

Pandemic episodes, CO₂ emissions and global temperatures

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ABSTRACT

This paper deals with the relationship between the CO₂ emissions and the global temperatures across the various pandemic episodes that have been taken place in the last 100 years. To carry out the analysis, first we conducted unit root tests finding evidence of nonstationary I(1) behavior, that means that a shift in time causes a change in the shape of distribution. However, due to the low statistical power of unit root tests, we also used a methodology based on long memory and fractional integration. Our results indicate that the emissions display very heterogeneous behaviour in relation with the degree of persistence across pandemics. The temperatures are more homogeneous, finding values for the orders of integration of the series smaller than 1 in all cases, and thus showing mean reverting behaviour.

Keywords: CO₂ emissions; global temperatures; pandemic; unit roots; ARFIMA models.

JEL Classification: C22, C25

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1. Introduction

Over the last 100 years the temperature on the Earth's surface has been rising significantly (see Nicholls et al., 1996; Jones and Wigley, 2010; and Folland et al., 2018; among others) caused by the effect of the burning and emissions of fossil fuels, industrialization and greenhouse gas concentration in the atmosphere (Anderegg et al., 2010; Beckage et al., 2018, etc.). Nevertheless, it is important to consider other factors such as solar irradiance, which are innate in the climate system, and which also affect this situation. According to Zickfeld et al. (2012), McMillan and Wohar (2013) and Zickfeld et al. (2016), the temperature and the concentration of carbon dioxide in the atmosphere exhibit a close correspondence. Also, National Oceanic and Atmospheric Administration (NOAA) and authors such as Laat and Maurellis (2004), Hansen et al. (2010), Cahill et al. (2015) and Sanz-Pérez et al. (2016) support the hypothesis that the carbon dioxide concentration and temperatures exhibit the same behavior and move in a very similar way.

In recent times we have seen that an infectious disease named SARS-CoV-2, of the Coronaviridae family and which caused the COVID-19 disease, was identified in Wuhan City, China, in December 2019 (see Hui et al., 2020 and World Health Organization¹) causing an unprecedented cessation of human activities and affecting global energy use and CO₂ emissions.

The confinement imposed on the population as a sanitary measure has brought about drastic changes in energy use with an impact on CO₂ emissions. The OECD report (2020) indicates that the virus will cause a negative supply shock to the world economy, by forcing factories to shut down and disrupting global supply chains. This has resulted in a decrease of 5.8% in global fossil CO₂ emissions during the first quarter of 2020 (see Liu et al., 2020). According to Le Quéré et al. (2020) and their sensitivity tests, the

¹ <https://www.who.int/news-room/q-a-detail/q-a-coronaviruses>

decrease in annual fossil CO₂ emissions from the severe and forced confinement of world populations has been between -4.2% (if pandemic restrictions are lifted by mid-June) to -7.5% (if some restrictions remain worldwide until the end of 2020). According to some researchers, these rates of decrease are similar to those which are necessary year after year over the next few decades to limit climate change and prevent warming of 1.5 °C.

Doing an extensive review of the bibliography, most of the literature tends to focus on studies based on temperatures and CO₂, separately. On the one hand, researchers have focused their efforts to study global temperatures using stochastic processes and trends (see see, e.g., Bloomfield, 1992; Bloomfield and Nychka, 1992; Galbraith and Green, 1992; Woodward and Gray, 1993, 1995; Koenker and Schorfheide, 1994; Zhang and Basher, 1999; Harvey and Mills, 2001; Fomby and Vogelsang, 2003; Gil-Alana, 2003, 2005, 2008a,b; Vogelsang and Franses, 2005; Mills, 2006, 2010; Gay-Garcia et al., 2009; Hendry and Pretis, 2013; Kaufmann et al., 2006, Kaufmann et al., 2010, 2013; Estrada et al., 2013; Chang et al., 2016, etc.). On the other hand, emissions have also been studied by many authors: Sun and Wang (1996); Slottje et al. (2001); Alby (2006); Ezcurra (2007); Chang and Lee (2008); Romero-Avila (2008); Lee et al. (2008); Lee and Chang (2009); Nourry (2009); Panopoulou and Pantelidis (2009); Christidou et al. (2013); Yavuz and Yilanci (2013); Ahmed et al. (2016); Tiwari et al. (2016); Gil-Alana and Solarin (2018); Gil-Alana and Trani (2018); among others. Finally, other authors such as McMillian and Wohar (2013), Zhang et al. (2019), Ying et al. (2020) and Gil-Alana and Monge (2020) have taken into consideration the two variables together using various methodologies such as unit root tests and autorregression models (McMillian and Wohar, 2013), multilayer and multivariable network methods (Zhang et al., 2019), multilayer climate network approach (Ying et al., 2020) and fractional integration (Gil-Alana and Monge, 2020).

