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Abstract

The goal of this paper is to test for the presence of long memory in final energy demand in Portugal. Our findings suggest the presence of long memory in aggregate and disaggregate energy demand in Portugal. All fractional-difference parameters are positive and lower than 0.5 indicating that the series are both stationary and mean reverting. In addition, our findings also indicate that there are no clear seasonal effects over the degree of fractional integration.

These results have important implication for the design of environmental policies. First positive policy shocks are likely to be more effective in moving energy consumption away from its predetermined target. Second, those policies may cause energy demand to revert to its (new) trend over a long period of time. Third, our results also suggest that switching between types of energy will be easier given that all components of aggregate final energy demand have long range dependency.

Finally, given the strong connection of the energy sector with the rest of the economy, energy policies may be transmitted to other sectors of the economy and may also have impacts on the real economy. Moreover, positive shocks associated with permanent energy policies stimulating the switch to renewable energy sources may contribute to changing the energy consumption mix and to the reduction of carbon dioxide emissions.

Keywords: Long memory, final energy demand, environmental policy, ARFIMA model, Portugal.

JEL Codes: C22, ,O13, Q41.

1. Introduction

The permanent increase in fossil fuel prices, its extreme volatility - especially over the last five years - along with the growing concerns about greenhouse gas emissions (GHG hereafter) and climate change has encouraged the discussion about the energy production, consumption mix as well as the design and the effectiveness of energy policy. This paper aims to contribute to this discussion by testing for the presence of long memory in final energy demand in Portugal. as a result of a policy and/or geo-economic-political shocks.

There is an vast literature using univariate nonparametric and parametric methods to test the stationary properties of energy consumption, production and prices series both with or without structural breaks (see, for example, Serletis, 1992; Altinay and Karagol, 2004; Lee and Chang, 2005 and 2008; Lee, 2005; Narayan and Smyth, 2005 and 2007; Al-Iriani, 2006; Chen and Lee, 2007; Hsu et al., 2008; Joyeux and Ripple, 2007; Lee and Chang, 2008; Maslyuk and Smyth, 2008 and 2009; Narayan et al., 2008; Elder and Serletis, 2008 and Pereira and Belbute, 2010).

The general motivation of these studies is to determine whether the time path of energy consumption, production or prices changes are transitory or permanent after a shock. Having (or not) a unit root has important implications for public policy design and effectiveness, for companies'/firms' strategies and for modeling and forecasting purposes. First, given the strong connection and significance of the energy sector to other sectors of the economy, if shocks to energy consumption and/or production are permanent then such "innovations" may be transmitted to other sectors of the economy as well as to macroeconomic variables (Lean e Smyth, 2009; Gil-Alana et al., 2010).

Second, the understanding of the stationary properties of energy time series is crucial for the design and the effectiveness of public policies. In particular, if energy consumption and/or production are stationary, then public policies that promote energy efficiency, fuel switching or the reduction of GHG emissions, for example, will tend to have long-lasting effects. In contrast, if the energy time series have a unit root, such policies will only have transitory effects (Lean and Smyth, 2009; Gil-Alana et al., 2010; Pereira and Belbute, 2010; Apergis and Tsoumas, 2012.

Finally, a high degree of persistence means that energy consumption and/or production returns to its trend path after a shock, i.e. current values of energy variables are determined by its past values. Therefore past behavior can be used for energy modeling and to formulate forecasts about future movements of energy demand and/or production (Lean and Smyth, 2009)[1].

Nevertheless, as Diebold and Rudebush (1989) note, the unit root tests only provide evidence about the existence (or absence) of a permanent component but not its extent, i.e. the unit root test only confirms that the current value of a variable is determined by its past behavior but is unable to identify how distant in time that influence extends. Moreover, traditional autoregressive univariate unit root tests are typically limited to the $I(0)/I(1)$ dichotomy. Their power to reject the null hypothesis depends on several factors such as structural breaks, non-linearities and fractional integration (or long memory), which affect most of the energy variables.

