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Does energy consumption by the US electric power secto exhibit long memory behaviour?

Luis A. Gil-Alana
Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

James Payne
Interim Dean and Professor of Economics
College of Arts and Sciences
Illinois State University

and

David Loomis
Institute for Regulatory Policy Studies
and Associate Professor of Economics
Department of Economics
Illinois State University

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ABSTRACT

This communication analyzes the energy consumption by the U.S. electric power by various energy sources through fractional integration. In doing so, we are able to determine the level of persistence of the shocks affecting each energy source. The results indicate long memory behavior as each energy source is highly persistent, displaying long memory along with autoregressive behavior and strong seasonal patterns.

Luis A. Gil-Alana
University of Navarra
Faculty of Economics
Edificio Biblioteca, E. Este
E-31080 Pamplona, Spain
alana@unav.es

David Loomis
Executive Director of the Institute for Regulatory Policy Studies
and Associate Professor of Economics
Department of Economics
Illinois State University
Normal, IL 61790-4200
dloomis@ilstu.edu

James E. Payne*
Interim Dean and Professor of Economics
College of Arts and Sciences
Illinois State University
Normal, IL 61790-4100
jepayne@ilstu.edu

1. Introduction

The examination of the stationarity properties of energy consumption is important on several fronts. First, if energy consumption is stationary in levels, shocks to energy consumption will have only transitory effects. On the other hand, if energy consumption has a unit root, requiring first-differencing to render stationarity, shocks to energy consumption will have permanent effects. Second, the distinction between the transitory or permanent nature of shocks has implications for the transmission of shocks from energy consumption to other sectors of the economy. Indeed, if shocks to energy consumption are persistent such shocks may be transmitted to other sectors of the economy.

With the exception of the study by Lean and Smyth (2009), previous research by Chen and Lee (2007), Narayan and Smyth (2007), Hsu et al. (2008), and Mishra et al. (2009) has focused on the stationarity of aggregate energy consumption across panels of countries using standard unit root procedures.[1] This short communication parallels the recent work by Lean and Smyth (2009) which dealt with the long memory processes for U.S. petroleum consumption by sector. Specifically, this study emphasizes the long memory properties in the consumption of various energy sources by the U.S. electric power sector: coal, natural gas, petroleum, hydroelectric, nuclear, total fossil fuel, total renewable energy, and total primary energy. In particular, we use fractional integration methodologies that permit us to study the standard cases of stationarity (d = 0) and unit roots (d = 1) as particular cases of interest. Moreover, allowing the order of integration to be a real value we allow for a richer degree of flexibility in the dynamic specification of the series, and, depending on the value of d we can determine if the series is I(0) stationary (d = 0); stationary with long memory (0 < d < 0.5); nonstationary but mean reverting ($0.5 \leq d < 1$); or nonstationary and non-mean-reverting ($d \geq 1$).

According to the *Energy Information Administration,* in 2008 the U.S. electric power sector primary energy consumption totaled 40,090 trillion Btu of which fossil fuels comprised roughly 69.4%, nuclear 21.1%, and renewable 9.2%. Given the importance of the electric power sector in the generation of primary energy for use by other sectors of the economy, it is crucial to understand the impact of shocks related to the use of energy sources by this sector. Moreover, the prevailing concerns over fossil fuel usage and the environmental consequences, the proposed cap and trade legislation, and the increased interest in alternative energy sources may very well change the future energy consumption patterns of the U.S. electric power sector.

