Long Memory in the Energy Consumption by Source of the United States: Fractional Integration, Seasonality Effect and Structural Breaks*

Memoria Larga en el Consumo de Energía en Estados Unidos: Integración Fraccional, Estacionalidad y Quiebres Estructurales

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Abstract

In this paper, long memory behavior of the energy consumption by source of the United States has been examined using the fractional integration technique for the three conventional cases of no regressors, an intercept, and an intercept and a linear trend. In addition, this study extends majority of past studies by considering the effects of seasonality and structural breaks. Using monthly data, it is found that across all the sources considered, energy consumption exhibits long memory with the degree of persistence largely ranging between 0 and 1. Also, the estimated results of the models with seasonality effect and structural breaks show that the energy consumption series have significantly strong seasonal pattern and autoregressive components, and the presence of structural breaks significantly alter the degree of persistence of most of the energy sources. The reports of this study have serious policy implications in the aspect of energy consumption mix, energy consumption efficiency and environmental concerns.

Key words: *Long memory, fractional integration, structural breaks.*

JEL Classification: *C22.*

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Resumen

Este trabajo examina el comportamiento de memoria larga del consumo de energía en Estados Unidos utilizando la técnica de integración fraccional. Este estudio extiende trabajos pasados incluyendo un análisis de estacionalidad y de quiebres estructurales. Utilizando datos mensuales se observa que todas las fuentes de consumo de energía consideradas exhiben memoria larga, estacionalidad y quiebres.

Palabras clave: *Memoria larga, integración fraccional, quiebres estructurales.*

Clasificación JEL: *C22.*

1. Introduction

Till date, energy, either renewable or non-renewable, is a factor whose importance cannot be undervalued in almost all contemporary economies. In fact, it can trigger economic crises depending on the level of dependence of an economy on its consumption or on it as a factor input into production processes. This is because there is hardly any sector of the economy that can stand independent of the energy sector. In light of this, this study assesses long memory behavior of energy consumption of the United States across various sources. This is carried out within the fractional integration framework which helps to determine the different degrees of persistence exhibited by the energy sources. This study further accounts for seasonality and structural breaks in the models.

Meanwhile, different degrees of persistence of energy consumption indicate different meanings, and thus have different policy implications. Critically, the higher the degree of persistence, the more difficult it is for the energy consumption to revert back to its predetermined or average target if any exogenous shock occurs. By implication, a tougher policy stance is required to control the effect of exogenous shock on the energy source whose consumption exhibits higher degree of persistence. For instance, given that the integration order is defined as d, a zero value indicates stationarity while a value of 1 shows the presence of unit root. Hence, if the integration value reveals that energy consumption is stationary ($d = 0$), the effect of shocks to energy consumption will be temporary and no policy, per se, is required to establish mean reversion (see Fallahi *et al.*, 2016). One can then go ahead to forecast the future values of energy consumption using its past values (see Apergis *et al.*, 2010; Lean and Smyth, 2009). If, on the other hand, unit root is contained in the energy consumption series ($d = 1$), the effect of shocks is rather not transitory, but permanent. Thus, public policy may not be able to reverse the effects of the shocks since there appears to be no trend path to return to.

Furthermore, energy has continually maintained a strong relationship with other sectors of the US economy. As this is true, whatever happens to energy consumption will be felt by other sectors of the economy, especially those that directly depend on the energy sector, such as the manufacturing, industrial, commercial and residential sectors. Intuitively, how much other sectors of the economy and several important macroeconomic indicators will be affected is a function of the level of persistence of the effect of shocks on energy consumption. The level of persistence in energy consumption is transmitted to other economic sectors and macroeconomic aggregates (see Lean and Smyth, 2009; Gil-Alana *et al.*, 2010; Barros and Gil-Alana, 2011).

However, using the fractional integration approach, there are no much studies on the persistence of energy consumption by source in the US despite the fact that energy is a crucial factor in the country. The available studies for the country either focused on a single disaggregate energy type or a sector (see, for instance, Lean and Smyth, 2009; Gil-Alana *et al.*, 2010). Also, accounting for seasonality and structural breaks are major deficiencies of the available few studies. Only Gil-Alana *et al.* (2010) gave attention to seasonality, while no existing studies on the degree of persistence of the US energy consumption by source allow for possible structural breaks in the series. This gap is thus aimed to be filled by this study by examining long memory in energy consumption by source of the US via the adoption of the fractional integration framework that is modified to include seasonality effect and structural breaks.

The rest of the paper is structured in the following order. Section 2 reviews past studies briefly. Section 3 describes the data and preliminary analyses. Section 4 gives the outlines of the methodology. Section 5 discusses the empirical findings. The closing remarks and relevant policy implications are highlighted in the Section 6.

