ANALYZING WATER-RELATED EQUITY INDICES IN TIMES OF COVID-19

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Abstract

The impact of COVID-19 on water-related equity indices is analyzed in this paper for different regions around the world by using fractionally integrated methods and an artificial neural network model. Using fractional integration, a lack of mean reversion is observed in all cases except in the USA, which means that, for these regions, a change in the trend will be permanent after COVID-19 unless additional measures are implemented. At the same time, a structural break is observed in all cases between the 4th and 10th of March 2020, likely due to the drastic lockdown imposed in many if not most countries. Long memory was tested for the post-break period and mean reversion was found not only in North America but also in Europe. Moreover, the results were strongly aligned with those obtained using the neural network model. This suggests that the water-related equity indices and associated levels of investments in water and related utilities have moved back to their pre-Covid-19 levels.

Keywords: Water-related equity indices; COVID-19; ARFIMA model; FCVAR model; machine learning

JEL Classification: C22; C54; E30; Q25

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1. INTRODUCTION

Prior to COVID-19, five major trends had been exerting an impact on the global water sector: 1) global warming causing the increase in extreme floods and droughts; 2) two billion people living in areas facing water stress; 3) the pressure on water resources and ecosystems due to rapid urbanization; 4) the emergence of megacities, which adds the challenge of extending water and sanitation services to roughly one billion people living in informal settlements not served by water grids and finally 5) aging infrastructures.

Access to clean water and suitable sanitation is crucial and has become of special relevance nowadays due to the coronavirus disease 2019 (COVID-19) which has been affecting the entire globe since December 2019 (Platto et al., 2021). Indeed, the World Health Organization (WHO) warned that the supply of safe water and the existence of hygienic conditions are key factors in ensuring proper health conditions and in tackling the spread of COVID-19 (WHO, April, May 2020). Nevertheless, the rapid spread of this pandemic brought about the implementation of lockdown procedures in many countries around the world (Lau et al., 2020; Roux et al., 2020).

The outbreak of COVID-19 caused many large users of water to downscale or reduce their activities. This in turn led to various situations such as: 1) a decrease in industrial demand; 2) the world's poorest suffering the greatest deficits in urban water and sanitation services; and 3) several countries imposing sanitary measures to contain the virus thereby affecting revenues and triggering a decline in capital expenditures in the short to medium term.

These drastic measures have exacerbated still further the poor living and health situation of millions of people, especially in developing countries, and have led to severe negative effects in various fields, such as those relating to finance and the economy (Cicala, 2020), environment (Chakraborty and Amity, 2020), individual mental health

(Yao et al., 2020), among others. Therefore, the pandemic is not just a health issue and all these factors should be taken into account in the response and recovery phases of COVID-19 (Neal, 2020). Given this panorama, there is an opportunity for the water sector to undertake an active leadership role. Sivakumar (2020) has recently reported the impact of COVID-19 on water planning and management due to the increase in water demand and lower water quality caused by the attempts to control the spread of the pandemic. Hence, there is a critical need for interdisciplinary research collaboration in order to address new water planning strategies. Several studies have examined the impact of COVID-19 from different points of view, such as how population flows drive the distribution of COVID-19 (Jia, 2020); the effects of travel restrictions on the COVID-19 spread (Chin Azzi et al., 2020); how the spread of COVID-19 and climate factors can be linked (Bashir et al., 2020; Wu et al., 2020) and how the environment, and in particular, surface water quality and air quality can be affected by the lockdown (Almond et al., 2020; Brodeur et al., 2021; Dang and Trinh, 2021; He et al., 2020; Mahat et al., 2020; Muhammad et al., 2020; Yunus et al., 2020). There are also a variety of methodological approaches to analyse the COVID-19 impact including, difference-in-difference models (He et al., 2020; Brodeur et al., 2021, and Almond et al., 2020), Regression Discontinuity Design (RDD) approach (Dang and Trinh, 2021), a generalized additive model (GAM) (Wu et al., 2020), among others. However, to the extent of our knowledge, the literature to be found regarding the effect of COVID-19 on water-related indices or prices is rather scant. Previous to this pandemic, the time trends, persistence and seasonality were analyzed by Monge and Gil-Alana (2020) by using a unified treatment based on long memory and fractional integration in water-related series for different regions all over the world (Asian Pacific and Russia, Europe, the United States, Latin America). As a continuation of that work, the goal of the present paper is to analyse how COVID-19 affects the water-related equity indices in the same regions studied in that work. Unlike that previous work in this one we take into account the Covid-19 pandemic along with other methodological differences such as the analysis of unit roots, the ARFIMA model of Sowell (1992), the FCVAR model of Johansen and Nielsen (2010, 2012) and the analysis of the subsamples based on the break due to Covid-19. In addition, the results were supported by an Artificial Neural Network (ANN) model using a Multilayer Perceptron (MLP) neural network for time series prediction.

The fractional integration method allows us determine the nature of exogenous shocks by simply looking at the past history of the data. Thus, if the order of integration of the series is lower than 1, shocks will have a transitory nature and the lower the value of the differencing parameter is, the faster the reversion to the mean will be. On the other hand, if the order of integration is equal to or higher than 1, shocks are expected to have permanent effects, producing a change in the long-term projection of the series.

We have examined the time series properties of water-related equity indices from December 2, 2019 until February 5, 2021 using daily data. One of the interesting results is that using ARFIMA models, we observe lack of mean reversion in all cases except in the US, which means that, for these countries a change in the trend after the COVID-19 pandemic will have a permanent effect unless drastic measures are carried out by the national authorities. On the other hand, a structural break is observed between the 4th and 10th of March 2020 by using Bai and Perron’s (2003) method due, most likely, to the drastic lockdown enforced by the pandemic in many countries. Interestingly, using long memory methods again after this structural break, it was observed that in Europe and the US, in contrast to the other regions, the trends revert back to the original without the need for additional measures. Also, good agreement was observed between the results using an Artificial Neural Network model and those using ARFIMA models, corroborating the results obtained with fractional integration.

The rest of the paper is structured as follows. The next section briefly reviews the literature on the effects of COVID-19 on water and water-related series as well as the situation before this pandemic. In the following section we provide the data source and the methodology applied in the paper. Section 4 shows the main empirical results, while the final section presents the main conclusions of this work.

2. LITERATURE REVIEW

COVID-19 is the name of the disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). According to the World Health Organization (WHO) COVID-19 was first identified in December 2019 in Wuhan, China, subsequently it was declared a Public Health Emergency of International Concern on January 30, 2020, and eventually a pandemic on March 11, 2020 (World Health Organization 2020). Water management plays a key role in the efforts to control this pandemic being the basis for hand hygiene and access to safe water, including water disinfection and sanitary treatment (WHO, April, May, 2020). However, the scarcity of drinking water and the absence of proper hygiene practices were the main concerns for cities, especially in slum areas and refugee camps. Limited access to safe water is not just a problem in developing countries but it also has a global effect and this has been exacerbated under the current pandemic. For instance, at least two million people in the United States still have no access to piped water (Tostada and Biswas, 2020).

Previous to COVID-19, it had already been reported that rapid industrialization, pollution, the increasing demand of water for agriculture, and the growth of the world population might bring about further scarcity of water supply which was fit for human consumption (see, e.g., Just et al., 1983; Renetta, 2002, 2015; Shearling et al., 2006; House-Peters and Chang, 2011; Barenblat et al., 2014 and Smith and Zhao, 2015 among many others).