To this end, this short communication will determine whether various energy consumption measures by the U.S. electric power sector exhibit long memory behavior. Section 2 describes the data and methodology along with the results. Section 3 provides concluding remarks

2. Data, Methodology, and Results

Monthly data from January 1973 to May 2009 on energy consumption by the U.S. electric power sector by source denoted in trillion Btu was obtained from the *Energy Information Administration*: coal, natural gas, petroleum, hydroelectric, nuclear, total fossil fuel, total renewable energy, and total primary energy. All data have been converted into natural logarithms.[2]

Two well-known characteristics of the data examined in this study are the degree of dependence across time and the seasonality. Based on these features two plausible specifications that have been widely employed in univariate contexts in the time series literature are the unit root model with seasonal short run dynamics, and the alternative of a

seasonal unit root model with non-seasonal AR(MA) components. Thus, for example, if we believe that a series is nonstationary with respect to the long run component, first differences may be adopted, and we can consider a process of the form:

$$y_t = \beta' z_t + x_t; \quad (1 - L)x_t = u_t; \quad \phi_s(L^s)u_t = \varepsilon_t, \quad t = 1, 2, ... \quad (1)$$

where y_t is the time series we observe; β is a (kx1) vector of unknown coefficients; z_t is a (kx1) vector of deterministic terms that may include, for example, an intercept, a linear trend or seasonal dummy variables; and $\phi_s(L^s)$ is a seasonal AR polynomial describing the short run seasonal dynamics of the series. On the other hand, if we believe that the nonstationarity eminates from the seasonal structure, we can suppose that the series displays seasonal unit roots, and seasonal first differences should be adopted in this case. We can consider then a model of the form:

$$y_t = \beta' z_t + x_t; \quad (1 - L^s)x_t = u_t; \quad \phi(L)u_t = \varepsilon_t, \quad t = 1, 2, ... \quad (2)$$

where s is equal to 12 for monthly data. Unit root models of the form of (1) have become standard practice in applied time series econometrics. Also, the seasonal unit root model of the form of (2) has become a standard practice as well. However, a limitation of the above approaches is the emphasis on integer degrees of differentiation, being 0 in case of stationarity and 1 with nonstationary models. It is well known that standard procedures to test these models have extremely low power if the true data generating process is fractionally integrated with an order of integration close to, but smaller than 1 (see Diebold and Rudebusch, 1991; Hassel and Wolters, 1994; Lee and Schmidt, 1996).

In this study, we extend models (1) and (2) to the fractional case and thus, consider processes of the form:

$$y_t = \beta' z_t + x_t; \quad (1 - L)^d x_t = u_t; \quad \phi_s(L^s)u_t = \varepsilon_t, \quad t = 1, 2, ... \quad (3)$$

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and

$$y_t = \beta' z_t + x_t; \quad (1 - L^s)^{d_s} x_t = u_t; \quad \phi(L)u_t = \varepsilon_t, \quad t = 1, 2, \dots \quad (4)$$

where d and d_s may be non-integer values. Note that in (3) the process displays long memory with respect to the long run or zero frequency as long as d > 0, while the seasonality is described through a stationary AR model. On the contrary, in model (4) seasonality is long memory if d_s > 0 and the short run dynamics are described through a non-seasonal AR process. Also, in equation (3), if d = 0, we have a seasonal AR process, while, if d = 1, a model with a unit root; in (4), d_s = 0 produces a non-seasonal AR, while d_s = 1 is a seasonal unit root model.

The methodology employed in this paper is based on the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing procedure developed by Robinson (1994) that permits us to test models (3) and (4). The latter method tests the null hypothesis:

$$H_o: d \ (or \ d_s) = \ d_o \ (or \ d_{so}) \quad (5)$$

in (3) (or (4)) for any real value d_o (or d_{so}). It has the advantage that it does not require preliminary differencing to render the series stationary since it is valid for any real value d (or d_s), encompassing both the stationary (d, d_s < 0.5) and nonstationary (d, $d_s \geq$ 0.5) hypotheses. Moreover, this approach does not require Gaussianity with a moment condition only of order two required, and is robust against conditional heteroscedastic errors.