2. PAST STUDIES IN VIEW

Studies on the assessment of stationarity properties of energy indicators are not scarce. This is because, apart from the need to examine their stationarity behaviour for appropriate policy formulations and implementations following the occurrences of shocks, certain multivariate analyses involving time series and panel data require that the variables be checked for unit root in order to determine the appropriate estimation technique. For instance, the Ordinary Least Square (OLS) technique breaks down if the series under consideration observe mixed integration orders, i.e. I(0) and I(1). In this case, the Autoregressive Distributed Lag (ARDL) model is the most appropriate.

So, aggregate and disaggregate energy indicators, such as energy consumption, energy prices, energy production have been assessed for unit root in the

literature using univariate parametric models (for instance, see Shahbaz *et al.*, 2014; Joyeux and Ripple, 2007; Lee and Chang, 2008, Kahia *et al.*, 2017; Narayan and Smyth, 2005; Esen and Bayrak, 2017; Dogan, 2014; Pereira and Belbute, 2014; Fasanya *et al.*, 2018; Mishra *et al.*, 2009; and Salisu *et al.*, 2017, among others). The studies are diverse between those that consider unit root models with and without structural breaks, as well as those that make use of time series and panel data. As also summarily reported by Belbute (2016), evidences of unit root are concluded by the parametric univariate unit root tests when no structural breaks are considered. On the other hand, stationarity is established by unit root models with structural breaks. In the case of panel unit root models, the null hypothesis of unit root is rejected in most cases, thus concluding that panel energy consumption data are largely stationary.[1]

From the foregoing, two facts can be safely inferred. Firstly, studies on the stationarity properties of energy consumption have not reached any consensus, although majority conclude non-stationarity depending on whether structural breaks are considered or not, and whether the variables are time series or panel data. However, the inability of most of these studies to establish stationarity is due to the poor power of the parametric univariate unit root models to reject the null hypothesis in the presence of fractional integration, structural breaks, seasonal effects, etc. (see Gil-Alana *et al.*, 2010; Apergis and Payne, 2010 and Narayan and Smyth, 2007). Secondly, Diebold and Rudebush (1989) and Belbute (2016) soundly reveal that the unit root models only explain that the past values of a variable determine its present behaviour, but are deficient in indicating how long the influence lasts. This is because the conventional unit root models only indicate if the series is I(1) or I(0). They are unable to indicate if the integration order is not strictly 0 and 1. Thus, the ability to understand the different degree of persistence is limited.

In light of these two facts, empirical studies have been driven towards the likelihood of economic variables to observe varying persistence levels. In order words, integration order of variables can be any number on the number line, not necessarily an integer. This thus favours the fractional integration technique in the assessment of long memory in economic variables. Unfortunately, this technique has gained more prominence only in major macroeconomic indicators like national output/gross domestic products, unemeployment, exchange rates, inflation, stock market indices, consumption, etc. (see Diebold and Rudebush, 1989; Diebold *et al.*, 1991; Caporale and Gil-Alana, 2008; Gil-Alana, 2002, etc.).

However, only in recent times has the literature been witnessing studies examining long memory in energy indicators. These studies include Lean and Smyth (2009), Gil-Alana *et al.*, 2010; Gil-Alana, 2012; Apergis and Tsoumas (2011), Barros *et al.* (2012) and Elder and Serletis (2008). The studies largely find that the energy indicators exhibit long memory with the level of persistence ranging between 0 and 1.

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[1]   See Smyth (2012) for a comprehensive review of studies on the stationarity properties of energy consumption and production.

This paper therefore parallels these few studies in the energy literature by examining long memory in the energy consumption of the US across various sources within the fractional integration framework. It extends majority of these studies by giving consideration to structural breaks and seasonality. Fractional integration methods can also be bias if structural breaks and seasonal fluctuations are present, but are not accounted for.

3. DATA AND PRELIMINARY ANALYSES

Monthly frequency data for nine energy consumption sources in the United States are considered for analysis. The energy consumption sources are coal, natural gas, petroleum, nuclear, hydroelectric, geothermal, biomass, solar and wind. The data spans from January, 1973 to August, 2018, except for solar (December, 1983 to August, 2018) and wind (January, 1983 to August, 2018). Also, for the sake of analysis, natural logarithm is taken for the data, except solar and wind due to the zero energy consumption values recorded for some months. The United States Energy Information Administration (US-EIA) is the source of all the data and they are measured in Quadrillion Btu.

Next, necessary preliminary analyses results are turned to. Starting with the descriptive statistics of the data (see Table 1), petroleum is the most averagely consumed, followed by natural gas and coal. These three energy sources particularly fall under the non-renewable or fossil fuel energy type. On the other hand, the renewable energies are insignificantly consumed compared to the fossil fuels, but are on the increase in recent times due to their low carbon emission and global warming. Also, the data are not too widely dispersed, as revealed by the standard deviation statistic, but still, the dispersion is higher for the fossil fuels. The Jarque-Bera statistic further shows that only petroleum consumption is normally distributed.