COVID-19 has changed people's habits and lifestyles with regard to the demand for water, with subsequent implications for water management issues. In this vein, Wiener (2020) analyzed daily consumption patterns in Karlsruhe (Germany) during the month of March 2020, revealing an anomalous change in the regime of outflows before and during the adopted restrictive measures (Wiener, 2020). In particular, they observed that water consumption was distributed more gradually in the mornings after lockdown in comparison to a rapid fall around 8:00 am at the beginning of March 2020. In order to extend this local study to a wider range, Balco et al. (2020) analyzed how the change in activities influenced the demand for water in five Apulian towns (Italy) during lockdown. They observed that a two hour delay in waking up (about 10.00 a.m.) directly affected the water demand, starting from this time and continuing smoothly until 14.00–15.00. Hence, the classic peak in water demand corresponding to lunchtime was no longer evident, which is in good agreement with the results from Wiener (2020). On the other hand, the water demand pattern was unchanged during the evening and night time, or it even fell, as was the case of bigger towns, which could be due to the total absence of commuters during lockdown (Balco et al., 2020). Therefore, the results of this study highlight how user habits are one of the dominant factors in drinking water consumption trends. Therefore, the prediction of consumption peaks remains a complex task, characterized by both deterministic trends and stochastic random variability.

In order to delve deeper in this matter, we focus in this paper on water-related equity indices, as this is a factor that can balance water supply and demand, and we use fractionally integrated methods and an artificial neural network model to analyse the impact of the Covid-19 pandemic on the data, as described in the methodology section. Numerous water pricing systems and related structure services can be found around the world (Rogers et al., 2002; Carvalho et al., 2012). According to Hoque and Wichern's research (2013), one of the reasons behind this fact is the arbitrariness in price-setting strategies due to faulty rate-setting practices. Recently, Grafton et al. (2020) proposed a systematic procedure for water pricing in order to manage water pricing reforms. It requires, at least the following: (i) scoping, in order to identify stakeholders, to understand the status quo, to identify possible risks, consequences, and options; (ii) risk and options assessment, in order to assess different options, including stress testing and decision making; and (iii) monitoring and implementation, in order to monitor, revise and consult.

The behavior of water equity indices and other water-related series has been analyzed from different points of view in recent decades. Some authors, such as Worthington and Hoffman (2008) and Monteiro and Rosetta-Palma (2011) analyzed the impact of water tariffs on customers. Other authors focused on water price elasticity (Espy et al., 1997; Dalhousie et al., 2003; Marzano et al., 2018). Espy et al. (1997) evaluated the price elasticity of water demand by using meta-regression analysis (MRA). Dalhousie et al. (2003) studied income elasticities, and Sabri (2014) focused on household size elasticity. Krause et al. (2003) analyzed the elasticity and scarcity in water from a residential and local point of view, showing that price elasticity is very sensitive to water scarcity. Other authors such as Dinar and Schwabe (2015) focused on water policy and proposed a pricing mechanism for implementing optimal water policy in the frame of the water economy. Other studies include all environmental externalities in relation to water allocation policy within the regulatory mechanism, such as the National Research Council (2005), and the Millennium Ecosystem Assessment (2005), including the references therein.

Most recently, Monge and Gil-Alana (2020) have studied the time series properties and possible structural breaks in the water equity indices in different regions around the world by using fractional integration methods. An interesting conclusion reached in this work is that the series are highly persistent, meaning that after an unexpected rise, the series will take a very long time to recover by themselves, therefore the original levels/trends in the data will not be recovered unless robust policy measures are adopted. In the present work we extend that analysis to include the Covid-19 period and we use additional methods.

3. DATA AND METHODOLOGY

The data examined in this research paper, obtained from the Thomson Reuters Eikon database, corresponds to Refinitiv Water & Related Utilities Indices[1]. These indices are equity indices that provide liquid and tradable exposure for companies (between 30-50 companies) from different regions (Global, Europe, the United States, Latin America, Asia, Pacific and Russia) involved in water usage and stewardship (water purification, water utilities and infrastructure, and water equipment and materials).

According to Refinitiv, who provided us with the database[2], the indices are formed by shares of investee companies with sites located in areas of high-water stress, with no water management initiatives, without sustainable ocean/sea practices or policies, among other features. Also, these indices take into account: 1) the water usage through the average amount of water consumed and reclaimed by the investee companies (in cubic meters) per million euros of revenue of investee companies. 2) The untreated discharged waste water through the total amount in cubic meters of untreated waste water discharged by the investee companies expressed as a weighted average. 3) The water recycled and

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[1] Data are available from the authors upon request.

[2] https://eikon.thomsonreuters.com/index.html

reused through the weighted average percentage of water recycled and reused by investee companies, and 4) The water emissions through the weight in tonnes of water emissions generated by investee companies per million of currency invested, expressed as a weighted average.

Following Grossman (1976; 1978), Kyle (1985), Vives (1995a, b), Amador and Weill (2012), Berardi (2021), among others, we use these indices formed by aggregate average prices because they can provide perfect aggregate information and act as a substitute for private information in markets.

As mentioned before according to Hui et al. (2020) and the World Health Organization (WHO), the virus known as COVID-19 was identified in Wuhan City, China, in December 2019. We use daily prices from December 2, 2019 until February 5, 2021.

The water-related equity indices across the different regions (Global, Europe, the United States, Latin America, Asia, Pacific and Russia), and which are determined by the use and stewardship of water, are represented in Figure 1. In each of the regions analyzed, the same behavior can be seen due to the restrictions and policies imposed by the different governments to deal with the pandemic, which affected price behavior between the first and second quarters of 2020.