We begin by performing standard non-seasonal and seasonal unit root tests on the disaggregated energy consumption measures. For the non-seasonal case, we employed the ADF test (Dickey and Fuller, 1979) along with the tests of Phillips and Perron (1988) and Ng and Perron (2001). For the seasonal case, given the monthly nature of the data, we use

both the Beaulieu and Miron (1993) and Dickey et al. (1984) procedures. Though we do not report the results based on these methods, evidence of nonstationarity was found in the majority of the cases (i.e. unable to reject the unit root and seasonal unit root models at standard significance levels). However, the inability to reject the presence of a unit root may be due to the low power of these procedures, if indeed, the data are (seasonally or non-seasonally) fractionally integrated. Thus, we implement the procedures described by equations (3) and (4).

Table 1: Estimates of d and 95% Confidence Intervals based on model (6)

d - estimates	No regressors	An intercept	A linear time trend
Coal	[0.615 (0.693) 0.779]	[0.576 (0.631) 0.711]	[0.519 (0.602) 0.700]
Hydroelectric	**[0.834 (0.914) 1.010]**	[0.712 (0.803) 0.914]	[0.712 (0.803) 0.914]
Natural gas	[0.616 (0.713) 0.828]	[0.444 (0.545) 0.688]	[0.454 (0.560) 0.696]
Nuclear	[0.566 (0.655) 0.766]	[0.627 (0.688) 0.778]	[0.588 (0.672) 0.775]
Petroleum	[0.661 (0.727) 0.811]	[0.520 (0.582) 0.676]	[0.509 (0.584) 0.683]
Total fossil fuel	[0.654 (0.728) 0.813]	[0.473 (0.533) 0.619]	[0.415 (0.503) 0.610]
Total primary	[0.695 (0.767) 0.850]	[0.512 (0.557) 0.622]	[0.403 (0.489) 0.593]
Total renewable	[0.830 (0.907) 0.998]	[0.722 (0.808) 0.912]	[0.722 (0.808) 0.912]

Notes: In bold the cases where the unit root cannot be rejected at the 5% level.

Table 1 displays the estimates of d in model (3) under the assumption that the error term u_t follows a seasonal AR(1) process.[3] Therefore, the model considered is

$$y_t = \beta' z_t + x_t; \quad (1 - L)^d x_t = u_t; \quad u_t = \rho_s u_{t-12} + \varepsilon_t, \quad t = 1, 2, ..$$

(6)

Across all the energy consumption measures, we consider three standard cases: (1) no regressors (i.e. $z_t = 0$ in (6)); (2) an intercept ($z_t \equiv 1$); and (3) an intercept with a linear time trend ($z_t = (1, t)'$). From Table 1 most of the estimates of d (reported in parenthesis within the brackets) are in the interval (0, 1), thus rejecting both the I(0)-trend stationary

representation and the unit root model. However, we fail to reject a unit root for hydroelectric in the case of no regressors. For the remaining series the unit root is always rejected in favor of smaller degrees of integration.

Table 2 focuses on the selected model for each energy source according to the deterministic terms. We observe that for hydroelectric and total renewable energy the time trend is not required,[4] and the highest values for d are obtained for hydroelectric (d = 0.803) and total renewable energy (d = 0.808), followed by nuclear (d = 0.672) and coal (d = 0.602). Note that the confidence intervals reported do not include a unit root for any energy source within the electric power sector. Furthermore, none of the energy sources yield estimates of d strictly below 0.5 (i.e. stationary region). In addition, the seasonal AR coefficient estimates are generally large, indicating a strong influence of this component as well.

Table 2: Estimates of the Parameters based on Selected Models in Table 1

d - estimates	Intercept	Time trend	d (95% band)	AR coeff.
Coal	736.00 (8.50)	2.255 (3.88)	[0.519 (0.602) 0.700]	0.890
Hydroelectric	263.69 (10.23)	-----	[0.712 (0.803) 0.914]	0.681
Natural gas	247.33 (4.38)	0.611 (1.86)	[0.454 (0.560) 0.696]	0.866
Nuclear	72.686 (2.00)	1.506 (4.71)	[0.588 (0.672) 0.775]	0.846
Petroleum	309.38 (13.25)	-0.635 (-4.32)	[0.509 (0.584) 0.683]	0.508
Total fossil fuel	1281.2 (10.57)	2.338 (3.86)	[0.415 (0.503) 0.610]	0.878
Total primary	1625.0 (11.50)	4.055 (5.92)	[0.403 (0.489) 0.593]	0.920
Total renewable	267.97 (9.97)	-----	[0.722 (0.808) 0.912]	0.694