Table 2 displays the results of the unit root tests. Intentionally, three different unit root tests are carried out in order to ensure robustness since they conclude stationarity under different assumptions and they differ in their power to reject the null hypothesis. For the case of absence of structural breaks, Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) tests due to Dickey and Fuller (1979) and Philips and Perron (1988) respectively are employed. The results show evidence of non-stationarity in most scenarios. These unit root tests have been proved to be bias in the presence of structural breaks in the series, as mostly common to high frequency time series data (Fasanya *et al.*, 2018). Hence, the unit root test with structural breaks due to Perron and Vogelsang (1993) unit root test is carried out. Still, the results are mixed, but vary relatively from the outcomes of the tests without structural breaks. For instance, the fossil fuels show stationarity under the unit root models with intercept, and intercept and trend, but non-stationarity is the case under the unit root test with structural breaks. This shows the need to account for structural breaks, on one hand. On the other hand, the inability of the tests to yield a conclusive report may be due to their

TABLE 1
STATISTICAL PROPERTIES

Energy Source	Mean	Maximum	Minimum	Std. Dev.	Jarque-Bera	Obs.
Coal	1.5244	2.1335	0.8442	0.2971	18.7684	548
Natural Gas	1.8497	3.4200	0.9601	0.4530	29.6624	548
Petroleum	2.9387	3.5698	2.2281	0.2482	5.9319**	548
Nuclear	0.5043	0.7808	0.0621	0.2049	52.6428	548
Hydroelectric	0.2382	0.3574	0.1457	0.0440	11.5639	548
Geothermal	0.0118	0.0199	0.0014	0.0055	62.4293	548
Biomass	0.2623	0.4469	0.1149	0.0805	23.8692	548
Solar	0.0113	0.1067	–0.0000	0.0177	2208.0640	416
Wind	0.0411	0.2514	0.0000	0.0629	203.1273	428

** indicates the non-rejection of the null hypothesis of normal distribution of the series at 5% significance level.

TABLE 2
UNIT ROOT PROPERTIES

Energy Source	Tests without Breaks						Test with Breaks	
	ADF			PP			Perron-Vogelsang	
	None	Const.	Trend	None	Const.	Trend	Const.	Trend
Coal	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
Natural Gas	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
Petroleum	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
Nuclear	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Hydroelectric	I(1)	I(0)	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)
Geothermal	I(0)	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)
Biomass	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)
Solar	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Wind	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)

I(0) and I(1) respectively indicate stationarity at level and first difference.

poor performance if the series observe fractional integration and seasonality (see Gil-Alana *et al.*, 2010). Hence, the non-seasonal and seasonal fractional integration models are implemented.

FIGURE 1
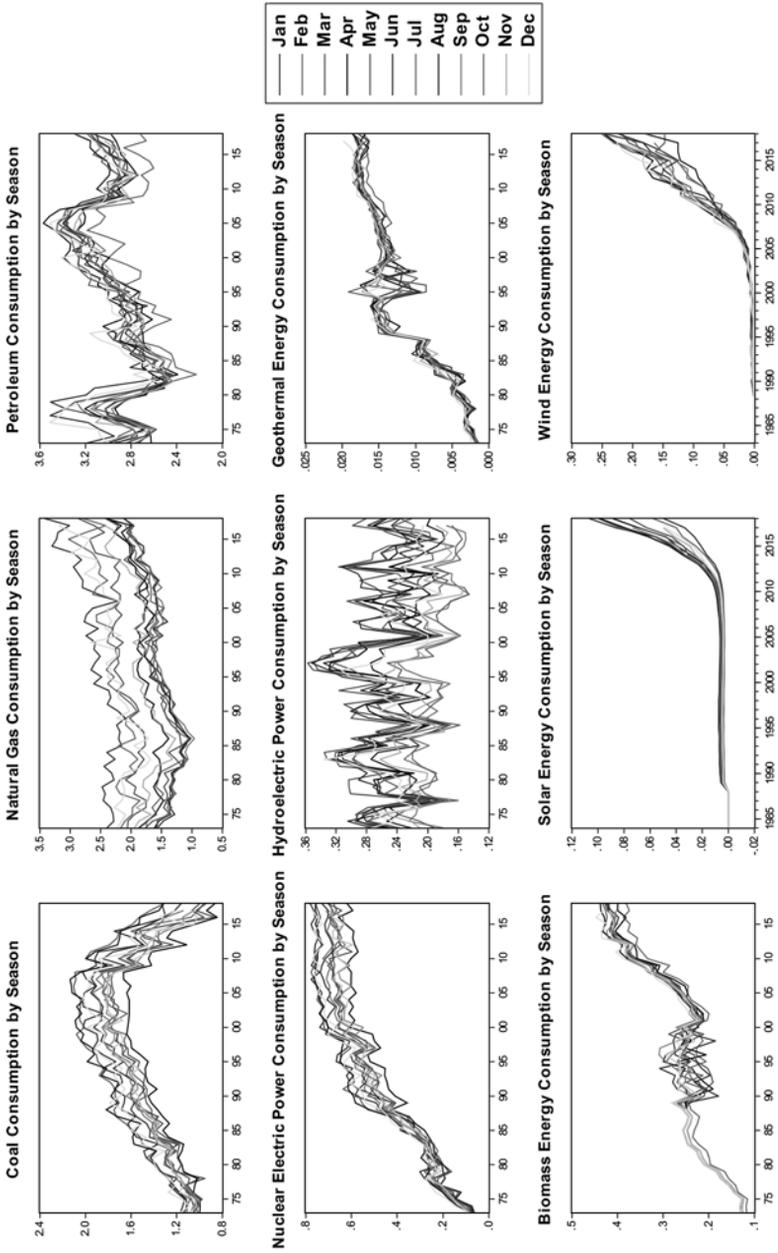
In order to have a foresight of the likely presence of seasonality effect in the energy consumption variables, seasonal graphs are constructed to show the variations in the mean energy consumption across months. Figure 1 shows significant differences in the energy consumed. Seasonality is more feasible for coal, natural gas, petroleum, nuclear electric power and hydroelectric power. It is mild for geothermal and biomass, while the early years of solar and wind indicate no seasonality.