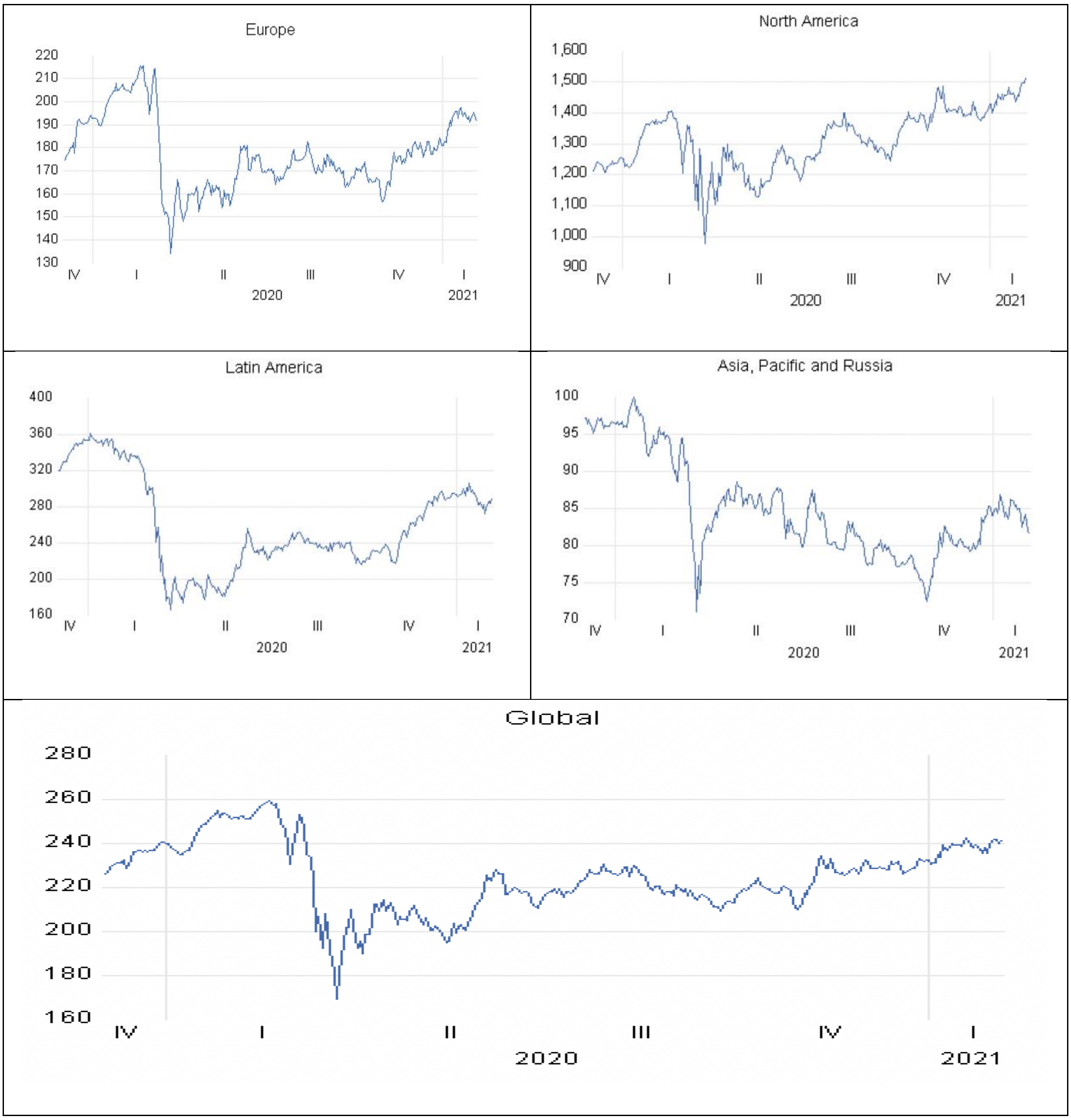
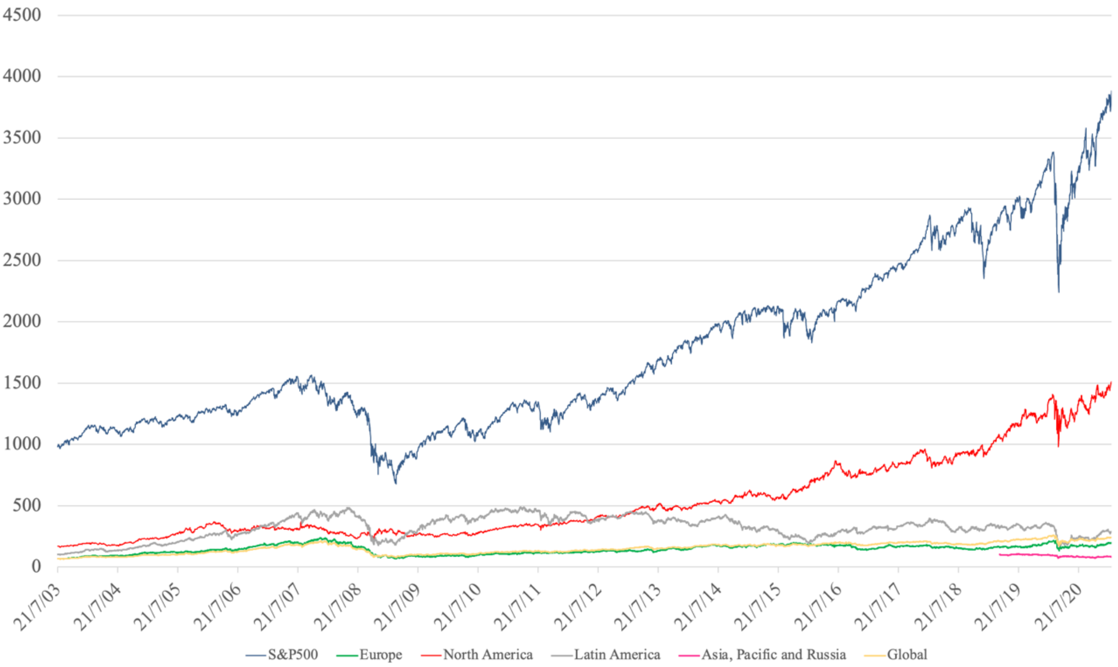


Figure 1. Time series plots of water-related equity indices

Data source: Refinitiv Water and Utilities (from Thomson Reuters Eikon). The X axis of each graph refers to the period analyzed for each region that stretches from December 2, 2019 to February 5, 2021. The Y axis indicates the daily closing price of each of the indices listed in the financial markets.

On the other hand, and focusing on the comparison between the water equity indices of each region against the S&P 500 stock index, and taking the whole period mentioned before into account, we observe in Figure 2 that the water indices for the case of North America follow a similar trend with the stock index, while the rest of the regions apparently do not.

Figure 2: S&P stock market prices and water-related equity indices



We use techniques based on unit roots, fractional integration and fractional cointegration. The reason for using these techniques stems from the fact that we want to examine if the statistical properties of the data have changed with the eruption of the Covid-19 pandemic. In fact, by means of using first unit root methods, we can determine if exogenous shocks in the data have transitory or permanent effects depending on whether the series are stationary I (0) or nonstationary I (1). Then, we use fractional integration due to the greater flexibility it allows in the specification of the models, based on the fractional nature of the number for the order of integration. This allows us, for example, to consider nonstationary though mean reverting processes if the order of integration is in the range [0.5, 1). Fractional cointegration is used to examine long run co-movements in the data from a fractional viewpoint.

4.1. Unit roots

To analyse the stationarity of our dataset we employ ADF unit root tests established by Fuller (1976) and Dickey and Fuller (1979). Non-parametric estimates of the spectral density of u_t at the zero frequency have also been used following the methodology proposed by Phillips (1987) and Phillips and Perron (1988). Finally, the unit root tests proposed by Kwiatkowski et al. (1992), Elliot, Rothenberg and Stock (1996) and Ng and Perron (2001) have been used to take into account their deterministic trends. We conclude that all the tests produced the same results.

4.2. ARFIMA (p, d, q) model

The non-stationary nature of numerous financial and economic time series is an important characteristic that can be described by several models. The standard approaches used until the 1980s were to apply deterministic functions of time where the residuals on the regression model were I(0) stationary. With the research carried out by Nelson and Plosser (1982) there was a consensus that the non-stationary component of most series was stochastic and the use of unit roots or first differences I(1) was the route to take. However, to achieve stationarity I(0), the number of differences does not necessarily have to be an integer value, since it can be any point on the real line and therefore a fractional value.

Observations that are far apart in time but highly correlated is a feature of long memory which is able to be captured by the I(d) models. The form of this model is:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

where x_t represents a time series, d represents any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and the covariance stationary I(0) process is represented by u_t where the spectral density function, that is positive and finite at the zero frequency, might display a type of time dependence in the weak form. For this reason, we can state if u_t is ARMA (p, q), x_t is ARFIMA (p, d, q). From equation (1), the polynomial $(1 - L)^d$ is expressed in terms of a binomial expansion where for all real d, x_t depends not only on a finite number of past observations but also on the whole of its history. Thus, a higher value of d implies a higher level of association between the observations of the series. Given the parameterization in (1), one can differentiate between various cases depending on the value of the parameter d, and several specifications based on (1) can be noted. Thus, if $d < 0$, x_t is said to be anti-persistent, with the series exhibiting zero spectral density at the origin (Dittmann and Granger, 2002) and switching signs more frequently than a random process. The process is short memory or I(0) when $d = 0$ in (1). This occurs because $x_t = u_t$. Long memory or long range dependence ($d > 0$) is the name given when there is a high degree of association over a long time. With this last assumption, the process is still covariance stationary if $d < 0.5$ because the infinite sum of the autocovariances is still finite. Our interpretation of this can also be related to the issue of mean reversion. If the series reverts to the mean, shocks will be transitory and this happens when d is smaller than 1. In contrast to the above, shocks are expected to be permanent when $d \geq 1$. Following the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979) we choose the most appropriate ARFIMA model. Also, we present our results following the maximum likelihood process suggested by Sowell (1992) instead of using other procedures (Geweke and Porter-Hudak, 1983; Phillips, 1999; 2007; Robinson, 1994;1995a,b; etc.) that usually produce very similar results.

4.3 FCVAR model

The Fractionally Cointegrated Vector AutoRegressive (FCVAR) model is a generalization of Johansen's (1996) Cointegrated Vector AutoRegressive (CVAR) model to allow for fractional processes of order d that co-integrate to order $d-b$ with $b>0$. The FCVAR model was introduced by Johansen (2008) and developed by Johansen and Nielsen (2010; 2012). The advantage of this model is the ability to use stationary and non-stationary time series.

