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Water prices: persistence, mean reversion and trends

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Abstract

Time series referring to water prices at different regions all over the world are examined in this paper by using fractionally integrated methods. We look at series corresponding to the following regions: Asia Pacific and Russia, Europe, United States and Latin America as well as global data. The results indicate large degrees of persistence, with the values of the differencing parameter being close to one in all cases and higher under the assumption of uncorrelated errors. If autocorrelation is permitted, a small degree of mean reversion is found in all except the Latin American series. The possibility of structural breaks is also investigated and the results indicate the presence of multiple breaks in the data: three in the case of Latin America and global data; four in Europe and USA and five for the Asian Pacific and Russia. Nevertheless, we do not observe a significant change in the degree of persistence across subsamples and once more mean reversion is found if autocorrelation is permitted.

Keywords: Fractional integration; Persistence; Water prices

Highlights

- This research paper is to understand water prices and their behaviour with a daily time frequency, from January 2010 to January 2020.
- We examine the time trends, persistence and seasonality in a unified treatment based on long memory and fractional integration in water prices data in United States, Latin America, Europe, Asia Pacific and Russia, and taking also into account global prices around the world.

Introduction

Water, that is the source of life, is considered to be the ‘blue gold’ or ‘the oil of the 21st century’ (Coy, 2002), because of its scarcity nowadays. Population and industrial activities continue to grow in the world, increasing the need for clean water. Looking at the numbers provided by the U.S.

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Geological Survey (USGS) and knowing that 70% of the earth's surface is made up of water, it should be noted that 97% is saltwater that cannot be used for consumption, irrigation or industrial uses. Of the remaining 3%, only 1% of water resources are available for human consumption.

In the report published in 2002, the American Water Resources Association (AWRA, 2002) mentioned that the water industry was rapidly transforming into a global business where the annual revenues were estimated at US$300 billion, predicting that they would double because of scarcity and the industry maturing. As was the case with the gas, electricity and telecommunication industries, the new economy of water is being consolidated through privatization and market competition. The concept of 'water economy' is due to the agreement between the water and socio-economic side based on water sources, users, physical infrastructure that connects water and consumers and the different institutions that assign property rights, rules and water allocation standards (see Tsur, 2020).

In 2019, the rapid industrialization, pollution, the growing agricultural use of water, and the growth of the world population may bring about further scarcity in the water supply that is fit for human consumption. There is a considerable body of literature on urban and industrial water demand (see, among others, Baumann *et al.* (1997), Renzetti (2002, 2015); Olmstead *et al.* (2007), House-Peters & Chang (2011), Baerenklau *et al.* (2014) and Smith & Zhao (2015)). Literature related to agricultural demand includes Just *et al.* (1983), Moore *et al.* (1994), Howitt (1995), Mundlak (2001), Tsur *et al.* (2004), Scheierling *et al.* (2006), Schoengold *et al.* (2006) among many others. According to the report of the United Nations (2019), today there are 7.76 billion people living in the world and it is expected that in 2050 there will be 9.73 billion people.

Figure 1, illustrated by the United Nations (UN), represents the Sustainable Development Goals (SDGs) regions from 1952 to 2020, using the medium-variant projection with 95% prediction intervals from 2020 to 2100.

Areas that have experienced a lack of water for consumption include China, Egypt, India, Israel, Pakistan, Mexico, parts of Africa and the United States (Colorado, California, Las Vegas and the East Coast), among others. In the United States the chemical compound methyl tertiary butyl ether (MTBE), which is an additive in unleaded gasoline, can be found in well water from California to Maryland. These facts are not limited to the West, since Russia, China and elsewhere show high levels of pollution, thus limiting the amount of fresh water available for human use. Research papers such as Diamond (2005), Bazilian *et al.* (2011), De Amorim *et al.* (2018) and Mahlknecht *et al.* (2020), among others, analyze the link between these issues, the risks and how they are interconnected.

Everything mentioned above leads to another important factor that balances the supply and demand of a good or service, and that is the price. Related to water tariff (see Pinto & Marques, 2015) and according to OECD (1999), the procedures and elements which determine a customer's bill is the tariff. The charge is any part of that bill and the rate is any unit price.

Until very recently, water has been subsidized and supplied at low or no cost because the foundation of these policies was that water is a basic service of life. Berg & Tschirhart (1995) were the ones who started the research line about public services in general. In many places, these policies have created an infrastructure crisis and have left many of the poorest sectors of society without access to good clean water. Middle East, the South of Europe, the United States West Coast, Cape Town, among other regions mentioned Garrone *et al.* (2019) are examples of these issues. In another research line, Hanemann (1993) highlights that there is a need for a distinct approach due to the unique features of water related industries where higher capital intensity and technical characteristics, institutional status and environmental importance, among others, are connected to the public/private economic nature of these services and their social value.

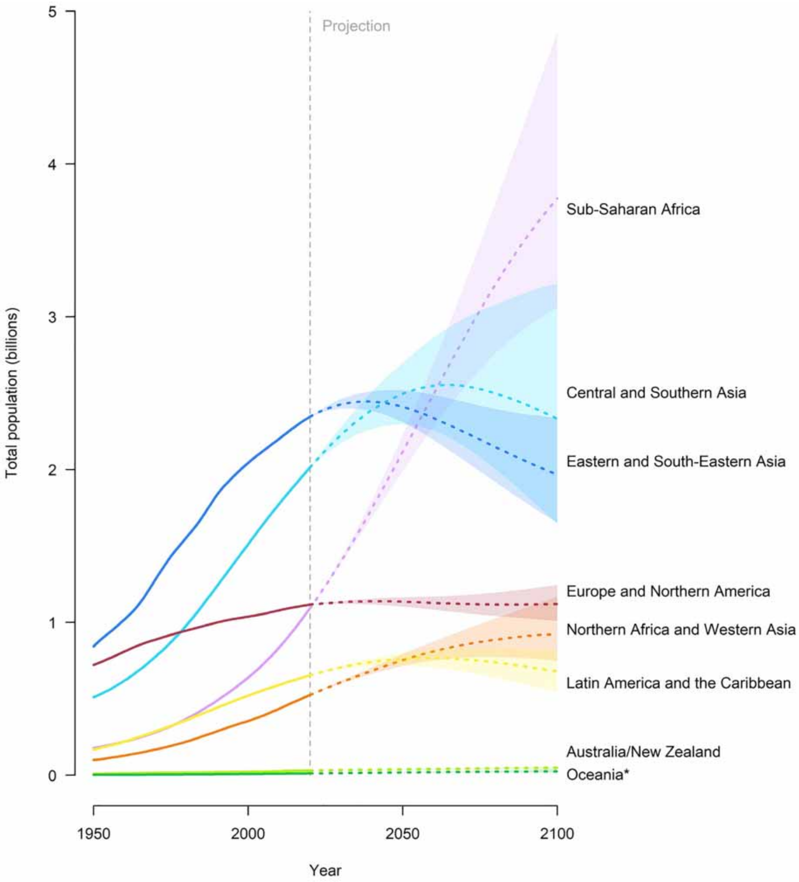

Fig. 1. Sustainable Development Goals regions. *Source*: United Nations (2019). (*excluding Australia and New Zealand).