4. METHODOLOGY

Following the empirical knowledge that the degree of differentiation of economic series can be any fractional number other than a real integer, the fractional integration methodology is favoured in this study. The baseline fractional integration model is started with, and it is specified thus:

$$(1) \qquad\qquad y_t = \gamma' z_t + x_t; \quad t = 1, 2, \ldots, n$$

where the observed time series is y_t, γ is the vector of unknown coefficients and z_t is the vector of deterministic factors of the process y_t. The deterministic factors may include an intercept, a linear time trend and structural breaks.

The I(d) or fractionally integrated model of order d $\left(x_t \sim I(d)\right)$ is of the form:

$$(2) \qquad\qquad (1-L)^d x_t = \mu_t$$

where the lag operator, defined as $L\,x_t = x_{t-1}$, is L, d is a real number which may take up a fractional value and μ_t is assumed to follow a I(0) process, i.e. white noise or covariance stationary process.

The expansion of $(1-L)^d$ in equation (2) can be binomially expressed in terms of infinite order, thus reflecting a slow and monotonic declining weights. It is given thus:

$$(3) \qquad (1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j}(-1)^j L^j = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \ldots$$

Therefore,

$$(4) \qquad (1-L)^d x_t = x_t - dx_{t-1} + \frac{d(d-1)}{2!}x_{t-2} - \frac{d(d-1)(d-2)}{3!}x_{t-3} + \ldots$$

d is the fractional integration order. It indicates the extent of persistence of the series being considered. Specifically, higher value of the d estimate implies a greater persistence level of the series. In particular, a value of d below the unit line,

but above 0, i.e. $0 < d < 1$, would mean that the series will observe a reversion to its mean value in case there is an occurrence of shocks. By further implication, this implies that the series long memory exhibit long memory behaviour, but the effects of shocks are transitory as they die out hyperbolically (slowly) in the long run. Within the 0 and 1 range, it is also important to note that the rate at which the effect of shocks dies out differs. For instance, it dies out faster when $0 < d < 0.5$ than the case of $0.5 < d < 1$. On the other hand, a value of d above the unit line, i.e. $d \geq 1$, indicates non-stationarity and non-mean reversion in the series. Indeed, this scenario implies that the effects of shocks are permanent. Only if strong policies are put in place would there be mean reversion later in the long run. The other scenarios are when $d = 1$ (random walk), and $d = 0$ (stationarity), thus making $x_t = \mu_t$.

Next, seasonality is considered in the fractionally integrated processes. Monthly energy consumption series cannot be strictly disassociated from seasonal fluctuations, thus making studies like Gil-Alana and Robinson (2001) and Gil-Alana *et al.* (2010) to consider seasonality within the fractional integration framework. Therefore, the two standard approaches of accounting for seasonality in univariate models, such as the fractional integration model of this study, are used. The first assumes unit root with seasonal short-run dynamics while the other is based on the assumption that the model has seasonal unit root with non-seasonal AR(MA) components. These two seasonality assumptions are independently reflected in the fractional integration model.

In the case of unit root with seasonal short-run dynamics, for instance, the y_t process is re-expressed as:

$$(5) \qquad (1-L)^d x_t = \mu_t; \ \ \delta_s\left(L^s\right)\mu_t = \varepsilon_t$$

Where L^s becomes the seasonal lag operator given as $L^s x_t = x_{t-s}$, and $\delta_s\left(L^s\right)$ represents the seasonal AR polynomial that explains the seasonal dynamics of the series in the short-run. Definitions of other parameters remain the same.