To introduce the FCVAR model, we present first the non-fractional CVAR model. With Y_t, $t=1,\dots,T$ being a p-dimensional I(1) time series, the CVAR model is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L^i Y_t + \varepsilon_t. \qquad (2)$$

where Δ^b and $L_b = 1 - \Delta^b$ represent the difference and the lag operator. These are utilized to derive the FCVAR model. We then find:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L_b^i Y_t + \varepsilon_t, \qquad (3)$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \, \Delta^b L_b^i Y_t + \varepsilon_t, \qquad (4)$$

where, ε_t is p-dimensional independent and identically distributed with mean zero, and variance-covariance matrix Ω. The parameters α and β are $p \times r$ matrices, where $0 \leq r \leq p$. In matrix β the columns are the cointegrating relationships and $\beta' X_t$ are the stationary combination, i.e., the long-run equilibrium, which is integrated to order d, and the short-run parts from the long-term equilibrium are integrated to order $d-b$. The coefficients in α correspond to the velocity of adjustment unto equilibrium. Hence, $\alpha\beta'$ is the adjustment long-term and Γ_i represents the short-run behavior of the variables.

Compared with the CVAR model, there are two other parameters in the FCVAR model. The order of fractional integration of the observable time series is represented by the parameter d. The degree of fractional cointegration, that is, the reduction in fractional integration order of $\beta' X_t$ compared to X_t itself, is represented by the parameter b.

The relevant ranges for b are $(0, \frac{1}{2})$, in which case the equilibrium errors are fractional of order greater than $1/2$ and hence non-stationary although mean-reverting, and $(\frac{1}{2}, 1]$, in which case the equilibrium errors are fractional of the order less than $1/2$ and are stationary (Dolatabadi et al., 2015). Note that for $d = b = 1$, the FCVAR models is reduced to the CVAR model, which is therefore nested in the FCVAR model as a special case.

As an intermediate step toward the final model, we consider a version of model (3) with d = b as an assumption of no persistence in the cointegration vectors and a constant mean term for the cointegration relations. That is to say:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d \, {L_d}^i X_t + \varepsilon_t. \tag{5}$$

The simple model considered is the following:

$$\Delta^d (X_t - \mu) = L_d \alpha \beta' (X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^d \, {L_d}^i X_t + \varepsilon_t, \tag{6}$$

where μ represents the level parameter that shifts each of the series by a constant to avoid the bias related to the starting values in the sample. $\beta' \mu = -\rho'$ represents the mean stationary cointegrating relations.

The asymptotic analysis in Johansen and Nielsen (2012) shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \ldots, \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$. Several empirical papers such as Baruník and Dvořáková, 2015; Maciel, 2017; Aye et al., 2017; Dolatabadi et al., 2018; Jones, Nielsen and Popiel, 2014; Gil-Alana and Carcel, 2020; Poza and Monge, 2020; Monge and Gil-Alana, 2021a,b.; Monge, 2022; among others have used FCVAR models.

The MATLAB codes for the FCVAR model estimation are provided in Nielsen and Popiel (2018).

5. EMPIRICAL RESULTS

5.1 Unit roots

We employed three standard unit root/stationarity tests (the Augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test) to analyze the statistical properties of the water-related indices for the World, Europe, United States, Latin America and Asia, Pacific and Russia. The results, displayed in Table 1 suggest that the selected time series are all non-stationary I(1). Performing the analysis on the first differences we observe that the series are all stationary I(0). This is to be expected, noting that the above methods only consider integer degrees of differentiation, i.e., 0 for stationary series and 1 for nonstationary ones. Thus, in what follows, we permit more flexibility in the dynamic specification of the model by allowing fractional differentiation throughout the previously described ARFIMA approach.

Table 1. Unit root tests results

	ADF			**PP**			**KPSS**	
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(ii)	(iii)
				Original Data				
Europe	0.0586	-2.4172	-2.3970	0.1025	2.0988	-2.0753	0.3305*	0.2624
North America	0.7237	-1.2856	-2.2183	0.8228	-2.0671	-3.2055	1.1836	0.2454

Latin America	-0.5307	-1.3025	-0.9791	-0.5189	-1.4958	-1.1922	0.4521*	0.3626
Asia, Pacific and Russia	-0.8867	-2.1025	-2.3110	-0.8276	-2.2353	-2.6251	1.4182	0.3208
Global	0.0596	-1.8144	-1.7601	0.0781	-2.1583	-2.1234	0.2821*	0.2712
First differences								
Europe	-15.2347*	-15.2133*	-15.1941*	-15.2152*	-15.1936*	-15.1743*	0.0849*	0.0651*
North America	-12.0780*	-12.0988*	-12.1003*	21.7325*	-22.0709*	-22.2638*	0.0816*	0.0482*
Latin America	-10.9587*	-10.9466*	-11.0484*	-19.5759*	-19.5526*	-19.5087*	0.2485*	0.0826*
Asia, Pacific and Russia	-7.9653*	-17.9348*	-17.9366*	-18.0111*	-18.0096*	-18.0163*	0.0721*	0.0217*
Global	-10.4554*	-10.4401*	-10.4465*	-17.1063*	-17.0807*	-17.0646*	0.0798*	0.0489*

*(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. * Denotes a statistic significant at the 5% level. For ADF and PP, the 5% critical value with T=310 is -1.9418 for no deterministic components; -2.8707 with an intercept; -3.4245 with a linear time trend. For KPSS, the 5% critical value with T=310 is 0.4630 with an intercept component; 0.1460 with a linear time trend.*

5.2 Fractional integration

Due to the low power of the unit root methods under fractional alternatives (Diebold and Rudebusch, 1991, Hassler and Wolters, 1994, and Lee and Schmidt, 1996), we also employ fractionally integrated methods, and use ARFIMA (p, d, q) models to study the persistence of the water indices in different regions and throughout the world. The Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) are used to select the appropriate AR and MA orders in the models. A point of caution should be adopted here since the AIC and BIC may not necessarily be the best criteria for applications involving fractional models (Hosking, 1981; Beran et al., 1998).

Table 2 displays the estimates of the fractional differencing parameter d and the AR and MA terms, using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of p, q ≤ 2, for each time series.

Table 2. Results of long memory tests

Long memory test						
Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
Europe	310	ARFIMA (2, d, 2)	0.8589472	0.1716683	[0.57, 1.14]	I(1)
North America	310	ARFIMA (1, d, 1)	0.8836099	0.0658179	[0.78, 0.99]*	I(d)
Latin America	310	ARFIMA (2, d, 2)	0.8392252	0.4346263	[0.12, 1.55]	I(1)
Asia, Pacific and Russia	310	ARFIMA (1, d, 1)	1.0875727	0.0845577	[0.95, 1.23]	I(1)
Global	310	ARFIMA (1, d, 1)	1.0944927	0.0693758	[0.98, 1.21]	I(1)

*: Statistical evidence of mean reversion ($d < 1$) at the 5% level.

We observe from Table 2 that the estimates of d are in all cases very close to 1, ranging from 0.83 (Latin America) to 1.09 (Global); in the case of Europe, North America and Latin America, the value of d is below 1 for the three time series, though mean reversion is only observed in the case of the US since for the other two series along with Asia, Pacific and Russia and the Global series the unit root null hypothesis cannot be rejected, which is consistent with the unit root results reported in the previous section.[3] Thus, for all except the North American data, shocks are expected to be permanent, causing a change in trend and thus, strong measures will be required by the authorities to recover the original trends. The result obtained for North America is very interesting since

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[3] Note that from all regions except North America, the 95% confidence intervals include the value of 1, implying the non-rejection of the null hypothesis of a unit root.

the United States is the only country in the industrialized world without a regulatory system, such as Ofwat in the United Kingdom, responsible for monitoring rates and performance.