According to Renwick & Green (2000), Rogers *et al*. (2002), Martínez-Espiñeira & Nauges (2004), Grafton *et al*. (2011, 2015), Mansur & Olmstead (2012), Asci *et al*. (2017), Beecher & Gould (2018), Rougé *et al.* (2018), among others, the new pricing policies are moving towards real cost pricing to address financial sustainability and economic efficiency, equity, fairness and resource conservation and also with these objectives try to avoid the water scarcity.

Following Rogers *et al*. (2002) and Carvalho *et al.* (2012), there are many different price setting systems and structures for water and related services around the world because municipalities run water utilities in some countries and private companies in others. This fact occurs for several reasons, one of them is the faulty rate setting practices causing arbitrariness in price-setting strategies (Hoque & Wichelns, 2013). Therefore, the recovery of financial costs alone along with the recovery of environmental and social costs is a difficult milestone (Zetland & Gasson, 2013).

Based on the above comments, one of the novelties of this research paper is to understand water prices and their behaviour with a daily time frequency. This paper contributes to the literature in the analysis of water prices from a time series viewpoint by focusing on some its features such as seasonality, time trends and persistence. For this purpose, we examine the time series properties of water prices from January 2010 to January 2020 using daily data. Another contribution of this work is that for the first time we jointly examine the three features (time trends, persistence and seasonality) in a unified treatment based on long memory and fractional integration, which has not been jointly studied so far in water prices data by regions such as the United States, Latin America, Europe, Asia Pacific and Russia, also taking into account global prices around the world. The dataset was obtained from the Thomson Reuters Eikon database.

The rest of the paper is structured as follows. The next section briefly reviews the literature on water prices, followed by the methodology applied in the paper. The next section describes the data and presents the main empirical results, while the final section concludes the paper.

About water prices

In the literature, a limited number of studies has considered the behavior of water prices. There is research related with the impact of water tariffs on customers surveyed by numerous authors, including Worthington & Hoffman (2008) and Monteiro & Roseta-Palma (2011). Also, there are meta-analysis studies that use meta-regression analysis (MRA) to identify the price elasticity of water demand (see Espey *et al*., 1997; Dalhuisen *et al*., 2003; Marzano *et al*., 2018), income elasticities (Dalhuisen *et al*., 2003) and, more recently, the most common analysis in the literature has focussed on household size elasticity (see Sebri, 2014) and elasticity and scarcity in water from a residential and local point of view. In this context, for example, Krause *et al*. (2003) argue that price elasticity is very sensitive to water scarcity.

There are others studies based on water economics (see, e.g. Dinar & Schwabe, 2015) with the objective of proposing a pricing mechanism that implements the optimal water policy inside the context of a comprehensive water economy. The National Research Council (2005), Milennium Ecosystem Assessment (2005) and the references therein contribute by including within the regulatory mechanism all environmental externalities in relation to water allocation policy. There is a growing literature that studies the pricing mechanisms, taking into account the environmental allocation of water (see Weber *et al*. (2016), Tsur & Zemel (2018), Grant & Langpap (2019), Jack & Jayachandran (2019) and Tsur (2019), among others).

This empirical paper focuses its attention on transitory shocks (associated with trend stationary processes) and permanent shocks (related to difference stationary processes), focusing on the degree of persistence observed in the series and using fractional integration. The contributions of the paper are two-fold. First, to our knowledge this is the first paper that proposes to study the time series properties of the price of water in different regions such as the United States, Latin America, Europe, Asia Pacific and Russia using daily data. Second, in this paper we use some developed methods based on the concepts of long run dependence and long memory using fractional integration. Fractional integration is more general than the standard methods that exclusively use integer orders of differentiation (i.e. AR(I)MA models), allowing for a higher degree of flexibility in the dynamic specification of the model. Moreover, the possibility of structural breaks is also investigated, still within the framework of fractional integration (see the following section for more specific details).

Methodology

We use techniques based on long memory and fractional integration. For this purpose we define an integrated process of order 0 or I(0) as a second order stationary process with the infinite sum of the autocovariances (γ_j) assumed to be finite. Alternatively, in the frequency domain, the spectral density function is defined as the Fourier transform of the autocovariances, i.e.:

$$f(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j \cos \lambda_j, \quad -\pi < \varepsilon \leq \pi \tag{1}$$

and an I(0) process can be defined as a process with a density function that is positive and finite at the zero frequency. These are broad definitions that include not only the white noise model but also many others, including, for example, weakly autocorrelated structures such as the one produced by the stationary and invertible ARMA form. At the other extreme, we have nonstationary processes, defined as having unit roots or integrated of order 1, i.e. I(1) processes, which, in their simplest form, is the random walk model:

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

where L is the lag operator ($Lx_t = x_{t-1}$) and u_t is I(0). In this context, if u_t is weakly autocorrelated, for example, if it follows an ARMA(p, q) process, x_t is then said to be an ARIMA(p, 1, q) process. However, both the stationary I(0) and the nonstationary I(1) are specific cases within a more flexible and general type of model known as fractional integration or I(d) where 'd' can be any real value and thus, potentially fractional. We can extend the model in (2) to the fractional case such that:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{3}$$

where u_t is I(0) and 'd' can be 0 (short memory), a value between 0 and 1 (fractional integration), 1 (a unit root model), or even above 1 (see Robinson (2003), Doukham *et al.* (2003) and Gil-Alana & Hualde (2009) for a review of these models and long memory in general).