Based on equation (5), the specific model for the seasonal AR(1) process is:

$$(6) \qquad y_t = \beta' z_t + x_t; \ \ (1-L)^d x_t = \mu_t; \ \mu_t = \rho_s \mu_{t-12} + \varepsilon_t; \ \ t = 1, 2,\ldots,n$$

The seasonal fractional integration model based on the second assumption gives:

$$(7) \qquad \left(1-L^s\right)^{d_s} x_t = \mu_t; \ \ \delta(L)\mu_t = \varepsilon_t$$

where s indicates the 12 months in a year. Definitions of other parameters remain the same.

Also, the estimated model based on equation (7) for the non-seasonal AR(1) process is:

(8) $y_t = \beta' z_t + x_t;\ (1-L)^{d_s} x_t = \mu_t;\ \mu_t = \rho_s \mu_{t-1} + \varepsilon_t;\ t = 1, 2, \ldots, n$

Again, d and d_s in equations (5) - (8) can be fractional values. If d is positive, then the process in equation (5) is said to exhibit long memory in the zero or long-run frequency, while the nature of the seasonality is described by the stationary AR model. More so, if $d = 0$, there is seasonal AR process, but unit root is the case if $d = 1$. Considering equation (6), seasonality exhibits long-run attribute while the short-run dynamics reveal non-seasonal AR process if d_s is greater zero ($d_s > 0$). However, if $d_s = 0$, the outcome is non-seasonal AR, but if $d_s = 1$, the model exhibits seasonal unit root.

In all, the approach of Robinson (1994) is employed to estimate the differencing parameter, d. It tests the $H_0 : d(d_s) = d_0(d_{so})$ in equations (5) - (8) for any real value of $d_0(d_{so})$. The approach is superior to other techniques developed for evaluating the fractional integration properties of time series data because for at least two reasons. First, it allows the consideration of three standard scenarios in empirical analysis: (a) no deterministic terms, i.e. $z_t = 0$, (b) an intercept, i.e. $z_t = 1$, (c) an intercept with a linear time trend, i.e. $z_t = (1,t)'$. In fact, the three standard cases can also be modified to include structural breaks, such as is done in this study.

Second, initial differencing of the series in order to induce stationarity is not required before estimation, as it works well for both non-stationarity ($d, d_s \geq 0.5$) and stationarity ($d, d_s < 0.5$) cases of the series.

5. Empirical Results

The empirical results are uniquely presented under two scenarios. The first assumes the absence of structural breaks while the second accounts for structural breaks. For each scenario, non-seasonally and seasonally fractionally integrated models are estimated. In addition, across all the energy sources, three conventional cases of fractional integration models- no deterministic terms, an intercept and a linear time trend- are considered. However, the best model based on the significance of the deterministic terms, has its estimates reported.

5.1. Model without Structural Breaks

Model without structural breaks is started with. Table 3 reports the results for of d when no seasonality is put into consideration. Except for natural gas whose value is significantly greater than 1, the estimates of all other energy consumption sources fall between 0 and 1. Specifically, the estimates of petroleum, solar and wind energy consumption are between 0 and 0.5 while the energy consumed of coal, hydroelectric power, nuclear electric power, geothermal and biomass are well over 0.5 but less than 1. The value of hydroelectricity, however, is still reasonably close to the threshold of 1 upon which unit root is established.

Thus, the unit root hypothesis is rejected for all the energy measures, except hydroelectricity. By further implication, they all exhibit long memory, implying that shocks to energy consumption will be permanent for natural gas. For the energy sources (petroleum, solar and wind) with $0.5 < d < 1$ consumption will observe long memory with the effects of shocks reverting rather slowly. The remaining energy sources also exhibit long memory since $0 < d < 0.5$, but shocks will be transitory as they revert very quickly; they are thus said to be stationary with long memory, and so require no strong government policies to tackle the effects of the shocks.

Next, seasonality is allowed for to assess long memory in the energy sources. The results for the two standard approaches of accounting for seasonality are reported. The estimates of d under the assumption that the residual term μ_t observes seasonal AR(1) process. Table 4 displays the results. It is seen that there is a significant difference between the results and those reported in Table 3 (when no seasonality was considered). For instance the d estimates are smaller when seasonality is put into consideration, except for petroleum consumption. In fact, it is too glaring and surprising for natural gas whose value dropped from 1.4165 to as low as 0.4689, thus implying that the persistence or long memory with no mean reversion explained to be exhibited by it is due to non-consideration of seasonality. When seasonality is accounted for, the true nature of natural gas consumption is that it is stationary mean reverting, thus implying that shocks will be temporary and revert very quickly. For others too, except petroleum,