Our main objective in this research paper is to conduct a serious statistical analysis about the statistical properties of various time series dealing with global temperatures and global CO₂ emissions. We use techniques based on long memory and fractional integration that allow the number of differences to be taken in the series to render them stationary by fractional numbers. More in particular, we use fractionally integrated AutoRegressive Moving Average ARMA (ARFIMA) models, and thus allowing for a fractional degree of differentiation in the level of the series of global annual temperatures (land temperatures, land and ocean temperatures and Northern and Southern hemisphere temperatures) as well as annual global CO₂ emissions from 1880 to 2014, taking into consideration the eight large pandemic events around the world, prior to the present one caused by COVID-19.

The motivation that is behind this work is that previous studies that have investigated the nonstationarity/stationarity of the series under investigation only have considered integer degrees of differentiation, i.e., 0 for stationary series, and 1 for nonstationary ones, not considering cases where the degree of differentiation may be a fractional value between 0 and 1. In fact, many recent studies have shown that many climatological and CO₂ emissions-related time series display a long memory pattern, implying different results than those obtained based on classical analysis and that only used integer degrees of differentiation. (See, e.g., Barassi et al., 2010; Belbute and Pereira, 2017; Gil-Alana and Trani, 2019 for papers dealing with CO₂ emissions and Vera-Valdes, 2020; Mangat, M. E. Reschenhofer, 2020; Gil-Alana and Monge, 2020; Awe and Gil-Alana, 2021 and others for papers with temperature data).

The paper is organized as follows: Section 2 briefly describes the techniques used in the paper, while Section 3 presents the dataset and Section 4 contains the main empirical results. Finally, Section 5 concludes the paper.

2. Methodology

2.1. Unit roots methods

There exist many different ways of testing for unit-roots. The most common ones are those of Fuller (1976) and Dickey and Fuller (1979), the ADF tests. They are asymptotically optimal when the data are stationary. Other more updated unit root methods are those proposed in Phillips and Perron (PP, 1988), Kwiatkowski et al. (KPSS, 1996), Elliot et al. (ERS, 1996), Ng and Perron (NP, 2001), etc.

2.2. ARFIMA (p, d, q) model

To carry out this research we employ long memory methods based on fractional integration where the number of differences required to render a series $I(0)$ stationary is a fractional value.

Following a mathematical notation, given a time series x_t , where $t = 1, 2, \dots$, we say it is integrated of order d (and denoted as $x_t \approx I(d)$) if:

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (1)$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$, defined as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Thus, u_t may display some type of time dependence of the weak form, i.e., the type of an invertible and stationary Autoregressive Moving Average (ARMA) form, i.e.,

$$\phi(L) u_t = \theta(L) \varepsilon_t, \quad t = 1, 2, \dots, \quad (2)$$

where $\phi(L)$ refers to the AR polynomial, $\theta(L)$ to the MA one, and ε_t is a white noise process. In such a case, if u_t is ARMA (p, q), x_t is said to be fractionally integrated ARMA, i.e. ARFIMA (p, d, q).

Depending on the value of the differencing parameter d , several specifications based on (1) can be observed: the process would be short memory or $I(0)$ when $d = 0$ in (1). This occurs because $x_t = u_t$. The high degree of association between observations which are far distant in time receives the name of long memory and occurs when $d > 0$. Within this last assumption, the process is still covariance stationary if $d < 0.5$ with the autocorrelations decaying hyperbolically slowly.