Processes such as those given by Equation (3) with $d > 0$ belong to a category of long memory, so named because of the large degree of association between observations far distant in time. They are characterized because the sum of their autocorrelation is infinite, or, alternatively, in the frequency domain, because the spectral density function has a singularity or pole at the smallest (zero) frequency, i.e.:

$$f(\lambda) \rightarrow \infty \text{ as } \lambda \rightarrow 0 \tag{4}$$

Granger (1980) was the first to propose these models, noting that many aggregated data presented an extremely large value in the estimated spectrum at the smallest frequency, (i.e. as in Equation (4)), consistent with first differentiation, but once the series were differenced, the estimated spectrum displayed a value close to zero at the zero frequency, i.e.:

$$f(\lambda) \rightarrow 0, \text{ as } \lambda \rightarrow 0 \tag{5}$$

which was an indication of over-differentiation. These models became popular in the 1990s through the works of Sowell (1992), Baillie (1996), Gil-Alana & Robinson (1997), Robinson & Zaffaroni (1997), Breidt *et al.* (1998), Silverberg & Verspagen (1999) and others, and they have also been employed more recently in the analysis of other commodity prices such as Gil-Alana & Gupta (2014), analyzing historical oil prices; Gil-Alana *et al.* (2015), examining precious metals prices such as gold, silver, rhodium, palladium and platinum; Monge *et al.* (2017a, 2017b) with crude oil prices, Monge & Gil-Alana (2019) studying the behavior of lithium and cobalt and Bouri *et al.* (2019) analyzing the behavior of cryptocurrencies, among many others.

Note that, for any real value d, the polynomial in the left hand side in Equation (3) can be expressed in terms of its binomial expansion, such that:

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots \tag{6}$$

and thus, Equation (3) can be expressed as:

$$x_t = d\,x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t \tag{7}$$

implying that higher the value of ‘d’ is, the higher the level of dependence between the observations is. Therefore, the parameter ‘d’ can be taken as a measure of the degree of persistence in the data.

We estimate the differencing parameter ‘d’ by using a version of a testing procedure developed by Robinson (1994) which is based on the frequency domain representation of the Whittle function. Among the advantages of this method, one is that it is valid for all range of values of ‘d’, not being restricted to the stationary region ($d < 0.5$); also, it allows the incorporation of deterministic terms such as an intercept or time trends and its limiting distribution is standard N(0,1). One limitation of the I(d) approach is that some authors argue that this may be a spurious phenomenon caused by the presence of structural breaks in the data that have not been taken into account (Ohanissian *et al.*, 2008). Thus, in addition to the presented methodology, the presence of structural breaks is also taken into account in the paper by using Bai & Perron’s (2003) methodology along with its extension to the fractional case in Gil-Alana (2008).

Data and empirical results

The data examined in this research paper, obtained from Thomson Reuters Eikon database, correspond to:

- Thomson Reuters Global Water & Related Utilities;
- Thomson Reuters United States Water & Related Utilities;
- Thomson Reuters Latin America Water & Related Utilities;
- Thomson Reuters Asia Pacific & Russia Water & Related Utilities;
- Thomson Reuters Europe Water & Related Utilities.

These indices collect the entire water process until it reaches the final consumers, through the performance of the listed companies. We use daily prices from January 12, 2010 until January 10, 2020.

Table 1 shows the average, minimum and maximum data of water prices by regions and globally. According to the results presented in the table, we see that the price of water on average and the maximum is in the United States. The minimum price is in Europe.

Table 1. Summary of time series.

	Global (US$)	United States (US$)	Latin America (US$)	Asia Pacific and Russia (US$)	Europe (US$)
Mean	167.15	624.6	109.14	132.55	147.52
Min.	96.62	253.1	91.24	93.78	80.65
Max.	240.35	1,282	122.45	173.47	196.58

Figure 2 plots the indices that represent the prices of water at the World, Europe, United States, Latin America and Asia Pacific and Russia.

Assuming y_t below is each of the time series we observe, we start by considering the following regression model:

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - B)^{d_o} x_t = u_t, \quad t = 1, 2, \ldots, \tag{8}$$

testing the null hypothesis:

$$H_o\colon d = d_o, \tag{9}$$

In Equation (8) for d_o-values from 0, 0.01, … until 1.99 and 2, under three different modelling assumptions: (1) $\beta_0 = \beta_1 = 0$ a priori in Equation (8); (2) $\beta_1 = 0$ a priori, and (3) with β_0 and β_1 unknown and freely estimated from the data. In Table 2 we suppose u_t is a white noise process and report the estimated values of d along with the 95% confidence intervals of the non-rejection values with the test of Robinson (1994). We marked in bold the selected models according to the deterministic terms. We see that the time trend is only required in the case of United States prices (a significant time trend is usually related with the technological change); for the remaining cases, the intercept seems to be sufficient. Focusing on persistence by means of d, we see that the estimated values of d are close to 1 in all cases. However, we also observe some slight differences across the regions. Thus, for example, the I(1) null hypothesis cannot be rejected in the cases of Asia Pacific and Russia, Europe and Latin America; this hypothesis is rejected in favor of mean reversion (i.e. $d < 1$) for the United States, and it is rejected in favor of alternatives with $d > 1$ for the global series. For the United States, the time trend is found to be significantly positive (Table 3), but the fact that it is found to be significantly smaller than 1 indicates to us that shocks in the series will be mean reverting though taking long periods of time to disappear completely.

Tables 4 and 5 refer to the cases where u_t in Equation (8) is autocorrelated. Here, we employ a non-parametric approach developed by Bloomfield (1973) that approximates ARMA structures with very few parameters (see Gil-Alana (2004) for the application of this model in the context of fractional integration). The first thing we observe in these two tables is that along with the United States, the time trend is now also required in the cases of Europe and the global case in the three cases with a significant positive coefficient. More importantly, evidence of a small degree of mean reversion is found in four out of the five series examined, with values of d statistically significantly below 1. In fact, only for Latin America, can the I(1) hypothesis not be rejected. Nevertheless, the estimates of d are very large in all cases, ranging between 0.88 (Latin America) and 0.91 (Asia Pacific, Europe and Russia) and thus implying large degrees of persistence in the data.

The large degree of persistence observed in the results presented across Tables 2–5 can be a consequence of the presence of structural breaks which have not been taken into account. In fact, this is a