TABLE 3
COEFFICIENT ESTIMATES BASED ON MODEL 2

Energy Source	d (95% confidence interval)	Intercept (t-value)	Linear time trend (t-value)
Coal	0.7125 (0.62, 0.81)	–0.3562 (–2.07)	--------
Natural Gas	1.4165 (1.30, 1.53)	0.5194 (1.82)	--------
Petroleum	0.4372 (0.39, 0.49)	–0.0606 (–1.98)	0.0002 (2.11)
Nuclear	0.7525 (0.68, 0.83)	–1.4580 (–6.19)	0.0038 (3.92)
Hydroelectric	0.9331 (0.83, 1.04)	--------	--------
Geothermal	0.7011 (0.51, 0.90)	–1.5526 (–7.92)	0.0043 (5.48)
Biomass	0.5644 (0.51, 0.62)	–0.6385 (–8.91)	0.0021 (8.54)
Solar	0.4994 (0.50, 0.501)	--------	--------
Wind	0.4992 (0.50, 0.501)	--------	--------

TABLE 4
COEFFICIENT ESTIMATES BASED ON MODEL 6

Energy Source	d (95% confidence interval)	Intercept (t-value)	Linear time trend (t-value)	AR (t-value)
Coal	**0.6558** (**0.58, 0.73**)	−0.2633 (−1.92)	--------	0.8763*** (38.20)
Natural Gas	**0.4689** (**0.38, 0.56**)	0.2316 (2.08)	--------	0.9370*** (59.90)
Petroleum	**0.4612** (**0.40, 0.52**)	--------	--------	0.7812*** (29.00)
Nuclear	**0.7393** (**0.66, 0.82**)	−2.4603 (−7.85)	0.0042 (2.00)	0.7430*** (26.30)
Hydroelectric	**0.7884** (**0.70, 0.87**)	--------	--------	0.6972*** (22.70)
Geothermal	**0.6494** (**0.58, 0.72**)	-0.4555 (−0.88)	0.0027 (2.73)	0.3103*** (8.13)
Biomass	**0.5053** (**0.44, 0.67**)	−0.3412 (−1.91)	0.0016 (4.01)	0.5866*** (17.10)
Solar	0.4989 (0.50, 0.51)	--------	--------	0.9872*** (198.00)
Wind	**0.4257** (**0.35, 0.50**)	−0.0757 (−1.51)	0.0005 (5.27)	0.8091*** (18.30)

*** indicates significance at 1% critical level. Values in bold indicate significant alteration to the d estimates (level of persistence) from their original values in Table 3.

TABLE 5
COEFFICIENT ESTIMATES BASED ON MODEL 8

Energy Source	d (95% confidence interval)	Intercept (t-value)	Linear time trend (t-value)	AR
Coal	**0.4737** (**0.38, 0.56**)	−0.2860 (−3.05)	0.0005 (1.76)	0.4062*** (7.87)
Natural Gas	**0.6487** (**0.51, 0.79**)	--------	--------	0.6194*** (14.40)
Petroleum	**0.6338** (**0.56, 0.71**)	--------	--------	−0.3827*** (−7.86)
Nuclear	**0.6205** (**0.54, 0.70**)	−1.4626 (−8.96)	0.0039 (6.19)	0.2800*** (5.27)
Hydroelectric	**0.3034** (**0.17, 0.44**)	--------	--------	0.6066*** (11.10)
Geothermal	**0.7697** (**0.68, 0.86**)	−1.5525 (−6.19)	0.0042 (4.18)	−0.1265** (−2.08)
Biomass	**0.6585** (**0.58, 0.74**)	−0.6613 (−7.27)	0.0022 (6.37)	−0.1956*** (−3.57)
Solar	0.4953 (0.48, 0.51)	--------	--------	0.8813*** (37.20)
Wind	0.4950 (0.48, 0.51)	--------	--------	0.4819*** (10.90)

*** and ** indicate significance at 1% and 5% critical levels respectively. Values in bold indicate significant alteration to the d estimates (level of persistence) from their original values in Table 3.

the reduced *d* estimates indicate that although long memory is still established, shocks will experience faster mean reversion unlike when no seasonality is accounted for. The high values and significance of the AR component further substantiates the need to account for seasonal effect.

Also, credence is given to seasonality in long memory assuming that the fractional integrated model has non-seasonality AR(1) μ_t. Once again, Table 5 shows a significant drop in the estimates of *d* of most of the energy sources. However, two other energy sources (geothermal and biomass) join petroleum to observe a rise in the estimate of *d.* Critically, it is discovered that these three energy sources have their AR coefficients to be negative, thus being the reason for the increase in their *d* estimates. It is also discovered that the AR components are really smaller than when the error term is assumed to observe seasonal AR(1) process, but they are all significant. Notwithstanding, long memory is still observed since the *d* estimates still fall within the interval of 0 and 1. Also, the energy consumption across all sources are sensitive to seasonality, although the effect is higher when the error term is assumed to follow a seasonal AR(1) process.