5.3 FCVAR model ($d \neq b$)

Next, the FCVAR model proposed by Johansen and Nielsen (2012), where the fractional integration and the classical CVAR model join is used in order to test the possible existence of persistence in the long run co-movements of the series. Table 3 summarizes the results of the FCVAR model.

Table 3: Results of the FCVAR model

	d	**b**
Panel I: Water-related equity indices in Europe, North America, Latin America, Asia, Pacific and Russia and Global	$d = 1.016$ (0.033)	$b = 1.016$ (0.000)
Panel II: Water-related equity indices in Europe, North America, Latin America, Asia, Pacific and Russia	$d = 0.724$ (0.173)	$b = 0.724$ (0.153)

We follow the indications suggested by Jones, Nielsen and Popiel (2018) concerning the lag value (k = 3). Also, we consider deterministic components and cointegration rank (r) to get our results. We observe from Table 3, Panel I (where the global water index is included) that the order of integration of the individual series is about 1.016, while the reduction in the degree of integration in the cointegrating regression is of exactly the same magnitude, 1.016; in fact, it seems to support the hypothesis of cointegration in its classical way with 1 and 0 as the orders of integration for the parent series and the equilibrium relationship respectively. In Table 3, Panel II (in which the global water series are not included), we observe that the order of integration of the individual series is about 0.724, while the reduction in the degree of integration in the cointegrating regression is again of exactly the same magnitude, 0.724, which indicates once more that the order of integration $(d - b) = 0$, implying I(0) cointegrating errors. Thus, according to these results there exists a long run equilibrium relationship between the water-related equity indices around the world.

5.4 Structural breaks

In order to verify if COVID-19 has caused a structural change since its appearance in December 2019, we use Perron and Vogelsan (1992) and Bai and Perron (2003) approaches for detecting breaks in the data. The break dates, for the daily case are reported in Table 4. We observe that the break dates take place between March 4 and March 11 in 2020 in all series, the time of the start of worldwide restrictions in the wake of the Covid-19 pandemic.

Table 4: Structural breaks

Time Series	Structural break dates at significance level 5%
Thomson Reuters Europe Water & Related Utilities	March 10, 2020
Thomson Reuters United States Water & Related Utilities	March 10, 2020

Thomson Reuters Latin America Water & Related Utilities	March 04, 2020
Thomson Reuters Asia Pacific & Russia Water & Related Utilities	March 11, 2020
Thomson Reuters Global Water & Related Utilities	March 10, 2020

Next, we perform the ARFIMA (p, d, q) model before and after these structural changes. The results are presented in Table 5.

Table 5. Results of long memory tests for Structural breaks

Long memory test						
Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
Before the structural break						
Europe	72	ARFIMA (1, d, 2)	0.555143	0.325576	[0.02, 1.09]	I(1)
North America	72	ARFIMA (1, d, 1)	0.376036	0.475184	[-0.41, 1.16]	I(0), I(1)
Latin America	68	ARFIMA (1, d, 2)	1.224315	0.270315	[0.78, 1.67]	I(1)
Asia, Pacific and Russia	73	ARFIMA (0, d, 0)	1.1079674	0.1305756	[0.89, 1.32]	I(1)
Global	72	ARFIMA (2, d, 1)	0.7773011	0.2236962	[0.41, 1.14]	I(1)
After the structural break						
Europe	238	ARFIMA (2, d, 2)	0.5553656	0.2425283	[0.16, 0.95]	I(d)
North America	238	ARFIMA (1, d, 1)	0.7884243	0.0767203	[0.66, 0.92]	I(d)

Latin America	242	ARFIMA (2, d, 2)	1.0749852	0.1982927	[0.75, 1.40]	I(1)
Asia, Pacific and Russia	237	ARFIMA (1, d, 1)	1.0768235	0.1192057	[0.88, 1.27]	I(1)
Global	238	ARFIMA (1, d, 1)	0.99275982	0.08955445	[0.84, 1.14]	I(1)

Looking at the results prior to the structural break (upper panel) we observe that though there is considerable heterogeneity for the values of d across the series, the confidence intervals are wide and the unit root null hypothesis cannot be rejected in any single case. However, focusing on the results after the structural break caused by COVID-19 we see that two regions, Europe and North America, have a mean reverting behavior

indicating that it will not be necessary to take such strong additional measures since the series will return by themselves to their long term projections. In the remaining regions (Latin America, Asia, Pacific and Russia) and worldwide, strong policy measures should be adopted to recover the original levels/trends in the data, since otherwise the series will not recover by themselves even in the long run. [4]

Based on the results obtained up to this point and in order to add further accuracy and rigor to this study, we have also used advanced computational intelligence techniques based on machine learning to forecast the water-related indices in the five regions listed above.

We use a Multilayer Perceptron (MLP) neural network for time series prediction. This methodology presents interesting features such as its nonlinearity or the lack of an

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[4] Note that the existence of mean reversion in these two cases (Europe and North America) during the Covid-period but not before is related with the wide confidence intervals obtained with the first subsample data, which are (0.02, 1.49) for Europe and even wider (-0.02, 1.16) for North America. Thus, mean reversion might also take place during the first subsample in both cases.

underlying model (non-parametric) to obtain the results. Also, the MLP neural network is one of the most widely implemented neural networks based on the back-propagation rule where the errors are propagated through the network, and allows the adaption of the hidden processing elements. In addition, the MLP has massive interconnectivity that means that any element of a given layer feeds all the elements of the next layer and it is trained with error correction learning.

To find out which is the most robust prediction model and following Mapuwei et al. (2020), we use the Mean Squared Error (MSE) and Root Mean Square Error (RSME) as criteria for the prediction.

In Table 6 we present the accuracy of the time series using an Artificial Neural Network (ANN) model. The results obtained in both cases are in line with the literature, which states that the most prominent machine learning technique used in time series forecasting is the Artificial Neural Networks, obtaining values very close to zero and indicating that this is the best model with which to predict the time series under examination.

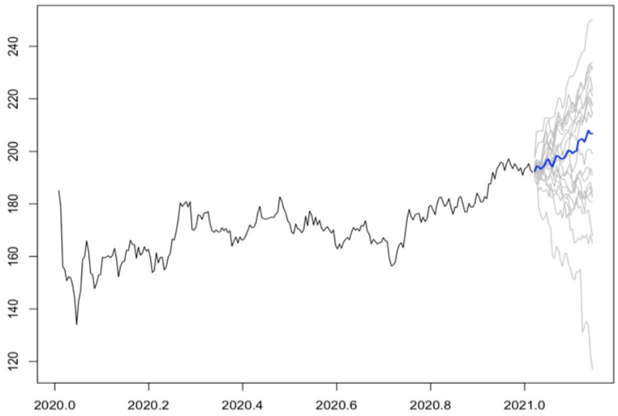
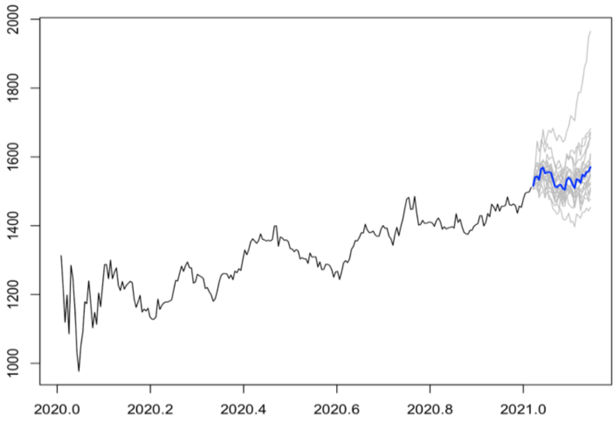
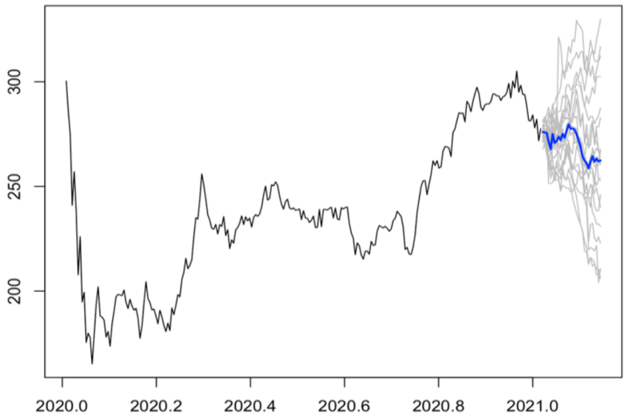
Table 6: Forecast accuracy of the time series of water-related equity indices after structural break using the ANN model

	RMSE of the ANN model	**MSE of the ANN model**
Europe	0.062	0.0039
North America	0.024	0.0006
Latin America	0.057	0.0033
Asia, Pacific and Russia	0.038	0.0015

Global	0.041	0.0017

Finally, to corroborate the behavior of water indices in the different regions (and based on the fractional differencing parameter d), we plot the series in Figure 2. In the charts, the black line represents the original time series and the prediction for the next 30 periods are represented in blue.