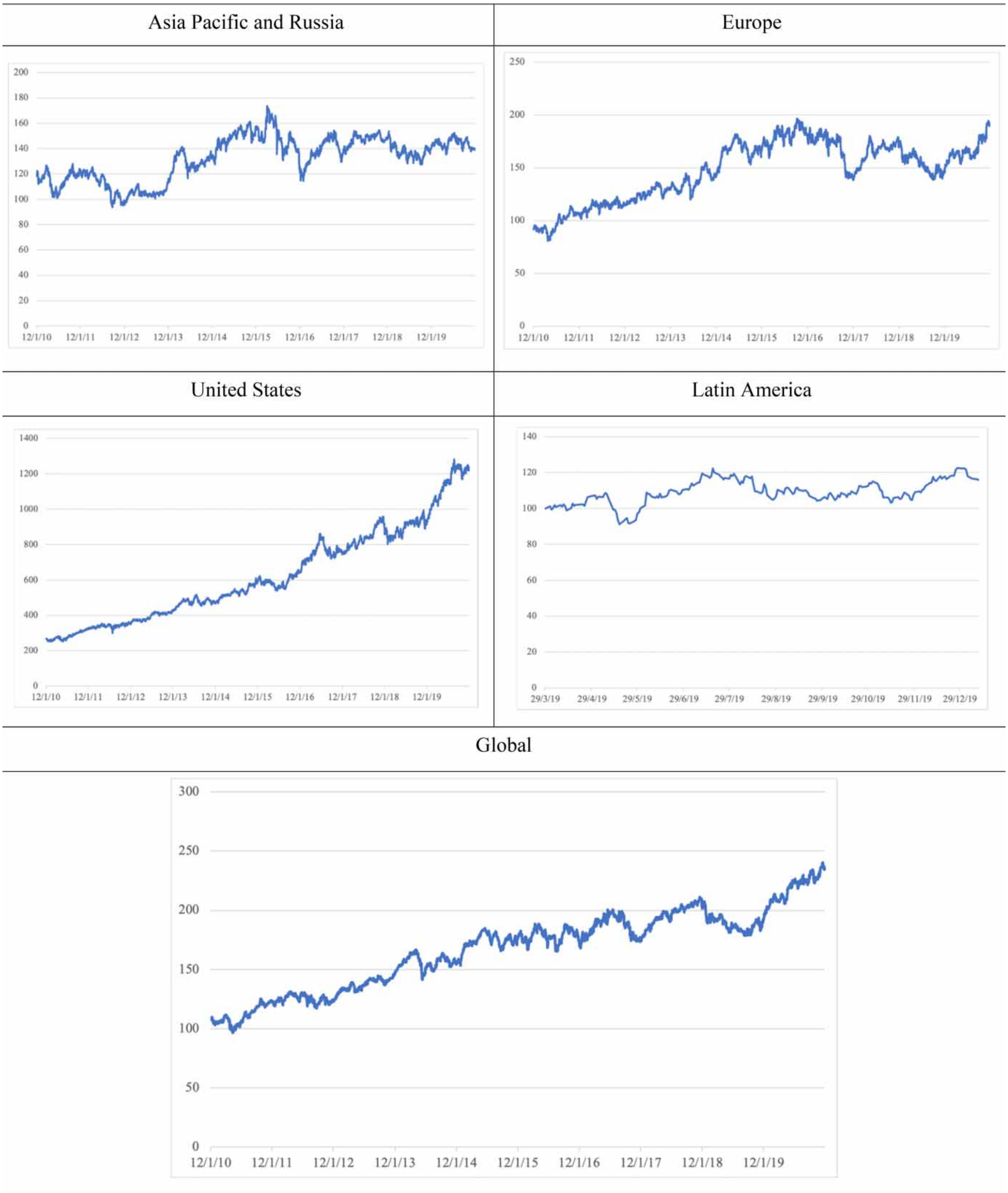

Fig. 2. Time series plots.

Table 2. Estimates of d under the assumption of white noise errors.

Series	No terms	Anintercept	A linear time trend
Asia Pacific and Russia	0.99 (0.96, 1.02)	**1.00 (0.94, 1.03)**	1.00 (0.94, 1.03)
Europe	1.00 (0.97, 1.03)	**0.98 (0.95, 1.02)**	0.98 (0.95, 1.02)
USA	0.97 (0.94, 1.01)	0.95 (0.92, 0.98)	**0.95 (0.92, 0.98)**
Latin America	0.98 (0.89, 1.10)	**1.03 (0.93, 1.16)**	1.03 (0.93, 1.16)
Global	1.01 (0.98, 1.04)	**1.04 (1.00, 1.07)**	1.04 (1.00, 1.07)

The selected models in terms of the deterministic components are given in bold; 95% bands of the non-rejection values of d using Robinson (1994) are in parentheses.

Table 3. Estimates of d under the assumption of white noise errors.

Series	No terms	Anintercept	A linear time trend
Asia Pacific and Russia	1.00 (0.94, 1.03)	120.40 (85.26)	–
Europe	0.98 (0.95, 1.02)	91.62 (53.70)	–
USA	0.95 (0.92, 0.98)	266.71 (40.31)	0.371 (4.18)
Latin America	1.03 (0.93, 1.16)	99.96 (55.68)	–
Global	1.04 (1.00, 1.07)	108.10 (22.52)	–

In the third and fourth columns, t-values are given in parentheses.

Table 4. Estimates of d under the assumption of autocorrelated errors.

Series	No terms	An intercept	A linear time trend
Asia Pacific and Russia	0.97 (0.92, 1.00)	**0.91 (0.87, 0.95)**	0.91 (0.87, 0.95)
Europe	0.97 (0.92, 1.00)	0.91 (0.86, 0.96)	**0.91 (0.86, 0.96)**
USA	0.95 (0.90, 0.99)	0.90 (0.87, 0.95)	**0.90 (0.86, 0.94)**
Latin America	0.92 (0.79, 1.10)	**0.88 (0.72, 1.10)**	0.88 (0.71, 1.10)
Global	0.97 (0.93, 1.02)	0.91 (0.87, 0.96)	**0.91 (0.87, 0.96)**

The selected models in terms of the deterministic components are given in bold; 95% bands of the non-rejection values of d using Robinson (1994) are given in parentheses.

Table 5. Estimates of d under the assumption of autocorrelated errors.

Series	No terms	An intercept	A linear time trend
Asia Pacific and Russia	0.91 (0.87, 0.95)	120.22 (86.04)	–
Europe	0.91 (0.86, 0.96)	91.63 (54.21)	0.036 (2.15)
USA	0.90 (0.86, 0.94)	266.54 (40.63)	0.367 (5.99)
Latin America	0.88 (0.72, 1.10)	100.21 (56.92)	–
Global	0.91 (0.87, 0.96)	107.97 (87.20)	0.048 (3.88)

In the third and fourth columns, t-values are given in parentheses.

classical argument that has been put forward by numerous authors in recent years (Diebold & Inoue, 2001; Granger & Hyung, 2004; Mikosch & Starica, 2004; Ohanissian *et al.*, 2008, etc.). Thus, we next perform Bai & Perron's (2003) approach for detecting breaks in the data. Identical results were obtained when using Gil-Alana's (2008) approach, which extends the previous method to the fractional case. We observe three breaks for Latin America; four in the case of Europe and the United States and five for Asia Pacific and Russia and the global case. The break dates are reported in the third column of Table 6.

In Tables 7–10 we display the estimates of d for each sub-sample and each series, once more for the three cases of: (1) no regressors, (2) with a constant, and (3) with a constant and a linear time trend.

Table 6. Structural breaks using Bai & Perron (2003).