5.1. Model with Structural Breaks

Empirical studies have proved that despite the fact that fractional integration models are superior to the conventional unit root models in evaluating the stationarity properties of time series variables and the level of persistence of shocks, they can be bias not only when the series observe seasonal changes, but also when there are significant structural shifts or breaks along their time paths.

TABLE 6
BAI-BERRON BREAK DATES

Energy Source	B1	B2	B3	B4
Coal	1983M06 (10.075)	1995M06 (14.357)	2011M09 (15.821)	--------
Natural Gas	--------	-------	--------	--------
Petroleum	1981M02 (17.003)	1990M09 (53.75)	2001M11 (6.025)	2008M02 (8.830)
Nuclear	1980M01 (25.999)	1989M06 (8.409)	1999M05 (6.800)	--------
Hydroelectric	2000M06 (6.572)	--------	--------	--------
Geothermal	1989M01 (23.542)	2008M03 (25.919)	--------	--------
Biomass	1983M01 (11.006)	1993M08 (31.846)	2001M01 (11.592)	2010M03 (10.773)
Solar	2013M02 (9.070)	--------	--------	--------
Wind	2012M10 (24.537)	--------	--------	--------

Retrospectively, the energy market is often faced with external shocks from both demand and supply sources. These have often affected its consumption at certain times. This study thus takes a further step to account for structural breaks. The Bai and Perron (2003) test that gives multiple structural break is considered to determine the breaks and their timings, after which they are modeled in the fractional integration equation to evaluate their significance. The identified break dates coincide with certain major world events, especially in the energy market. The events include the 1999/2000 Middle-east up-rise due to the series of OPEC cuts, 2008 global financial crisis, 2012/2013 Arab springs, 2011-2012 oil price boom, etc.

Having determined the structural breaks, their significance in the persistence level of the energy consumption sources is evaluated. In other words, this study further intends to show whether the presence of structural breaks can significantly alter (increase or reduce) the level of persistence of the consumption of the energy sources. However, nuclear energy consumption is not considered as no break dates are established for it. Table 7 reports the *d* estimates when seasonality is not put into consideration. The breaks are not significant for hydroelectric power consumption, but are largely significant for others. It is clearly seen that although the estimates are still within the range of 0 and 1, they are lower than estimates in Table 3 when no breaks are accounted for, especially for coal, petroleum, geothermal and biomass energy consumption.

TABLE 7
COEFFICIENT ESTIMATES BASED ON MODEL 2

Energy Source	d (95% confidence interval)	B1	B2	B3	B4
Coal	**0.6446[b]**	0.1941***	0.1181*	–0.1925***	--------
	(0.53, 0.76)	(2.84)	(1.73)	(–2.78)	
Petroleum	**0.3002[c]**	–0.1724***	–0.0325	–0.0131	–0.1580***
	(0.24, 0.36)	(–8.41)	(–1.53)	(–0.63)	(–7.39)
Nuclear	0.7516[c]	–0.0228	0.1480*	0.0985	--------
	(0.68, 0.83)	(–0.27)	(1.72)	(1.14)	
Hydroelectric		Insignificant breaks			
Geothermal	**0.6875[c]**	0.4452***	0.0441	--------	--------
	(0.63, 0.75)	(5.16)	(0.506)		
Biomass	**0.5398[c]**	0.0836*	0.0745	–0.1687***	0.0965**
	(0.48, 0.60)	(1.75)	(1.44)	(–3.49)	(2.02)
Solar	0.4991[a]	0.0211***	--------	--------	--------
	(0.50, 0.501)	(7.41)			
Wind	0.4984[a]	0.0723***	--------	--------	--------
	(0.49, 0.51)	(8.96)			

***, ** and * indicate significance at 1%, 5% and 10% critical levels respectively. a, b and indicate models without regressors, with an intercept, and with an intercept and a linear time trend. Values in bold indicate significant alterations to the d estimates (level of persistence) from their original values in Table 3.

TABLE 8
COEFFICIENT ESTIMATES BASED ON MODEL 6

Energy Source	d (95% confidence interval)	B1	B2	B3	B4	AR
Coal	**0.6195[b]**	0.1011***	0.0146	–0.0558*	--------	0.8785***
	(0.54, 0.70)	(3.42)	(0.49)	(–1.84)		(38.40)
Petroleum	**0.4365[b]**	–0.0685***	–0.0529***	–0.0189	–0.0284	0.7810***
	(0.38, 0.50)	(–3.85)	(–2.98)	(–1.07)	(–1.59)	(29.80)
Nuclear	**0.7426[c]**	–0.0879*	0.0630	0.0502	--------	0.7453***
	(0.66, 0.82)	(–1.87)	(1.34)	(1.07)		(26.50)
Hydroelectric	0.7834[c]	–0.1508**	--------	--------	--------	0.7002***
	(0.70, 0.87)	(–2.24)				(22.90)
Geothermal	**0.6206[c]**	0.4318***	0.0404	--------	--------	0.3146***
	(0.55, 0.69)	(5.83)	(0.544)			(8.39)
Biomass	**0.4848[c]**	0.0599*	0.0997***	–0.1389***	0.0479	0.5976***
	(0.42, 0.55)	(1.71)	(2.71)	(–3.95)	(1.35)	(17.50)
Solar			No convergence			
Wind	0.4210[a]	0.0094*	--------	--------	--------	0.8038***
	(0.34, 0.50)	(1.74)				(17.80)