The reading that we can make of the results obtained from the fractional d is as follows: we consider a process of reversion which means that the shocks disappear in the long run when d is smaller than 1, and the lower the value of d is, the faster the reversion process is. In contrast to the above, the shocks are expected to be permanent when $d \geq 1$.

Although there are several procedures to estimate the degree of differentiation d (see Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992; Robinson, 1995; Beran, 1995; etc.), we base our results on the maximum likelihood procedure (see Sowell, 1992) and we use the Akaike information criterion (AIC, Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) to select the right ARFIMA model.

3. Data

We use global annual temperature anomalies using data from meteorological stations; global annual temperature anomalies computed from land and ocean; and global annual temperature anomalies for the northern and southern hemispheres computed using land and ocean data² and we also use annual data from the Carbon Dioxide Information Analysis Center (CDIAC) of the global CO₂ emissions originating from fossil fuel burning³ to analyze the behavior of these variables in the long term during the periods of pandemics for the time period from 1880 to 2009.

² <https://cdiac.ess-dive.lbl.gov/trends/temp/hansen/data.html>.

³ https://cdiac.ess-dive.lbl.gov/trends/emis/tre_glob_2014.html.

Following the research done by Jordà et al. (2020) the dates that we have used for our analysis are collected in the following table⁴:

Event	Start	End
Global Flu Pandemic	1889	1890
Sixth Cholera Pandemic	1899	1923
Encephalitis Lethargica Pandemic	1915	1926
Spanish Flu	1918	1920
Asian Flu	1957	1958
Hong Kong Flu	1968	1969
SARS	2002	2004
H1N1 Pandemic	2009	2009

Figure 1 plots the original data of the global fossil fuel CO₂ emissions and the four annual anomalies in the temperature series mentioned above indicating the pandemic periods. Although there is a constant increase in the trend across the sample, in periods of a pandemic it is observed that the temperatures stabilize/decrease with respect to the trend.

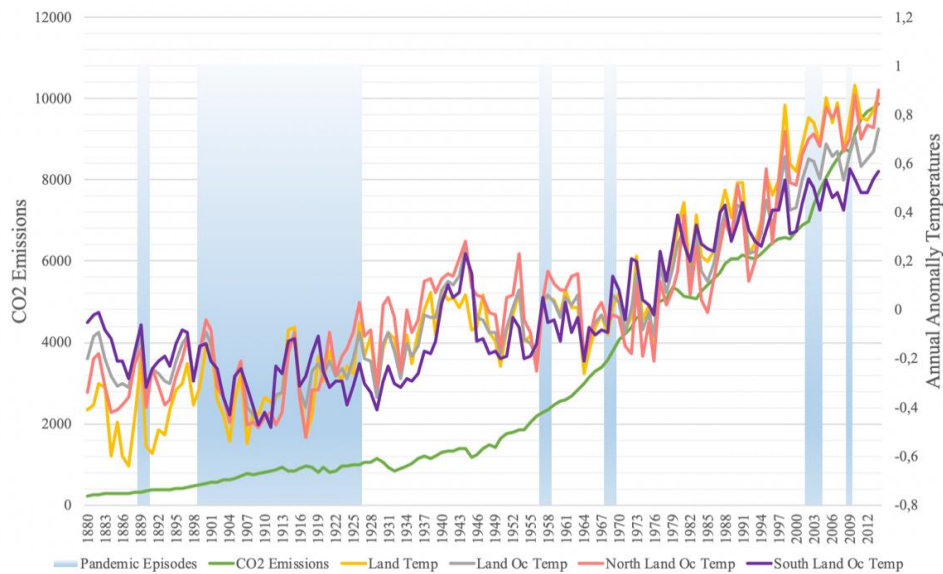


Figure 1. Pandemic episodes, global fossil-fuel CO₂ emissions and annual anomaly in temperatures.