Series	No. of breaks	Break dates
Asia Pacific and Russia	5	08.08.2011; 05.02.2013; 29.08.2014; 29.02.2016; 06.02.2018
Europe	4	13.07.2011; 11.09.2013; 97.04.2015; 05.10.2016
USA	4	05.06.2012; 13.03.2014; 28.01.2016; 16.07.2018
Latin America	3	19.06.2019; 15.08.2019; 02.12.2019
Global	5	14.07.2011; 10.01.2013; 29.07.2014; 08.04.2016; 16.07.2018

Table 7. Estimates of d for each subsample: White noise case.

Region	Subsample	No regressor	An intercept	A time trend
Asia Pacific and Russia	1st period	0.96 (0.90, 1.04)	**0.98 (0.92, 1.06)**	0.98 (0.92, 1.06)
	2nd period	0.99 (0.93, 1.07)	**0.98 (0.91, 1.05)**	0.98 (0.91, 1.05)
	3rd period	0.99 (0.93, 1.07)	**1.00 (0.92, 1.09)**	1.00 (0.92, 1.09)
	4rd period	0.99 (0.93, 1.07)	**1.01 (0.93, 1.11)**	1.01 (0.93, 1.11)
	5th period	0.99 (0.93, 1.06)	**0.97 (0.90, 1.06)**	0.97 (0.90, 1.06)
	6th period	0.98 (0.93, 1.05)	**0.93 (0.87, 1.01)**	0.93 (0.87, 1.01)
Europe	1st period	0.98 (0.91, 1.05)	**0.98 (0.91, 1.08)**	0.98 (0.91, 1.08)
	2nd period	1.00 (0.94, 1.08)	**0.97 (0.91, 1.05)**	0.97 (0.91, 1.05)
	3rd period	1.01 (0.94, 1.08)	**0.99 (0.93, 1.07)**	0.99 (0.93, 1.07)
	4rd period	0.99 (0.92, 1.06)	**0.95 (0.84, 1.07)**	0.95 (0.84, 1.07)
	5th period	0.98 (0.93, 1.03)	**0.96 (0.92, 1.02)**	0.96 (0.92, 1.02)
USA	1st period	0.98 (0.92, 1.04)	0.79 (0.74, 0.85)	**0.78 (0.73, 0.85)**
	2nd period	1.01 (0.95, 1.09)	0.94 (0.88, 1.01)	**0.94 (0.88, 1.01)**
	3rd period	1.01 (0.95, 1.08)	0.90 (0.84, 0.97)	**0.90 (0.84, 0.97)**
	4rd period	1.00 (0.94, 1.06)	**0.97 (0.92, 1.04)**	0.97 (0.92, 1.04)
	5th period	0.99 (0.92, 1.06)	0.94 (0.87, 1.04)	**0.94 (0.87, 1.04)**
Latin America	1st period	0.95 (0.78, 1.19)	**1.11 (0.95, 1.34)**	1.11 (0.95, 1.34)
	2nd period	0.87 (0.66, 1.16)	**0.83 (0.65, 1.18)**	0.82 (0.61, 1.18)
	3rd period	0.96 (0.82, 1.16)	**0.89 (0.70, 1.18)**	0.89 (0.70, 1.18)
	4rd period	0.87 (0.59, 1.24)	**0.98 (0.75, 1.28)**	0.99 (0.78, 1.26)
Global	1st period	0.98 (0.92, 1.07)	**1.04 (0.96, 1.14)**	1.04 (0.96, 1.14)
	2nd period	0.99 (0.93, 1.07)	**0.98 (0.90, 1.08)**	0.98 (0.90, 1.08)
	3rd period	0.99 (0.93, 1.07)	**1.22 (1.04, 1.19)**	1.11 (1.04, 1.20)
	4rd period	0.98 (0.92, 1.06)	**1.03 (0.95, 1.11)**	1.02 (0.95, 1.11)
	5th period	1.00 (0.95, 1.07)	**1.04 (0.97, 1.12)**	1.04 (0.97, 1.12)
	6th period	0.99 (0.92, 1.07)	0.99 (0.91, 1.08)	**0.99 (0.91, 1.08)**

The selected models in terms of the deterministic components are given in bold; 95% bands of the non-rejection values of d using Robinson (1994) are given in parentheses.

Table 8. Coefficient estimates for each subsample: White noise case.

Region	Subsample	No regressor	An intercept	A time trend
Asia Pacific and Russia	1st period	0.98 (0.92, 1.06)	120.364 (96.30)	–
	2nd period	0.98 (0.91, 1.05)	108.388 (98.10)	–
	3rd period	1.00 (0.92, 1.09)	120.940 (87.91)	–
	4rd period	1.01 (0.93, 1.11)	155.215 (74.76)	–
	5th period	0.97 (0.90, 1.06)	124.067 (101.8)	–
	6th period	0.93 (0.87, 1.01)	141.981 (112.4)	–
Europe	1st period	0.98 (0.91, 1.08)	91.618 (73.58)	–
	2nd period	0.97 (0.91, 1.05)	114.860 (85.20)	–
	3rd period	0.99 (0.93, 1.07)	142.285 (88.40)	–
	4rd period	0.95 (0.84, 1.07)	173.368 (72.02)	–
	5th period	0.96 (0.92, 1.02)	170.162 (97.78)	–
USA	1st period	0.78 (0.73, 0.85)	266.460 (76.87)	0.1844 (4.69)
	2nd period	0.94 (0.88, 1.01)	383.537 (94.01)	0.2684 (1.98)
	3rd period	0.90 (0.84, 0.97)	516.346 (90.82)	0.3332 (2.29)
	4rd period	0.97 (0.92, 1.04)	700.443 (85.87)	–
	5th period	0.94 (0.87, 1.04)	917.532 (91.79)	0.8334 (2.28)
Latin America	1st period	1.11 (0.95, 1.34)	99.900 (51.73)	–
	2nd period	0.83 (0.65, 1.18)	110.280 (65.50)	–
	3rd period	0.89 (0.70, 1.18)	109.507 (64.91)	–
	4rd period	0.98 (0.75, 1.28)	108.998 (73.41)	–
Global	1st period	1.04 (0.96, 1.14)	108.098 (11.65)	–
	2nd period	0.98 (0.90, 1.08)	128.913 (11.65)	–
	3rd period	1.22 (1.04, 1.19)	147.126 (11.65)	–
	4rd period	1.03 (0.95, 1.11)	178.453 (11.65)	–
	5th period	1.04 (0.97, 1.12)	186.444 (11.65)	–
	6th period	0.99 (0.91, 1.08)	186.442 (134.7)	0.1291 (1.94)

Tables 7 and 8 refer to white noise errors, while the results in Tables 9 and 10 correspond to the weakly autocorrelated (Bloomfield, 1973) case.