Next, we allow for seasonality to display long memory and consider model (4) with non-seasonal AR(1) u_t, i.e.,

$$y_t = \beta' z_t + x_t; \quad (1-L)^{d_s} x_t = u_t; \quad u_t = \rho u_{t-1} + \varepsilon_t, \quad t = 1, 2, ..$$

(7)

Table 3 displays the estimates of d_s for each energy source. We first note that all values are in the range $(0, 1)$ rejecting the seasonal unit root model. Evidence of stationary seasonality $(d_s < 0.5)$ is obtained for hydroelectric, petroleum, and total renewable energy.

Table 3: Estimates of d_s and 95% Confidence Intervals based on Model (7)

d_s - estimates	No regressors	An intercept	A linear time trend
Coal	[0.511 (0.535)	[0.537 (0.563)	[0.551 (0.575)
Hydroelectric	[0.291 (0.317)	[0.295 (0.319)	[0.294 (0.318)
Natural gas	[0.445 (0.475)	[0.419 (0.450)	[0.444 (0.473)
Nuclear	[0.532 (0.555)	[0.483 (0.514)	[0.539 (0.563)
Petroleum	[0.259 (0.284)	[0.269 (0.295)	[0.278 (0.303)
Total fossil fuel	[0.481 (0.504)	[0.496 (0.523)	[0.492 (0.513)
Total primary	[0.545 (0.567)	[0.552 (0.579)	[0.567 (0.588)
Total renewable	[0.303 (0.330)	[0.303 (0.329)	[0.303 (0.329)

Table 4 focuses on the parameters of the selected models according to the specification given by (7). We observe that the estimates of d_s range between 0.303 for petroleum and 0.588 for total primary energy. We also notice that the AR coefficient estimates are smaller in the cases of coal, natural gas, nuclear, total fossil fuel, and total primary energy than those reported in Table 2, but larger for hydroelectric, petroleum, and total renewable.

**Table 4: Estimates of the Parameters based on Selected Models in Table 3**

d_s - estimates	Intercept	Time trend	d_s (95% band)	AR coeff.
Coal	763.92 (26.16)	2.356 (26.61)	[0.551 (0.575) 0.602]	0.668
Hydroelectric	258.71 (35.24)	-0.082 (-3.29)	[0.294 (0.318) 0.346]	0.841
Natural gas	167.76 (10.22)	0.804 (15.25)	[0.444 (0.473) 0.505]	0.676
Nuclear	157.57 (10.62)	1.390 (30.65)	[0.539 (0.563) 0.589]	0.787

Petroleum	258.85 (28.21)	-0.533 (-16.84)	[0.278 (0.303) 0.334]	0.812
Total fossil fuel	1193.2 (32.56)	2.652 (22.97)	[0.492 (0.513) 0.537]	0.537
Total primary	1603.5 (34.56)	4.180 (29.99)	[0.567 (0.588) 0.612]	0.527
Total renewable	248.80 (31.10)	0.160 (5.85)	[0.303 (0.329) 0.359]	0.849

So far we have two time series models for each energy source, one based on a long memory model with seasonal AR disturbances, and the other one using a seasonal long memory model with non-seasonal AR(1) errors. Note that a high degree of persistence and seasonality is common between the two cases. Figure 1 displays the first 120 impulse responses based on the two models for each energy source.