Figure 2. Forecast after the structural break in water-related equity indices

<table>
<tr><th>Forecast for Europe</th><th>Forecast for North America</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><th>Forecast for Latin America</th><th>Forecast for Asia, Pacific and Russia</th></tr>
<tr><td>
</td><td>
</td></tr>
<tr><th colspan="2">Global</th></tr>
</table>

In the fifth estimation we appreciate that the behavior obtained using the MLP neural network is in line with the results obtained using the ARFIMA model, where we observe that the series related with water indices in Europe and North America return by themselves to their long term projection. However, the same does not happen with the rest of the time series.

6. Concluding remarks

Following the research line started by Monge and Gil-Alana (2020), we have analyzed in this paper the behavior of water-related equity indices in different regions, all over the world, during the period of COVID-19 using indices provided by the Thomson Reuters Eikon Database. It is worth noting that data we have used are equity indices that encompass the entire water process until it reaches the final consumers, through the performance of the listed companies. Thus, these data can be used to compare the behavior of water-related indices between different countries along a period of time. To this purpose, we have applied methodologies based on unit roots, fractional integration and fractional cointegration along with structural break issues and ANN methods to analyze the time series properties in the long run.

Analyzing the long run behavior of water-related equity indices in the United States, Latin America, Europe, Asia, Pacific and Russia and globally, we observe that for all of them except the North American data, there is lack of mean reversion and shocks are expected to be permanent, causing a change in trend. Focusing on the cointegration analysis, we see that cointegration holds, finding evidence of an I(0) long run equilibrium relationship between the series.

Applying methodologies based on structural breaks (Perron and Vogelsan, 1992, and Bai and Perron, 2003) we find that a structural break occurs between March 04, 2020 and March 11, 2020, coinciding with the worldwide restrictions caused by the pandemic episode.

Having identified the structural break, we apply again ARFIMA (p, d, q) models to study the behavior of water equity indices before and after the breaks caused by COVID-19. We conclude that the series in Europe and North America will return by themselves to their long-term projections. For the rest of the regions, i.e., Latin America, Asia, Pacific and Russia and worldwide) there is no mean reversion and strong policy measures should be adopted to recover the original levels/trends, as otherwise the series will not return by themselves to their long run projections. According to the results, in the case of a negative shock in Europe and North America, the series will recover by themselves faster than the remaining areas.

Finally, to make the study more accurate and rigorous, based on the results obtained from fractional integration after the structural break, we also used advanced computational intelligence techniques based on machine learning to forecast the water-related series in the aforementioned five regions. We conclude that the results obtained using Artificial Neural Networks are in line with the results obtained using the ARFIMA model.

In line with the research done by Tsur et al. (2004), similar water pricing policies may have different impacts under different conditions, as we show for the cases of Europe and North America with respect to the rest of areas under examination. In fact, some items such as the volume of water used (i.e., volumetric), the size of the irrigated or cultivated area (i.e., per-area charges), the different forms of water markets (Dinar and Subramanian 1998), among others, affect water pricing policies. Thus, the features of each country and its geo-political-location can directly affect the results of the pricing policies applied. Moreover, these methods may also differ in the way they are implemented, and the information on which they are based. They may even differ in the efficiency performance of their outcomes and cost of implementation (Tsur and Dinar 1997). However, there is no unique superior pricing method and much depends on the situation under consideration. For example, when applying water pricing policies in developing countries, it could be taken into account, for instance, that irrigated agriculture consumes between 75% and 90% of all water used and contributes to about 38% of the world's food (FAO, 2010). On the other hand, most US water and wastewater systems depend entirely on power supplied by the electric grid (Sowby and Burian, 2017). Also, the mitigation of the COVID-19 pandemic by means of achieving good hygienic practices may have been challenging, especially in places where freshwater sources are scarce (Sustainability Times, 2020). Thus, identifying the conditions that are appropriate for each pricing method is a key factor when selecting the method to be used. In fact, the behavior of water-related series will depend to a large extent on the capacity of each region to adapt to the needs of the population and the availability of appropriate technologies. Other issues such as the presence of non-linearities in the data, still within the context of long memory processes will be examined in future papers.

References

Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. Biometrika, 60(2), 255-265.

Akaike, H. (1979). A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. Biometrika, 66(2), 237-242.

Almond, D., Du, X., Zhang, S. (2020). Did COVID-19 Improve Air Quality Near Hubei? National Bureau of Economic Research, No. W27086.

Amador, M., & Weill, P. O. (2012). Learning from private and public observations of others' actions. Journal of Economic Theory, 147(3), 910-940.

Asci, S., Borisova, T. & Dukes, M. (2017). Are price strategies effective in managing demand of high residential water users? Applied Economics 49(1), 66–77.

Aye, G. C., Carcel, H., Gil-Alana, L. A. and Gupta, R. (2017). Does gold act as a hedge against inflation in the UK? Evidence from a fractional cointegration approach over 1257 to 2016. Resources Policy, 54, 53-57.

Baerenklau, K. A., Schwabe, K. A. and Dinar, A. (2014). The residential water demand effect of increasing block rate water budgets. Land Economics 90(4), 683–699.

Bai, J., and P. Perron, 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18, 1–22.

Balacco, G., Totaro, V., Iacobellis, V., Manni, A., Spagnoletta, M. and Piccinni A.F. (2020). Influence of COVID-19 spread on water drinking demand: The case of Puglia region (Southern Italy). Sustainability 12, 5919.

Baruník, J. and Dvořáková, S. (2015). An empirical model of fractionally cointegrated daily high and low stock market prices. Economic Modelling, 45, 193-206.

Bashir, M. F., Ma, B., Bilal, Komal, B., Bashir, M.A., Tan, D., Bashir, M. (2020). Correlation between climate indicators and COVID-19 pandemic in New York, USA. Science of The Total Environment 728, 138835.

Beecher, J. and Gould, T. (2018). Pricing wastewater to save water: are theory and practice transferable? Utilities Policy 52, 81–87.

Beran, J. Bhansali, R. and Ocker, D (1998), On unified model selection for stationary and nonstationary short- and long-memory autoregressive processes, Biometrica 85, 4, 921-934.

Berardi, M. (2021). Learning from prices: information aggregation and accumulation in an asset market. Annals of Finance, 17(1), 45-77.

Brodeur, A., Cook, N., Wright, T., 2021. On the Effects of COVID-19 Safer-At-Home Policies on Social Distancing, Car Crashes and Pollution. Journal of Environmental Economics and Management, 109, 102506.

Carvalho, P., Marques, R. C. and Berg, S. (2012). A meta-regression analysis of benchmarking studies on water utilities market structure. Utilities Policy 21, 40–49.

Chakraborty, I. and Maity, P. (2020). COVID-19 outbreak: Migration, effects on society, global environment and prevention. Sci. Total Environ. 728, 138882.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Y Piontti, A. P., Mu, K., Rossi, L., Sun, K., Viboud, C., Xiong, X., Yu, H., Halloran, M.E., Longini, I.M. and Vespignani, A. (2020). The effect of travel restrictions on the spread of the novel 2019 coronavirus (COVID-19) outbreak. Science 368 (6489), 395–400.