⁴ To collect the dataset of each subsample, we have used nine years before and nine years after to analyze the cycle.

4. Results

We start the analysis by performing the three standard unit root tests outlined in Section 2. We select the Augmented Dickey-Fuller test (ADF) to examine the statistical properties of the original series and its differences to obtain robust results.

Table 1 displays the results, which suggest that the original data are nonstationary I(1) and the first differences are stationary I(0).

Augmented Dickey-Fuller Test			
	(i)	(ii)	(iii)
1. Global Flu Pandemic			
CO2 Emissions	3.026 (0.00803)**	1.549 (0.142)	-0.648 (0.528)
Land Temp	-0.637 (0.533)	-2.487 (0.00251)*	-2.714 (0.0168)*
Land Oc Temp	-0.508 (0.618)	-2.844 (0.0123)*	-2.697 (0.0174)*
North Land Oc Temp	-0.636 (0.534)	-2.439 (0.0276)*	-2.815 (0.0138)*
South Land Oc Temp	-0.529 (0.604)	-2.622 (0.0192)*	-2.481 (0.0264)*
2. Sixth Cholera Pandemic			
CO2 Emissions	0.783 (0.438)	-1.645 (0.1083)	-0.957 (0.345)
Land Temp	-1.760 (0.0863)	-3.345 (0.00186)**	-4.268 (0.000132)***
Land Oc Temp	-1.162 (0.252)	-3.441 (0.00142)**	-3.467 (0.00135)**
North Land Oc Temp	-1.424 (0.162)	-2.604 (0.0131)*	-3.082 (0.00387)**
South Land Oc Temp	0.862 (0.394)	-3.231 (0.00255)**	-3.474 (0.00132)**
3. Encephalitis Lethargica Pandemic			
CO2 Emissions	0.493 (0.626)	-2.002 (0.0562)	-2.841 (0.00902)**
Land Temp	-1.589 (0.124)	-2.984 (0.00628)**	-3.969 (0.00057)***
Land Oc Temp	-1.223 (0.232)	-2.660 (0.0134)*	-4.187 (0.000328)***
North Land Oc Temp	-1.552 (0.133)	-2.008 (0.0556)	-4.322 (0.000233)***
South Land Oc Temp	-0.741 (0.465)	-2.937 (0.00702)**	-2.894 (0.00797)**
4. Spanish Flu			
CO2 Emissions	1.326 (0.202)	-0.458 (0.653)	-1.648 (0.120)
Land Temp	-1.057	-3.018	-3.235

	(0.305)	(0.00816)**	(0.00555)**
Land Oc Temp	-0.979 (0.341)	-2.914 (0.0102)*	-2.868 (0.0117)*
North Land Oc Temp	-1.270 (0.221)	-2.276 (0.0369)*	-3.179 (0.00623)**
South Land Oc Temp	-0.722 (0.480)	-2.501 (0.0236)*	-2.407 (0.0294)*
5. Asian Flu			
CO2 Emissions	4.239 (0.000625)***	0.499 (0.625)	-1.432 (0.174)
Land Temp	-2.223 (0.141945)*	-2.666 (0.0176)*	-2.589 (0.0214)*
Land Oc Temp	-2.555 (0.0212)*	-3.015 (0.00871)**	-2.976 (0.010)*
North Land Oc Temp	-3.189 (0.00571)**	-3.133 (0.00684)**	-3.027 (0.00905)**
South Land Oc Temp	-1.468 (0.162)	-2.571 (0.0213)*	-2.692 (0.0175)*
6. Hong Kong Flu			
CO2 Emissions	2.524 (0.0226)*	-0.115 (0.910)	-2.636 (0.0196)*
Land Temp	-2.402 (0.0288)*	-2.310 (0.0355)*	-2.572 (0.0222)*
Land Oc Temp	-2.908 (0.0103)*	-2.830 (0.0127)*	-2.910 (0.0114)*
North Land Oc Temp	-2.433 (0.0271)*	-2.581 (0.0209)*	-2.593 (0.0213)*
South Land Oc Temp	-1.660 (0.116)	-1.605 (0.129)	-2.780 (0.0148)*
7. SARS Pandemic			
CO2 Emissions	2.901 (0.00993)**	0.710 (0.488)	-1.914 (0.0749)
Land Temp	0.543 (0.594)	-2.822 (0.0123)*	-3.817 (0.001683)**
Land Oc Temp	0.514 (0.614)	-2.545 (0.0216)*	-3.887 (0.00146)**
North Land Oc Temp	0.378 (0.710)	-2.520 (0.0228)*	-3.620 (0.00252)**
South Land Oc Temp	0.404 (0.691)	-2.801 (0.01281)*	-4.162 (0.000835)***
8. H1N1 Pandemic			
CO2 Emissions	2.330 (0.0399)*	-1.161 (0.273)	-1.885 (0.0921)
Land Temp	0.564 (0.584)	-3.335 (0.00756)**	-4.482 (0.00153)**
Land Oc Temp	0.690 (0.504)	-2.975 (0.0139)*	-4.262 (0.00211)**
North Land Oc Temp	0.730 (0.481)	-2.606 (0.0262)*	-3.050 (0.0138)*
South Land Oc Temp	0.429 (0.676)	-3.642 (0.00452)**	-4.769 (0.001017)**