Figure 1: Impulse Responses for the Two Selected Models for Each Series

Total primary	Total renewable
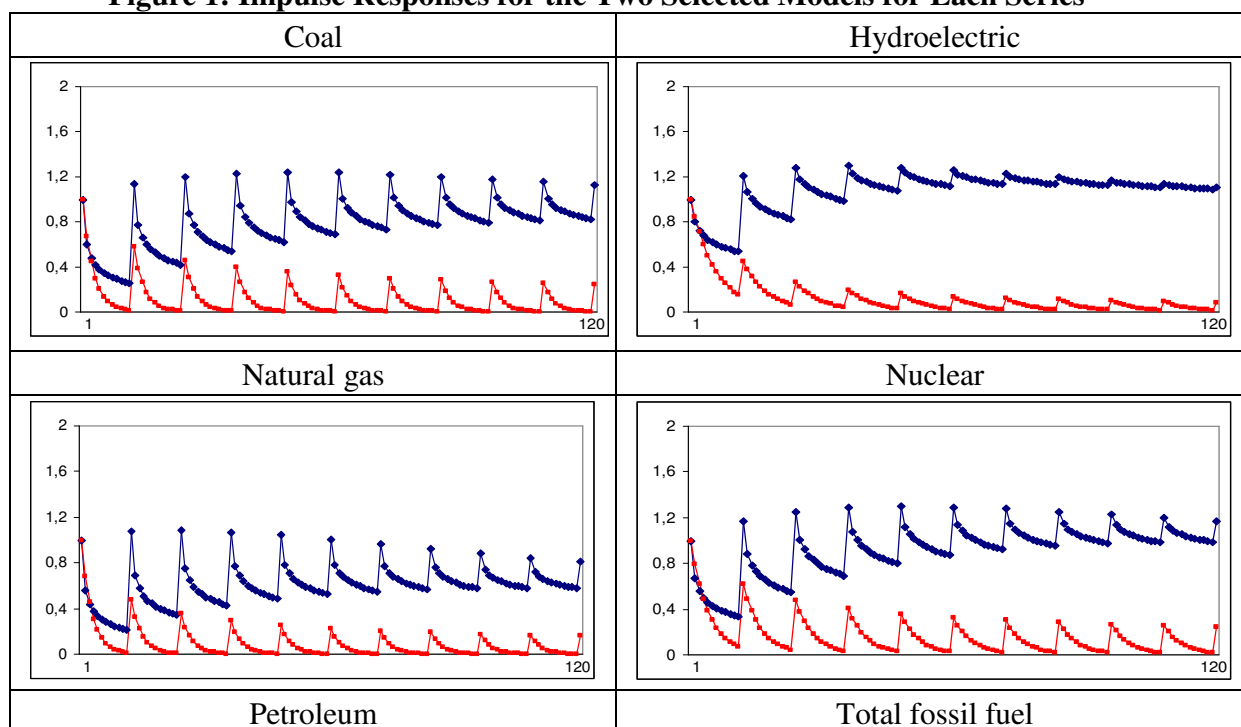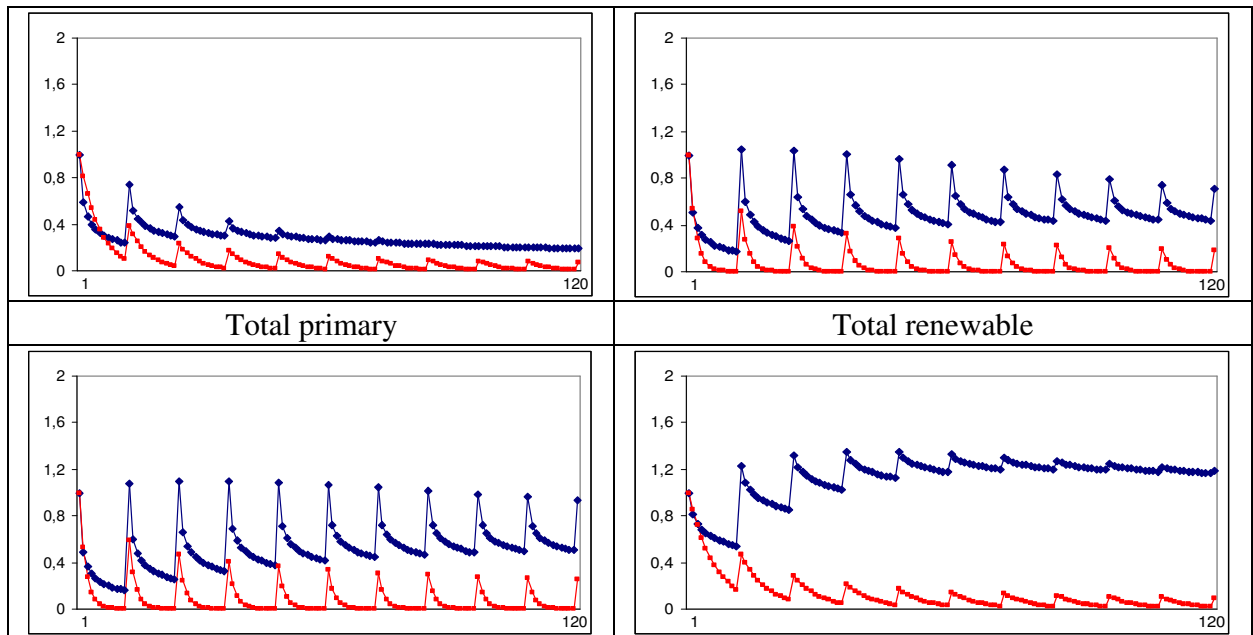
The thick line refers to the responses based on the model given by equation (6). The thin line refers to equation (7).