***, ** and * indicate significance at 1%, 5% and 10% critical levels respectively. a, b and indicate models without regressors, with an intercept, and with an intercept and a linear time trend. Values in bold indicate significant alterations to the d estimates (level of persistence) from their original values in Table 4.

TABLE 9
COEFFICIENT ESTIMATES BASED ON MODEL 8

Energy Source	d (95% confidence interval	B1	B2	B3	B4	AR
Coal	**0.3115[b]**	0.2362***	0.1302***	–0.2485***	--------	0.4603***
	(0.19, 0.43)	(4.95)	(2.84)	(–4.59)		(8.37)
Petroleum	**0.6429[a]**	–0.1172***	–0.0198	0.0119	–0.0593**	–0.4024***
	(0.56, 0.73)	(–3.82)	(–0.61)	(0.381)	(–1.99)	(–8.35)
Nuclear	**0.7197[b]**	0.0196	0.1492*	0.1686*	--------	0.2224***
	(0.65, 0.79))	(0.22)	(1.67)	(1.94)		(4.34)
Hydroelectric	**0.2790[a]**	–0.1156*	--------	--------	--------	0.6132***
	(0.14, 0.41)	(–1.79)				(11.50)
Geothermal	**0.7511[c]**	0.4390***	0.0524	--------	--------	–0.1163*
	(0.66, 0.84)	(5.08)	(0.60)			(–1.91)
Biomass	0.6517[c]	0.0711	0.1234**	–0.1723***	0.0762	–0.2132***
	(0.57, 0.74)	(1.45)	(2.32)	(–3.49)	(1.54)	(–3.85)
Solar			No convergence			
Wind	0.4920[a]	0.0606***	--------	--------	--------	0.4006***
	(0.47, 0.51)	(6.21)				(8.31)

***, ** and * indicate significance at 1%, 5% and 10% critical levels respectively. a, b and indicate models without regressors, with an intercept, and with an intercept and a linear time trend. Values in bold indicate significant alterations to the d estimates (level of persistence) from their original values in Table 5.

Next, structural breaks and seasonality are simultaneously accounted for within the fractionally integrated process. The results are presented in Tables 8 and 9. Considering the assumption that the residual term μ_t observes seasonal AR(1), Table 8 shows that the structural breaks are still largely significant. Also, AR components are significantly high. The large significance of the breaks and the AR components applaud and authenticate their joint modeling in the fractional integration equations. Again, the persistence level is significantly altered in 5 energy sources (coal, petroleum, nuclear, geothermal and biomass). The persistence becomes higher for nuclear energy consumption, but lower for the rest. Turning to the model with non-seasonal AR(1) μ_t, Table 9, as expected, provides that the AR components and structural breaks are significant. Except for biomass energy consumption whose place is taken by hydroelectric power consumption, the same energy sources whose d estimates are significantly altered in Table 8, still remains altered. However, persistence tends to be higher for petroleum and nuclear energy consumption and lower for others.

6. CONCLUSION AND POLICY IMPLICATIONS

The long memory behaviour of the energy consumption by source of the United States has been examined in this study. For this purpose, the fractional integration [$I(d)$] techniques in its baseline form, as well as its modified form to include seasonal effects and structural breaks, have been employed. The main findings of this study are that the consumption of energy across all sources considered has long memory, and strong seasonal patterns are established with significantly high autoregressive components. Also, the structural breaks are largely significant, and including them in the analysis alters the degree of persistence in most cases. Only in few instances do they not significantly alter the persistence level of the energy consumption. This signifies the importance of accounting for breaks.

There are policy implications of the findings established in this study. As noted by Belbute (2016), the presence of long memory may indicate a very strong energy consumption habit, rigidities in technological changes and energy substitutes. Therefore, energy policies, such as the granting of subsidies for more alternative energy sources, reduced consumption cost for energy sources that exhibit less persistence, sensitization on the improvement of energy efficiency, etc. will be more effective in ensuring reversion of energy use to its average consumption level, should there be shocks. Two or more of these policies can be combined depending on how high the degree of persistence.

Also, owing to the importance of energy in the US economy, every sector has close link with the energy sector. Therefore, permanent policy stance that encourages the consumption of renewable energies tends to contribute to environmental safety through the reduction in carbon emissions.

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