text{if } \alpha = 1. \end{cases} \quad (7)$$

The characterization of the Tsallis entropy is the same as that of the Shannon entropy except that for the Tsallis entropy, the degree of homogeneity under convex linearity condition is α instead of 1.

3. Results

3.1. Data Set. We utilize the world indices of ISE 30, FTSE 100, SP 500, NIKKEI 225, and DAX 30 in the pre-COVID-19 period (02.01.2019–17.11.2019) and post-COVID-19 period (18.11.2019–23.11.2020). Tables 1 and 2 summarize the statistics data of world indices of ISE 30, FTSE 100, SP 500, NIKKEI 225, and DAX 30 before and after the coronavirus pandemic. Tables 1 and 2 indicate varied average values for the data set, and the suitable standard deviations are varied. In Table 2, skewness for data set is negative; in Table 1, except for NIKKEI 225, others are negative. The kurtosis of two data sets is higher than 1. The Jarque–Bera (JB) test indicates that the normality of distribution for every series is strongly refused at 0.05 level, which means the overall energy terms' index distributions are nonnormal.

3.2. Conclusion: Entropy Approach. We apply the entropy technique for the volatility of world indices such as ISE 30, FTSE 100, SP 500, NIKKEI 225, and DAX 30 before and after the COVID-19 pandemic. For this, we compute Shannon, Tsallis, Renyi, and approximate entropies. In Tables 3 and 4, we initially provide varied forecasters for the Shannon entropy measure in the pre-COVID-19 period (02.01.2019–17.11.2019) and post-COVID-19 period (18.11.2019–23.11.2020). Later, we provide the Tsallis entropy for various values of the parameter and Renyi entropy measures for varied values of the parameter. Finally, we have obtained approximate entropy. When overall potential incidents have a similar probability, the entropy provides maximum value. In our experimental outcomes,

volatility indicates variation; this model shows linear and nonlinear dynamics. We obtain from the numerical outcomes that overall entropies are positive, so features of our data series are nonlinear. We find that the world indices of ISE 30, FTSE 100, SP 500, NIKKEI 225, and DAX 30 series have a great value of approximate entropy before and after the coronavirus pandemic. In the data series, when looking at world indices volatility before the coronavirus pandemic in Table 3 and Figure 1, volatility is mostly seen in FTSE 100, followed by ISE 30, NIKKEI 225, SP 500, and DAX 30. Similarly, in Table 4 and Figure 2, when we look at world indices after the coronavirus pandemic, volatility is mostly seen in ISE 30, followed by DAX 30, NIKKEI 225, SP 500, and FTSE 100. It is concluded that before the coronavirus pandemic, FTSE 100 data series is of higher volatility than other data series. Similarly, after the coronavirus pandemic, ISE 30 data series is of higher volatility than other data series. For the Shannon entropy estimators, before the coronavirus pandemic, it is clear that FTSE 100 series have larger values. In a similar way, for the measures of Tsallis and Rényi entropies, if we take attention that q and r are close to 1, then we obtain the Shannon entropy. After the coronavirus pandemic, it is clear that ISE 30 series have larger values.

Data Availability

Data are available from the website www.bloomberght.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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