Cicala, S. (2020). Early Economic Impacts of COVID-19 in Europe: A View from the Grid. Working paper.

Dalhuisen, J. M., Florax, R. J., De Groot, H. L. and Nijkamp, P. (2003). Price and income elasticities of residential water demand: a meta-analysis. Land Economics 79(2), 292–308.

Dang, H.-A. H., Trinh, T.-A. (2021). "Does the COVID-19 lockdown improve global air quality? new cross-national evidence on its unintended consequences". Journal of Environmental Economics and Management, 105, 102401.

Dickey, D. A and Fuller, W. A. (1979). Distributions of the estimators for autoregressive time series with a unit root, Journal of American Statistical Association, 74 (366), 427-481.

Diebold, F. X. and Rudebush, G. D. (1991). On the power of Dickey- Fuller tests against fractional alternatives. Economics Letters, 35, 155-160.

Dinar, A. and Schwabe, K. (2015). Handbook of Water Economics. Edgar Elgar Publishing, London.

Dinar, A., and A. Subramanian. 1998. Policy Implications from Water Pricing Experiences in Various Countries. Water Policy 1:239–50.

Dittmann, I., and Granger, C. W. J. (2002). Properties of nonlinear transformations of fractionally integrated processes. Journal of Econometrics, 110, 113-133.

Dolatabadi, S., Narayan, P. K., Nielsen and M. Ø., Xu, K. (2018). Economic significance of commodity return forecasts from the fractionally cointegrated VAR model. Journal of Futures Markets, 38(2), 219-242.

Elliot, G., T.J. Rothenberg and J.H. Stock (1996). Efficient tests for an autoregressive unit root, Econometrica 64, 813-836.

Espey, M., Espey, J. and Shaw, W. D. (1997). Price elasticity of residential demand for water: a meta-analysis. Water Resources Research 33(6), 1369–1374.

FAO. (2010). Water at a glance. Retrieved from http://www.fao.org/nr/water/docs/waterataglance.pdf.

Fuller, W. A. (1976). Introduction to Statistical Time Series, New York: JohnWiley. *Fuller Introduction to Statistical Time Series 1976*.

Garrone, P., Grilli, L. and Marzano, R. (2019). Price elasticity of water demand considering scarcity and attitudes. Utilities Policy 59, 100927.

Geweke, J. and Porter-Hudak, S. (1983). The estimation and application of long memory time series models. Journal of Time Series Analysis, 4 (4), 221-238.

Gil-Alana, L. A. and Carcel, H. (2020). A fractional cointegration VAR analysis of exchange rate dynamics. The North American Journal of Economics and Finance, Vol. 51.

Grafton, R. Q., Ward, M. B., To, H. and Kompas, T. (2011). Determinants of residential water consumption: evidence and analysis from a 10-country household survey. Water Resources Research 47(8), W08537.

Grafton, R. Q., Chu, L. and Kompas, T. (2015). Optimal water tariffs and supply augmentation for cost-of-service regulated water utilities. Utilities Policy 34, 54–62.

Grafton, R. Q., Garrick, D. E., and Horne, J. (2017). Water Misallocation: Governance Challenges and Responses. Report prepared for the World Bank Group’s Global Water Practice.

Grafton, R. Q., Chu, Lu, and Wyrwoll, P. (2020). The paradoz of water pricing: dichotomies, dilemmas, and decisiones. Oxford Review of Economic Policy 36, 86-107.

Grossman, S. (1976). On the efficiency of competitive stock markets where trades have diverse information. The Journal of finance, 31(2), 573-585.

Grossman, S. (1978). Further results on the informational efficiency of competitive stock markets. Journal of Economic Theory, 18(1), 81-101.

Hassler, U., and Wolters, J. (1994). On the power of unit root tests against fractional alternatives. Economics Letters, 45(1), 1-5.

He, G., Pan, Y., Tanaka, T., 2020. The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nature Sustainability, 3(1005-1011).

Hoque, S. F. and Wichelns, D. (2013). State-of-the-art review: designing urban water tariffs to recover costs and promote wise use. International Journal of Water Resources Development 29(3), 472–491.

Hosking, J.R.M. (1981), Modelling persistence in hydrological time series with using fractional differentiation, Water Resources Research 20, 1898-1908.

House-Peters, L. A. and Chang, H. (2011). Urban water demand modeling: review of concepts, methods, and organizing principles. Water Resources Research 47(5), W05401.

Hui, D. S.; Azhar, E. I.; Madani, T. A.; Ntoumi, F.; Kock, R.; Dar, O.; Ippolito, G.; Mchugh, T. D.; Memish, Z. A.; Drosten, C.; Zumla, A.; Petersen, E. (2020). The continuing 2019-nCoV epidemic threat of novel coronaviruses to global healthThe latest 2019 novel coronavirus outbreak in Wuhan, China. International Journal of Infectious Diseases, 91, 264-266.

Jia, J. S., Lu, X., Yuan, Y., Xu, G., Jia, J., and Christakis N. A. (2020). Population flow drives spatio-temporal distribution of COVID-19 in China. Nature 582, 389–394.

Johansen, S. (1996). Likelihood-based inference in cointegrated vector autoregressive models. New York, NY: Oxford University Press.

Johansen, S. (2008). A representation theory for a class of vector autoregressive models for fractional processes. Econometric Theory, 24, 651-676.

Johansen, S. and Nielsen, M. Ø. (2010). Likelihood inference for a nonstationary fractional autoregressive model. Journal of Econometrics, 158, 51-66.

Johansen, S. and Nielsen, M. Ø. (2012). Likelihood inference for a fractionally cointegrated vector autoregressive model. Econometrica, 80, 2667-2732.

Jones, M. E., Nielsen, M. Ø. and Popiel, M. K. (2014.) A fractionally cointegrated VAR analysis of economic voting and political support. Canadian Journal of Economics, 47, 1078-1130.

Just, R. E., Zilberman, D. and Hochman, E. (1983). Estimation of multicrop production functions. American Journal of Agricultural Economics 65(4), 770–780.

Krause, K., Chermak, J. M. and Brookshire, D. S. (2003). The demand for water: consumer response to scarcity. Journal of Regulatory Economics 23(2), 167–191.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1-3), 159-178.

Kyle, A. S. (1985). Continuous auctions and insider trading. Econometrica: Journal of the Econometric Society, 1315-1335.

Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Schubert, J., Bania, J. and Khosrawipour, T. (2020). The Positive Impact of Lockdown in Wuhan on Containing the COVID-19 Outbreak in China. Journal of Travel Medicine. 27(3), 1-7.

Lee, D., and Schmidt, P. (1996). On the power of the KPSS test of stationarity against fractionally-integrated alternatives. Journal of Econometrics, 73(1), 285-302.

Maciel, L. (2017). Technical analysis based on high and low stock prices forecasts: Evidence for Brazil using a fractionally cointegrated VAR model. Empirical Economics, V58(4), 1513-1540.

Mahato, S., Pal, S. and Ghosh, K. P. (2020). Effect of lockdown amid COVID19 pandemic on air quality of the megacity Delhi, India. Science of The Total Environment 730, 139086.

Mansur, E. T., and Olmstead, S. M. (2012). The value of scarce water: measuring the inefficiency of municipal regulations. Journal of Urban Economics 71(3), 332–346.

Mapuwei, T. W., Bodhlyera, O., and Mwambi, H. (2020). Univariate Time Series Analysis of Short-Term Forecasting Horizons Using Artificial Neural Networks: The Case of Public Ambulance Emergency Preparedness. Journal of Applied Mathematics, 2020.

Martínez-Espiñeira, R., and Nauges, C. (2004). Is all domestic water consumption sensitive to price control? Applied Economics 36(15), 1697–1703.