We observe that seasonality is a serious matter in all cases, and higher responses take place in all cases under the first specification, which is the one based on a non-seasonal I(d) process with seasonal AR(1) disturbances. Finally, we performed an in-sample forecasting experiment comparing the two models for each energy source using the last 60 observations via the modified Diebold and Mariano (1995) statistic as suggested by Harvey et al. (1997). The results, however, were unable to differentiate between the models in terms of performance at standard significance levels.

3. Concluding Remarks

In light of the importance of the U.S. electric power sector in the generation of primary energy for use by other sectors of the economy, it is crucial to understand the impact of shocks related to the use of energy sources by this sector. Indeed, the growing

environmental concerns over the consumption of fossil fuels in the generation of electricity and increased attention to renewable energy sources suggests that the energy consumption mix of the U.S. electric power sector may very well change. The impact of energy conservation and demand management policies (defined as a shock) on the various energy sources used by the electric power sector will depend in part on the response of these energy sources to such policy shocks. Thus, this short communication uses fractional integration to determine the level of persistence of the shocks affecting each energy source. The results indicate that each energy source consumed by the U.S. electric power sector is highly persistent, displaying long memory along with autoregressive behavior and strong seasonal patterns. The persistence associated with each energy sources suggests that shocks originating from the electric power sector may be transmitted to other sectors of the economy as well.

From certain perspectives, it might be argued our empirical work simplistic, as we do not take into account possible alternative features of our data. In particular, we did not check for the possibility of structural breaks or non-linearities in our time series. Admittedly, these are relevant issues, whose linkages with fractional integration are currently being investigated. Thus, in the context of breaks, methods such as those proposed by Gil-Alana (2008) and Ohanissian et al. (2008) could be implemented in these data to check if the conditions about persistence change. Non-linear fractionally integrated models (Caporale and Gil-Alana, 2007) on electric power data will be examined in future papers.

Endnotes

1. There is an enormous energy consumption-growth literature in which the unit root behavior of energy consumption is examined in the determination of the appropriate methodology for Granger-causality testing (see Payne, 2010a,b; Ozturk, 2010 for surveys of this literature).

2. The data are not seasonally adjusted.

3. Higher AR order lead essentially to the same results.

4. This is based on the t-values on the deterministic terms.

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