Indeed, most of the empirical literature that tests the null hypothesis of a unit root ignoring structural breaks in energy consumption and/or production shows that only for almost 1/3 of the countries analyzed is it possible to reject the unit root null hypothesis (see, for example, Narayan and Smyth, 2007; Hasanov and Telatar, 2011). Conversely, the majority of the studies that consider the presence of structural breaks find that energy variables are stationary around a broken trend (see Apergis and Payne, 2010; Narayan et al., 2010; Aslan and Kum, 2011, among others).

Furthermore, conventional unit root tests (with or without structural breaks) assume that the data generating processes are linear, which reduces their power to reject the null hypothesis (Choi and Moh, 2007).

Finally the ability of traditional unit root tests to reject the null is also affected by the presence of long memory, i.e. when the degree of integration of the data generating process is a non-integer number (Diebold and Rudebush, 1989; Lee and Schmidt, 1996).

There is now an emerging literature which considers the possibility that energy variables may follow a long memory process as a result of technological rigidities as well as of intertemporally dependent preferences. This long range dependence is characterized by a hyperbolically decaying autocovariance function, by a spectral density that tends to infinity as frequency tends to zero and by the self-similarity of aggregated summands. The intensity of

[1] For a complete literature review, see Smyth, R. (2012)

this phenomena can be measured either by a differencing parameter "d" or by a scaling parameter H. Both are related in the case of finite variance processes by $H = d + 1/2$[2].

A fractionally integrated process of order "d" [$I(d)$] where d is a real number, is a compromise between $I(0)$ and $I(1)$ processes whose degree of persistence is inconsistent with the dichotomy $I(0)/I(1)$. In other words, an $I(d)$ process is a generalization of the traditional dichotomy $I(0)/I(1)$ (Kumar and Okimoto, 2007) which provides a richer degree of flexibility in the specification of the dynamics of the time series. When "d" is statistically significant, then it is a measure of the *extension* of the inertia that characterizes the permanent component of the time series. In particular, when $0 < d < 0{,}5$ the time series is mean reverting but has long-memory. Contrary to short memory, long memory means a significant dependence between observations widely separated in time and therefore effects caused by shocks tend to decay slowly (or, alternatively, shocks have long lasting effects).

The long memory (or fractional integration) phenomena was first observed in natural sciences. The oldest and best known methods for detecting long-memory are the R/S analysis proposed by Mandelbrot and Wallis (1968) - based on the previous hydrological work of Hurst (1951, 1956 and 1957) – the GHP test (Geweke and Peter-Hudak, 1983), the modified rescaled range statistic (MRR) test (Lo, 1991) and the detrended fluctuations analysis (DFA) test (Peng et al., 1994), among others.

Testing for fractional integration in econometrics is more recent (Baillie, 1996) and the literature is mainly focused on macroeconomic variables like gross domestic product (Diebold and Rudebush, 1989, Gil-Alana and Robinson, 1997 and Gil-Alana, 2003,) consumption (Diebold and Rudebush, 1991 Gil-Alana and Robinson, 2001), inflation (Baillie et al. 1996, Gil-Alana, 2002a, Kumar and Okimoto, 2007), exchange rates (Diebolt et al., 1991, Ballie, 1996, Gil-Alana (2002b) and unemployment (Caporale and Gil-Alana, 2008).

Only recently has the presence of long range dependence been tested in the energy literature. Some of these studies test for long memory in energy consumption or production using univariate and multivariate Lagrange multiplier (LM) tests [see, for example, Nielson (2005) and Lean e Smyth (2009)[3]] but the majority applies a methodology to estimate the value of the fractional degree of integration function based on Whittle (1953) function (see, for example Dahlhaus, 1984) along with the method proposed and developed by Robinson (1994a) and

[2] Or by $H = d + 1/\alpha$ in the case of infinite variance processes

[3] The Nielsen (2005) multivariate LM test for fractional integration generalizes the univariate tests developed by Robinson (1994a) and Tanaka (1999) among others. Nevertheless, there are other LM tests available in the literature such as those proposed by Breitung and Hassler (2002) and Gil-Alana (2003).