Starting with the case of white noise errors, we see that significant time trends are found in four out of the five sub-periods in the United States and for the last subsample in the global series. Mean reversion is detected only for the United States case in the first and third subsamples, and in general we do not observe any systematic (increase/decrease) pattern in the values of d across the subsamples.

With autocorrelation, the time trend coefficient is statistically significant in many more cases than in the case of white noise errors, being positive in all except one single case (Asia Pacific and Russia, fourth subsample), and mean reversion takes now place in numerous subsamples: the last four subsamples in Asia Pacific and Russia: the first, second and fourth in Europe; in the first and fifth in the United States; in the third subsample for Latin America, and in the second and sixth subsamples for the global series. Nevertheless, as with the white noise case, the values of d are relatively high in most of the cases, the exceptions being the second and third subsamples in Latin America (0.67 and 0.38 respectively) and the fourth in the European case (0.62).

Table 9. Estimates of d for each subsample: Bloomfield case.

Region	Subsample	No regressor	An intercept	A time trend
Asia Pacific and Russia	1st period	0.99 (0.88, 1.11)	**1.07 (0.94, 1.22)**	1.07 (0.94, 1.22)
	2nd period	1.02 (0.91, 1.15)	**0.99 (0.88, 1.13)**	0.99 (0.87, 1.13)
	3rd period	0.98 (0.89, 1.09)	0.84 (0.76, 0.95)	**0.84 (0.76, 0.95)**
	4rd period	0.99 (0.88, 1.11)	0.85 (0.76, 0.96)	**0.84 (0.75, 0.96)**
	5th period	0.97 (0.89, 1.09)	0.84 (0.74, 0.94)	**0.84 (0.76, 0.94)**
	6th period	0.96 (0.87, 1.08)	**0.87 (0.79, 0.97)**	0.87 (0.80, 0.97)
Europe	1st period	0.97 (0.86, 1.09)	0.85 (0.75, 0.98)	**0.84 (0.73, 0.98)**
	2nd period	0.99 (0.91, 1.09)	0.86 (0.76, 0.98)	**0.86 (0.76, 0.98)**
	3rd period	1.00 (0.90, 1.13)	1.04 (0.92, 1.16)	1.04 (0.92, 1.17)
	4rd period	0.98 (0.87, 1.09)	0.62 (0.53, 0.79)	0.62 (0.52, 0.79)
	5th period	0.95 (0.89, 1.04)	0.95 (0.89, 1.04)	0.95 (0.89, 1.04)
USA	1st period	0.97 (0.89, 1.07)	0.79 (0.72, 0.92)	**0.80 (0.69, 0.92)**
	2nd period	0.97 (0.80, 1.08)	0.91 (0.82, 1.03)	**0.92 (0.83, 1.03)**
	3rd period	1.01 (0.92, 1.14)	0.94 (0.84, 1.07)	**0.94 (0.84, 1.07)**
	4rd period	0.99 (0.91, 1.09)	**0.94 (0.85, 1.06)**	0.94 (0.86, 1.06)
	5th period	0.96 (0.87, 1.11)	0.79 (0.72, 0.88)	**0.76 (0.67, 0.86)**
Latin America	1st period	0.83 (0.54, 1.21)	**1.06 (0.71, 1.51)**	1.07 (0.71, 1.51)
	2nd period	0.70 (0.21, 1.23)	**0.67 (0.37, 1.20)**	0.68 (0.33, 1.20)
	3rd period	0.88 (0.61, 1.25)	**0.38 (0.06, 0.77)**	0.37 (0.08, 0.77)
	4rd period	0.47 (0.19, 1.24)	**0.96 (0.16, 1.97)**	0.97 (0.03, 1.66)
Global	1st period	0.97 (0.87, 1.10)	0.89 (0.80, 1.02)	**0.90 (0.79, 1.02)**
	2nd period	0.97 (0.87, 1.11)	0.85 (0.76, 0.97)	**0.84 (0.74, 0.97)**
	3rd period	0.97 (0.88, 1.10)	**0.99 (0.91, 1.10)**	0.99 (0.91, 1.10)
	4rd period	0.97 (0.86, 1.08)	**0.89 (0.77, 1.04)**	0.89 (0.77, 1.04)
	5th period	0.99 (0.91, 1.08)	**0.89 (0.81, 1.00)**	0.89 (0.81, 1.00)
	6th period	0.97 (0.87, 1.10)	0.84 (0.76, 0.94)	**0.81 (0.71, 0.93)**

The selected models in terms of the deterministic components are given in bold; 95% bands of the non-rejection values of d using Robinson (1994) are given in parentheses.

Concluding comments

In this paper we have examined five time series referring to water prices in different regions all over the world, applying statistical methods based on long memory and fractional differentiation. As far as we are concerned there are no previous econometric works related to the price of water and using these methodologies.

We employ daily data of the water prices of the following four regions, Asia Pacific and Russia, Europe, the United States and Latin America, as well as global data. Our results indicate first that if the errors are uncorrelated, water prices do not show mean reversion in any of the series examined except for the United States data, where a positive time trend is also observed. That means that in the event of an exogenous shock increasing the price of water in the US, the series will revert by itself in the long run to its original trend, though it can take a very long time to recover completely. However, if autocorrelation is permitted, a small degree of mean reversion (i.e. an estimate of the differencing parameter significantly smaller than one) is detected in four of the series (Asia Pacific and Russia, Europe, the United States and global) while the I(1) hypothesis cannot be rejected for the

Table 10. Coefficient estimates for each subsample: Bloomfield case.