Table 1. Unit roots tests. (i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. Inside the parenthesis the p-value is reflected, outside the t-statistic with test critical value at 0,1% (***) ; 1% (**); 5% (*).

Identical results are obtained if other more updated unit root methods are used, such as those mentioned in the previous section. (These results are available from the authors upon request).

Our results so far indicate that all the original series are nonstationary I(1); however, due to the low power of the unit root methods under fractional alternatives⁵, we also perform different ARFIMA (p, d, q) models to study the persistence of the subsamples corresponding to the different periods of pandemic since 1880.

We select the most appropriate ARFIMA specification for each series for the Akaike information criterion (AIC; Akaike, 1973) and Bayesian information criterion (BIC; Akaike, 1979)⁶. We allow for ARFIMA models of the form "(0, d, 0)", "(1, d, 0)", "(2, d, 0)", "(0, d, 1)", "(0, d, 2)", "(1, d, 1)", "(1, d, 2)", "(2, d, 1)", "(2, d, 2)", i.e., we choose any ARFIMA(p, d, q) with p and q being smaller than or equal to 2. Once the various configurations were calculated, and following the selection criteria mentioned above, the results are collected in Table 2.

Long Memory test					
Data analyzed	Model Selected	d	Std. Error	Interval	I(d)
Global Flu Pandemic (GFP)					
CO2 Emissions	ARFIMA (2, d, 2)	1.999704	0.809815	[0.67, 3.33]	I(1), I(2)
Land Temp	ARFIMA (0, d, 0)	0.346508	0.272745	[-0.10, 0.80]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.309616	0.274918	[-0.14, 0.76]	I(0)
North Land Oc Temp	ARFIMA (0, d, 0)	0.316282	0.307083	[-0.19, 0.82]	I(0)
South Land Oc Temp	ARFIMA (0, d, 0)	0.347257	0.248897	[-0.06, 0.76]	I(0)
Sixth Cholera Pandemic (SCP)					
CO2 Emissions	ARFIMA (2, d, 2)	0.031729	0.724844	[-1.16, 1.22]	I(0), I(1)

⁵ See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

⁶ Note, however, that the AIC and the BIC may not necessarily be the best criteria in applications involving fractional differentiation. See, e.g. Beran (1998).