Marzano, R., Rougé, C., Garrone, P., Grilli, L., Harou, J. J. and Pulido-Velazquez, M. (2018). Determinants of the price response to residential water tariffs: meta-analysis and beyond. Environmental Modelling & Software 101, 236–248.

Milennium Ecosystem Assessment. (2005). Milennium Ecosystem Assessment, Ecosystems and Human Well-Being: Synthesis. Island Press, Washington, DC.

Monge, M. (2022). Bunker fuel, commodity prices and shipping market indices following the COVID-19 pandemic. A time-frequency analysis. International Economics, 172, 29-39.

Monge, M. and Gil-Alana, L. A. (2020). Water prices: persistence, mean reversion and trends. Water Policy 22, 1200–1216.

Monge, M., and Gil-Alana, L. A. (2021a). Lithium industry and the US crude oil prices. A fractional cointegration VAR and a Continuous Wavelet Transform analysis. Resources Policy, 72, 102040.

Monge, M., and Gil-Alana, L. A. (2021b). Spatial crude oil production divergence and crude oil price behaviour in the United States. Energy, 232, 121034.

Monteiro, H. and Roseta-Palma, C. (2011). Pricing for scarcity? An efficiency analysis of increasing block tariffs. Water Resources Research 47(6), W06510.

Muhammad, S., Long, X. and Salman, M. (2020). COVID-19 pandemic and environmental pollution: a blessing in disguise? Science of The Total Environment 728, 138820.

National Research Council. (2005). Valuing Ecosystem Services: Toward Better Environmental Decision-Making. National Academies Press, Washington, DC.

Neal M. J. (2020). COVID-19 and water resources management: reframing our priorities as a water sector. Water International, 45(5), 435-440.

Nelson, C.R. and C.I. Plosser (1982) Trends and random walks in macroeconomic time series: Some evidence and implications, Journal of Monetary Economics 10:2, 139-162.

Ng, S. and P. Perron (2001). Lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 519-1554

Nielsen, M. Ø. and Popiel, M. K. (2018). A Matlab program and user's guide for the fractionally cointegrated VAR model (Queen's Economics Department Working Paper No 1330). Ontario, Canada, K7L 3N6.

Perron, P. and T.J. Vogelsang (1992). Testing for a Unit Root in a Time Series with a Changing Mean: Corrections and Extensions, Journal of Business and Economic Statistics 10, 4, 467-470.

Phillips, P. C. (1987). Time series regression with a unit root. Econometrica, 55(2), 277-301.

Phillips, P. C. B. (1999). Discrete Fourier transforms of fractional processes. Department of Economics, University of Auckland.

Phillips, P. C. B. (2007). Unit root log periodogram regression. Journal of Econometrics, 138(1), 104-124.

Phillips, P.C.B. and P. Perron, (1988). Testing for a unit root in time series regression, Biometrika 75, 335-346.

Platto, S., Wang, Y., Zhou, J., Carafoli, E. (2021). History of the COVID-19 pandemic: Origin, explosion, worldwide spreading. Biochemical and Biophysical Research Communications, 538, 14-23.

Poza, C., and Monge, M. (2020). A real time leading economic indicator based on text mining for the Spanish economy. Fractional cointegration VAR and Continuous Wavelet Transform analysis. International Economics, 163, 163-175.

Renwick, M. E. and Green, R. D. (2000). Do residential water demand side management policies measure up? An analysis of eight California water agencies. Journal of Environmental Economics and Management 40(1), 37–55.

Renzetti, S. (2002). The Economics of Water Demands. Springer, Boston, USA.

Renzetti, S. (2015). Economic analysis of industrial water use. In The Handbook of Water Economics. Dinar, A., Schwabe, K. and Elgar, E. (eds). Edgar Elgar Publishing, London, pp. 87–102.

Robinson, P.M. (1994). Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M. (1995a). Gaussian semi-parametric estimation of long range dependence, Annals of Statistics 23, 1630-1661.

Robinson, P.M. (1995b). Log periodogram regression of time series with long range dependence, Annals of Statistics 23, 3, 1048-1072.

Rogers, P., De Silva, R. and Bhatia, R. (2002). Water is an economic good: how to use prices to promote equity, efficiency, and sustainability. Water Policy 4(1), 1–17.

Rougé, C., Harou, J. J., Pulido-Velazquez, M., Matrosov, E. S., Garrone, P., Marzano, R., Lopez-Nicolas, A., Castelletti, A. and Rizzoli, A. -E. (2018). Assessment of smart-meter-enabled dynamic pricing at utility and river basin scale. Journal of Water Resources Planning and Management 144(5), 04018019.

Roux, J., Massonnaud, C. and Crépey, P. (2020). COVID-19: One-Month Impact of the French Lockdown on the Epidemic Burden. medRxiv.

Scheierling, S. M., Loomis, J. B. and Young, R. A. (2006). Irrigation water demand: a meta-analysis of price elasticities. Water Resources Research 42(1), W01411.

Sebri, M. (2014). A meta-analysis of residential water demand studies. Environment, Development and Sustainability 16(3), 499–520.

Sivakumar, B. (2020). COVID-19 and water. Stochastic Environmental Research and Risk Assessment 35, 531-534.

Smith, V. K. and Zhao, M. -Q. (2015). Residential water management: an economic perspective on policy instruments. In Handbook of Water Economics. Dinar, A. & Schwabe, K. (eds). Edgar Elgar Publishing, London, pp. 103–125.

Sowby, R.B., Burian, S.J., 2017. Survey of energy requirements for public water supply in the United States. J. Am. Water Works Assoc. 109 (7), E320–E330.

Sustainability Times, 2020. Climate change and Covid-19 increase pressure on potable water resources. [Online]. Available. https://www.sustainability-times.com/environmental- protection/climate-change-and-covid-19-increase-pressure-on-potablewater-resources/ (Accessed 12 July 2020).

Sowell, F. (1992). Maximum likelihood estimation of stationary univariate fractionally integrated time series models. Journal of Econometrics, 53(1-3), 165-188.

Tortajada, C. and Biswas, A. K. (2020). COVID-19 heightens water problems around the world. Water International 45, 441– 442.

Tsur, Y., Roe, T., Doukkali, M. R. and Dinar, A. (2004). Pricing Irrigation Water: Principles and Cases From Developing Countries. Routledge, New York.

Tsur,Y., and A. Dinar. 1997. On the Relative Efficiency of Alternative Methods for Pricing Irrigation Water and Their Implementation. World Bank Economic Review 11: 243–62.

Vives, X. (1995a). Short-term investment and the informational efficiency of the market. The Review of Financial Studies, 8(1), 125-160.

Vives, X. (1995b). The speed of information revelation in a financial market mechanism. Journal of Economic Theory, 67(1), 178-204.

WatEner. (2020). Water Consumption and Demand Forecasting during COVID-19 Crisis. Available online: http: //watener.com/index.php/water-consumption-and-demand-forecasting-during-covid-19-crisis/ (accessed on 20 May 2020).

WHO, World Health Organization, (April 2020). Water, sanitation, hygiene, and management for the COVID-19 virus.

WHO, World Health Organization, (May 2020). Water, Sanitation, Hygiene and Waste Management for the COVID-19 Virus.

Worthington, A. C. and Hoffman, M. (2008). An empirical survey of residential water demand modelling. Journal of Economic Surveys 22(5), 842–871.

Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., Du, M. and Liu, M. (2020). Effects of temperature and humidity on the new daily cases and deaths of COVID-19 in 166 countries. Science of The Total Environment 729, 139051.

Yao, H., Chen, J. -H., and Xu, Y. -F. (2020). Patients with mental health disorders in the COVID-19 epidemic. The Lancet Psychiatry, 7(4), e21.

Yunus, A. P., Masago, Y. and Hijioka, Y. (2020). COVID-19 and surface water quality: improved lake water quality during the lockdown. Science of The Total Environment 731, 139012.