Region	Subsample	No regressor	An intercept	A time trend
Asia Pacific and Russia	1st period	1.07 (0.94, 1.22)	120.512 (96.87)	–
	2nd period	0.99 (0.88, 1.13)	108.394 (98.09)	–
	3rd period	0.84 (0.76, 0.95)	121.022 (91.01)	0.0780 (2.82)
	4rd period	0.84 (0.75, 0.96)	155.551 (77.63)	–0.0821 (–1.92)
	5th period	0.84 (0.76, 0.94)	124.499 (105.1)	0.0453 (2.12)
	6th period	0.87 (0.79, 0.97)	141.901 (113.7)	–
Europe	1st period	0.84 (0.73, 0.98)	91.599 (75.82)	0.0592 (2.30)
	2nd period	0.86 (0.76, 0.98)	114.716 (86.89)	0.0433 (1.74)
	3rd period	1.04 (0.92, 1.16)	142.124 (88.44)	–
	4rd period	0.62 (0.53, 0.79)	176.034 (95.79)	–
	5th period	0.95 (0.89, 1.04)	170.084 (97.81)	–
USA	1st period	0.80 (0.69, 0.92)	266.596 (76.08)	0.1834 (4.16)
	2nd period	0.92 (0.83, 1.03)	383.608 (94.29)	0.2661 (2.21)
	3rd period	0.94 (0.84, 1.07)	516.625 (90.43)	0.3467 (1.89)
	4rd period	0.94 (0.85, 1.06)	700.580 (86.12)	–
	5th period	0.76 (0.67, 0.86)	915.420 (98.74)	0.8667 (6.50)
Latin America	1st period	1.06 (0.71, 1.51)	99.941 (51.47)	–
	2nd period	0.67 (0.37, 1.20)	110.877 (73.24)	–
	3rd period	0.38 (0.06, 0.77)	108.683 (146.0)	–
	4rd period	0.96 (0.16, 1.97)	109.034 (73.47)	–
Global	1st period	0.90 (0.79, 1.02)	107.947 (120.7)	0.0560 (2.12)
	2nd period	0.84 (0.74, 0.97)	128.587 (130.6)	0.0463 (2.19)
	3rd period	0.99 (0.91, 1.10)	147.223 (141.8)	–
	4rd period	0.89 (0.77, 1.04)	177.987 (117.3)	–
	5th period	0.89 (0.81, 1.00)	186.771 (138.6)	–
	6th period	0.81 (0.71, 0.93)	186.050 (141.1)	0.1331 (5.49)

Latin American data. Nevertheless, the estimated values for the degree of integration are large in all cases, ranging from 0.88 to 0.91, thus implying large degrees of persistence, with long lasting effects from shocks.

Following the literature and knowing that the large degree of persistence observed in our results can be a consequence of the presence of structural breaks that have not been taken into account, we used Bai & Perron's (2003) and Gil-Alana's (2008) approaches for detecting breaks in the data. In that case, we observe three breaks for Latin America, four for Europe and United States and five for Asia Pacific and Russia and the global case. Estimating the differencing parameter for each subsample and each series, if the errors are white noise, mean reversion is only observed in the case of the United States. On the other hand, allowing for autocorrelation, the time trend is significant in a number of cases and mean reversion is found in many of the subsamples implying in these cases that shocks will have a transitory nature, returning to their original long trend projections after some periods of time.

An interesting conclusion in this work is that water prices are highly persistent. Thus, in the event of an exogenous shock, for example, unexpectedly increasing the price of water, strong policy measures should be adopted to recover the original levels/trends in the data, since otherwise the series will take a very long time to recover by themselves.

This paper can be extended in several directions. First, non-linear trends can also be considered, noting that fractional integration and non-linear structures are isssues which are very much related (Diebold & Inoue, 2001). In this context, the non-linear approach developed in Cuestas & Gil-Alana (2016) and based on the Chebyshev polynomials in time in the context of fractional integration can be implemented with this dataset. Moreover, in a multivariate context, fractional cointegration can also be examined to look at potential long run equilibrium relationships among the variables used in this work, and here, the fractional cointegration VAR (FCVAR) approach developed by Johansen & Nielsen (2010, 2012) can be performed. Work in all these directions is now in progress.

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Data availability statement

All relevant data are included in the paper or its Supplementary Information.

References

American Water Resources Association (AWRA) (2002). The new economy of water. *Water Resources Impact Magazine 4*(1), 1–34.

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.

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

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

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. *Journal of Econometrics 73*, 5–59.

Baumann, D. D., Boland, J. J. & Hanemann, M. W. (1997). *Urban Water Demand Management and Planning*. McGraw-Hill Professional, New York.

Bazilian, M., Rogner, H., Howells, M., Hermann, S., Arent, D., Gielen, D., Steduto, P., Mueller, A., Komor, P., Tol, R. S. J. & Yumkella, K. (2011). Considering the energy, water and food nexus: towards an integrated modelling approach. *Energy Policy 39*(12), 7896–7906.

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

Berg, S. V. & Tschirhart, J. (1995). Contributions of neoclassical economics to public utility analysis. *Land Economics 71*(3), 310–330.

Bloomfield, P. (1973). An exponential model in the spectrum of a scalar time series. *Biometrika 60*, 217–226.

Bouri, E., Gil-Alana, L. A., Gupta, R. & Roubaud, D. (2019). Modelling long memory volatility in the Bitcoin market: evidence of persistence and structural breaks. *International Journal of Finance and Economics 24*(1), 412–426.

Breidt, F. J., Crato, N. & de Lima, P. (1998). The detection and estimation of long memory in stochastic volatility. *Journal of Econometrics 83*, 325–334.