Land Temp	ARFIMA (0, d, 0)	0.409173	0.118911	[0.21, 0.60]	I(d)
Land Oc Temp	ARFIMA (0, d, 0)	0.547342	0.168255	[0.27, 0.82]	I(d)
North Land Oc Temp	ARFIMA (0, d, 0)	0.532731	0.120291	[0.33, 0.73]	I(d)
South Land Oc Temp	ARFIMA (0, d, 0)	0.546337	0.175783	[0.26, 0.84]	I(d)
Encephalitis Lethargica Pandemic (ELP)					
CO2 Emissions	ARFIMA (2, d, 2)	0.000752	0.379078	[-0.62, 0.62]	I(0)
Land Temp	ARFIMA (0, d, 0)	0.295605	0.132778	[0.08, 0.51]	I(d)
Land Oc Temp	ARFIMA (0, d, 0)	0.162323	0.280178	[-0.42, 0.51]	I(0)
North Land Oc Temp	ARFIMA (0, d, 0)	0.000695	0.000000	N/A	N/A
South Land Oc Temp	ARFIMA (0, d, 0)	0.542281	0.222463	[0.18, 0.91]	I(d)
Spanish Flu					
CO2 Emissions	ARFIMA (2, d, 2)	0.483415	0.194936	[0.16, 0.80]	I(d)
Land Temp	ARFIMA (0, d, 0)	0.122845	0.398497	[-0.53, 0.78]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.521546	0.353553	[-0.06, 1.10]	I(0), I(1)
North Land Oc Temp	ARFIMA (0, d, 0)	0.190815	0.448218	[-0.55, 0.93]	I(0)
South Land Oc Temp	ARFIMA (0, d, 0)	0.677094	0.248314	[0.27, 1.09]	I(1)
Asian Flu					
CO2 Emissions	ARFIMA (2, d, 2)	0.490717	0.570964	[-0.45, 1.43]	I(0), I(1)
Land Temp	ARFIMA (0, d, 0)	0.328255	0.294040	[-0.16, 0.81]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.221126	0.319530	[-0.30, 0.75]	I(0)
North Land Oc Temp	ARFIMA (0, d, 0)	0.264609	0.334664	[-0.29, 0.82]	I(0)
South Land Oc Temp	ARFIMA (0, d, 0)	0.036722	0.280214	[-0.42, 0.50]	I(0)
Hong Kong Flu					
CO2 Emissions	ARFIMA (0, d, 1)	0.391767	0.041207	[0.32, 0.46]	I(d)
Land Temp	ARFIMA (0, d, 0)	0.051361	0.302555	[-0.45, 0.55]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.000982	0.000000	N/A	N/A
North Land Oc Temp	ARFIMA (0, d, 0)	0.000577	0.000000	N/A	N/A
South Land Oc Temp	ARFIMA (0, d, 0)	0.000227	0.000000	N/A	N/A
SARS Pandemic					
CO2 Emissions	ARFIMA (0, d, 0)	1.106565	0.174356	[0.82, 1.39]	I(1)
Land Temp	ARFIMA (0, d, 0)	0.220313	0.276622	[-0.23, 0.68]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.175943	0.281709	[-0.29, 0.64]	I(0)
North Land Oc Temp	ARFIMA (0, d, 0)	0.151330	0.270351	[-0.29, 0.60]	I(0)
South Land Oc Temp	ARFIMA (0, d, 0)	0.000433	0.000000	N/A	N/A
H1N1 Pandemic					
CO2 Emissions	ARFIMA (0, d, 0)	0.597296	0.208375	[0.25, 0.94]	I(d)
Land Temp	ARFIMA (0, d, 0)	0.029406	0.304302	[-0.47, 0.53]	I(0)
Land Oc Temp	ARFIMA (0, d, 0)	0.000989	0.000000	N/A	N/A

North Land Oc Temp	ARFIMA (0, d, 0)	0,001622	0.000000	N/A	N/A
South Land Oc Temp	ARFIMA (0, d, 0)	0,000215	0.000000	N/A	N/A

Table 2. Results of long memory tests. The second column displays the selected model, indicating the orders for the AR and MA dynamics. Column 3 reports the estimates of d while Column 4 the associated standard error. The 95% confidence band is displayed in Column 5, and Column 6 indicate the nature of the process according to the estimated value of d .

Table 2 displays the estimates of the fractional parameter d and the AR and MA terms obtained using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of (p, q) with $p, q \leq 2$, for global annual temperatures (land temperatures, land and ocean temperatures and Northern and Southern hemispheres temperatures) and global annual CO₂ emissions in each pandemic subperiod.

Starting with the CO₂-emissions we see that the values of d range widely between 0.0007 (ELP) TO 1.9997 (GFP), and though the confidence intervals are, in some cases, very wide (clearly due to the small sample sizes in some of the periods examined) we observe that the $I(0)$ hypothesis cannot be rejected in the cases of the Sixth Cholera Pandemia (SCP), the Encephalitis Lethargica Pandemia (ELP), and the Asian Flu (AF), while the $I(1)$ null cannot be rejected for the Global Flu Pandemia (GFP), the Sixth Cholera Pandemia (SCP), the Asian Flu (AF) and the SARS; finally, these two hypotheses are rejected in favour of $I(d, 0 < d < 1)$ behaviour in the cases of Spanish Flu (SF), Hong Kong Flu (HKF) and the HINI Pandemia. Thus, the results here are very heterogeneous across the different periods of pandemics.

Focusing next on the temperatures, all values of d are now in the range (0, 1) implying fractional integration, and the highest values correspond to the Sixth Cholera Pandemia (SCP), with the values of d ranging between 0.4091 (Land Temp.) and 0.5473 (Land Oc. Temp.). In many cases, the $I(0)$ hypothesis cannot be rejected in any single case (GFP, AF, HKF or SARS) but neither for SF in three out of the four temperature series. In general, we observe that the orders of integration are smaller than 1 in all cases

for the temperature series (the only exception is Land Oc. Temp. for the Spanish Flu (SF)), implying mean reversion, with shocks having temporary effects and disappearing by themselves in the long run.

5. Concluding remarks

In this paper we have examined forty time series corresponding to the eight pandemic subsamples (Global Flu Pandemic, Sixth Cholera Pandemic, Encephalitis Lethargica Pandemic, Spanish Flu, Asian Flu, Hong Kong Flu, SARS Pandemic and H1N1 Pandemic) that have been taken place during the last 120 years to understand if these pandemic episodes follow a similar pattern.

Our first focus has been to analyze the statistical properties of these time series using unit roots methods. We started by performing ADF unit root tests and the results of these and other similar methods suggest that the series are nonstationary $I(1)$ while the first differences are stationary $I(0)$.

On the other hand, and in order to be more general, we also estimated the differencing parameter d in terms of a fractional model using an ARFIMA (p, d, q) approach. To select the right model, we combined all the possible (p, d, q) cases, with p and q smaller than or equal to 2 to find the best specification throughout AIC and BIC methods.

Our results indicate that for the CO_2 emissions the results are quite heterogeneous across the different pandemic periods and the intervals are in some cases very wide such that for example, for the Global Flu Pandemic, the $I(1)$ and the $I(2)$ hypotheses cannot be rejected, and for the SCP and AF the same happens for the $I(0)$ and $I(1)$ hypotheses; for SARS only the $I(1)$ cannot be rejected and for ELP, the $I(0)$ one; finally for SF, HKF and HINI, the estimated values of d are constrained between 0 and 1. Thus, only for the last

three subsamples (SF, HKF and HINI) there is some evidence of mean reversion and transitory shocks contrary to what happens in the rest of the cases. For the temperature series, mean reversion occurs in all cases, since all the estimated values of d are strictly smaller than 1, and the highest levels of persistence occur in the case of SCP and SP. For the remaining periods, the $I(0)$ hypothesis is rarely rejected. and thus the recovery of a shock will take place in a shorter period of time. These results are consistent with those presented in Gil-Alana and Monge (2020) where the emissions are found to be $I(1)$ or $I(d)$ with d close to 1 (as in the cases of the Global Flu Pandemic, the Sixth Cholera Pandemic, the Asian Flu and SARS Pandemics), while the temperatures display orders of integration strictly smaller than 1, and thus show mean reverting behaviour. These results suggest that in the event of exogenous shocks, temperatures will recover by themselves unlike what happens with the emissions in the majority of the cases where there is no reversion to the mean and strong actions should be adopted to recover the original long term projections.

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