Carvalho, P., Marques, R. C. & Berg, S. (2012). A meta-regression analysis of benchmarking studies on water utilities market structure. *Utilities Policy 21*, 40–49.
Coy, D. G. (2002). Looking at water: a view from Wall Street. *Water Resources Impact 4*, 14–18.
Cuestas, J. C. & Gil-Alana, L. A. (2016). A non-linear approach with long range dependence based on Chebyshev polynomials. *Studies in Nonlinear Dynamics and Econometrics 20*(1), 57–94.
Dalhuisen, J. M., Florax, R. J., De Groot, H. L. & Nijkamp, P. (2003). Price and income elasticities of residential water demand: a meta-analysis. *Land Economics 79*(2), 292–308.
De Amorim, W. S., Valduga, I. B., Ribeiro, J. M. P., Williamson, V. G., Krauser, G. E., Magtoto, M. K. & de Andrade, J. B. S. O. (2018). The nexus between water, energy, and food in the context of the global risks: an analysis of the interactions between food, water, and energy security. *Environmental Impact Assessment Review 72*, 1–11.
Diamond, J. (2005). *Collapse: How Societies Choose to Fail or Succeed*. Penguin, New York.
Diebold, F. X. & Inoue, A. (2001). Long memory and regime switching. *Journal of Econometrics 105*, 131–159.
Dinar, A. & Schwabe, K. (2015). *Handbook of Water Economics*. Edgar Elgar Publishing, London.
Doukham, P., Oppenheim, G. & Taqqu, M. S. (2003). *Long Range Dependence. Theory and Application*. Springer Science & Business Media, Boston, US.
Espey, M., Espey, J. & Shaw, W. D. (1997). Price elasticity of residential demand for water: a meta-analysis. *Water Resources Research 33*(6), 1369–1374.
Garrone, P., Grilli, L. & Marzano, R. (2019). Price elasticity of water demand considering scarcity and attitudes. *Utilities Policy 59*, 100927.
Gil-Alana, L. A. (2004). The use of the Bloomfield model as an approximation to ARMA process in the context of fractional integration. *Mathematical and Computer Modelling 39*(4), 429–436.
Gil-Alana, L. A. (2008). Fractional integration and structural breaks at unknown periods of time. *Journal of Time Series Analysis 29*, 163–185.
Gil-Alana, L. A. & Gupta, R. (2014). Persistence and cycles in historical oil price data. *Energy Economics 45*, 511–516.
Gil-Alana, L. A. & Hualde, J. (2009). Fractional integration and cointegration. An overview with an empirical application. *The Palgrave Handbook of Applied Econometrics 2*, 434–472.
Gil-Alana, L. A. & Robinson, P. M. (1997). Testing of unit roots and other nonstationary hypotheses in macroeconomic time series. *Journal of Econometrics 80*, 241–268.
Gil-Alana, L. A., Chang, S., Balcilar, M., Aye, G. C. & Gupta, R. (2015). Persistence of precious metal prices: a fractional integration approach with structural breaks. *Resources Policy 44*, 57–64.
Grafton, R. Q., Ward, M. B., To, H. & 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. & Kompas, T. (2015). Optimal water tariffs and supply augmentation for cost-of-service regulated water utilities. *Utilities Policy 34*, 54–62.
Granger, C. W. J. (1980). Long memory relationships and the aggregation of dynamic models. *Journal of Econometrics 14*, 227–238.
Granger, C. W. J. & Hyung, N. (2004). Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance 11*, 399–421.
Grant, L. & Langpap, C. (2019). Private provision of public goods by environmental groups. *Proceedings of the National Academy of Sciences 116*(12), 5334–5340.
Hanemann, W. M. (1993). *Designing New Water Rates for Los Angeles*. University of California, Berkeley. Retrieved from: http://opensiuc.lib.siu.edu/cgi/viewcontent.cgi?article=1421&context=jcwre
Hoque, S. F. & 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.
House-Peters, L. A. & Chang, H. (2011). Urban water demand modeling: review of concepts, methods, and organizing principles. *Water Resources Research 47*(5), W05401.
Howitt, R. E. (1995). Positive mathematical programming. *American Journal of Agricultural Economics 77*(2), 329–342.
Jack, B. K. & Jayachandran, S. (2019). Self-selection into payments for ecosystem services programs. *Proceedings of the National Academy of Sciences 116*(12), 5326–5333.
Johansen, S. & Nielsen, M. Ø. (2010). Likelihood inference for a nonstationary fractional autoregressive model. *Journal of Econometrics 158*, 51–66.

Johansen, S. & Nielsen, M. Ø. (2012). Likelihood inference for a fractionally cointegrated vector autoregressive model. *Econometrica 80*(6), 2667–2732.

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

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

Mahlknecht, J., González-Bravo, R. & Loge, F. J. (2020). Water-energy-food security: a nexus perspective of the current situation in Latin America and the Caribbean. *Energy 194*(1), 116824.

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

Martínez-Espiñeira, R. & 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. & Pulido-Velazquez, M. (2018). Determinants of the price response to residential water tariffs: meta-analysis and beyond. *Environmental Modelling & Software 101*, 236–248.

Mikosch, T. & Starica, C. (2004). Nonstationarities in financial time series, the long range dependence and the IGARCH effect. *Review of Economics and Statistics 86*(1), 378–390.

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

Monge, M. & Gil-Alana, L. A. (2019). Automobile components: lithium and cobalt. Evidence of persistence. *Energy 169*, 489–495.

Monge, M., Gil-Alana, L. A. & de Gracia, F. P. (2017a). Crude oil price behaviour before and after military conflicts and geopolitical events. *Energy 120*, 79–91.

Monge, M., Gil-Alana, L. A. & de Gracia, F. P. (2017b). US shale oil production and WTI prices behaviour. *Energy 141*, 12–19.

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

Moore, M. R., Gollehon, N. R. & Carey, M. B. (1994). Multicrop production decisions in western irrigated agriculture: the role of water price. *American Journal of Agricultural Economics 76*(4), 859–874.

Mundlak, Y. (2001). Production and supply. In *Handbook of Agricultural Economics*, Vol. 1. Gardner, B. & Rausser, G. C. (eds). A. Agricultural Production, Elsevier, Amsterdam, pp. 3–85.

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

OECD (1999). *Household Water Pricing in OECD Countries*. OECD Publishing, Paris.

Ohanissian, A., Russell, J. R. & Tsay, R. S. (2008). True or spurious long memory? *A new test. Journal of Business and Economic Statistics 26*(2), 161–175.

Olmstead, S. M., Hanemann, W. M. & Stavins, R. N. (2007). Water demand under alternative price structures. *Journal of Environmental Economics and Management 54*(2), 181–198.

Pinto, F. S. & Marques, R. C. (2015). Tariff structures for water and sanitation urban households: a primer. *Water Policy 17*(6), 1108–1126.

Renwick, M. E. & 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. & 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. (2003). Time series with long memory. In *Advanced Texts in Econometrics*. Robinson, P. M. (ed.). Oxford University Press, Oxford, UK.

Robinson, P. M. & Zaffaroni, P. (1997). Modelling nonlinearity and long memory in time series. *Fields Institute Communications 11*, 161–170.

Rogers, P., De Silva, R. & 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. & 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.

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

Schoengold, K., Sunding, D. L. & Moreno, G. (2006). Price elasticity reconsidered: panel estimation of an agricultural water demand function. *Water Resources Research 42*(9), W09411.

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

Silverberg, G. & Verspagen, B. (1999). *Long Memory in Time Series of Economic Growth and Convergence*. Eindhoven Center for Innovation Studies, Working Paper 99(80). Maastricht University, Maastricht.

Smith, V. K. & 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.

Sowell, F. (1992). Modelling long run behaviour with the fractional ARIMA model. *Journal of Monetary Economics 29*(2), 277–302.

Tsur, Y. (2019). *Water Pricing. Technical Report 1.19*. The Center for Agricultural Economic Research, The Hebrew University of Jerusalem.

Tsur, Y. (2020). Optimal water pricing: accounting for environmental externalities. *Ecological Economics 170*, 106429.

Tsur, Y. & Zemel, A. (2018). Water policy guidelines: a comprehensive approach. *Water Resources and Economics 23*, 1–13.

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

UN (United Nations) (2019). *World Population Prospects: The 2019 Highlights*. Department of Economic and Social Affairs, Population. Available from: https://population.un.org/wpp/Publications/Files/WPP2019_Highlights.pdf

Weber, M. A., Meixner, T. & Stromberg, J. C. (2016). Valuing instream-related services of wastewater. *Ecosystem Services 21*, 59–71.

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

Zetland, D. & Gasson, C. (2013). A global survey of urban water tariffs: are they sustainable, efficient and fair? *International Journal of Water Resources Development 29*(3), 327–342.

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