1994b) [see for example, Kumar and Smyth (2007), Elder and Serletis (2008), , Gil-Alana et al. (2010), Gil-Alana (2012), Apergis and Tsoumas (2011 and 2012) and Barros et al. (2012)].

In this paper we measure the degree of fractional integration in final energy demand in Portugal using an ARFIMA model. An ARFIMA model is a generalization of the ARIMA model which frees it from the dichotomy $I(0)/I(1)$, therefore allowing for the estimation of the degree of integration of the data generating process.

Overall the energy literature on long memory properties has focused almost invariably on total energy consumption in the United States. The absence of evidence of the degree of long range dependence in more advanced countries is an important void in the literature. This is a void that we intend to fill with this paper by concentrating on the case of final energy demand in Portugal and by considering not only final energy demand but also its major components. Furthermore, by identifying the intensity of the intertemporal dependency of each component of energy demand, we will be able to identify the policy implications of our findings not only in terms of energy efficiency policies but also the consumption and production energy mix.

The paper is organized as follows. Section 2 presents a brief description of the ARFIMA model. Section 3 presents the data set while section 4 presents the empirical evidence of long memory in aggregate energy demand and its components. Section 5 provides a summary of the results and discusses their policy implications.

2. Fractional Integration

A time series $x_{t,}$[4] (with $= 1, 2, \dots$) is said to be fractionally integrated of order d $(x_t \sim I(d))$ if it can be represented by

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

where L is the lag operator ($Lx_t = x_{t-1}$), d is a real number that captures the long run effect and u_t is $I(0)$.

By binomial expansion the filter $(1-L)^d$ provides an infinite-order L polynomial with slowly and monotonically declining weights,

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

and thus (1) can be written as:

[4] More precisely, $x_t = y_t - \beta z_t$ where β is the coefficients vector and z_t represents all deterministic factors of the process y_t.

$$x_t = dx_{t-1} - \frac{d(d-1)}{2}x_{t-2} + \frac{d(d-1)(d-2)}{3!}x_{t-3} + \cdots u_t \tag{3}$$

If d is an integer, then x_t will be a function of a finite number of past observations. In particular, when $d = 1$, then x_t is a unit root non-stationary process and therefore the effect of a random shock is exactly permanent. When $d = 0$, we will have $x_t = u_t$ and the time series is $I(0)$, weakly autocorrelated (or dependent) and with autocovariances decaying exponentially. More formally,

$$\gamma_j = {\alpha_1}^j, \quad \text{for} \quad j = 1, 2, \ldots. \text{ and } |\alpha_1| < 1 \tag{4}$$

But allowing d to be a real number provides a richer degree of flexibility in the dynamic specification of the series, and depending on the value of the parameter d we can determine different intensities of intertemporal dependencies. In particular, when d is a non-integer number, each x_t will depend on its past values far away in time. Moreover, the autocovariance function satisfies the following property

$$\gamma_j \approx c_1 j^{2d-1}, \quad \text{for} \ \ j = 1, 2, \ldots \ \text{ and } \ |c_1| < \infty \tag{5}$$

where "$\approx$ " means that the ratio between the two sides of (5) will tend to unity as $j \to \infty$. Assuming that the process x_t has a spectral distribution such that the density function $f(\lambda)$ is given by,

$$f(\lambda) = \frac{1}{2\pi}\left[\gamma_0 + 2\sum_{j=1}^{\infty}\gamma_j \, cos(\lambda j)\right] \tag{6}$$

then it can be shown that,

$$f(\lambda) \approx c_2 \lambda^{-2d}, \quad \text{para} \ \ \lambda \to 0^+ \ \text{e} \quad c_2 > 0 \tag{7}$$

where "$\approx$ " means that the ratio between the two sides of (7) will tend to unity as $\lambda \to 0^+$[5].

When $0 < d < 0{,}5$, the process, x_t, reverts to its mean but the autocovariance function (7) decreases very slowly and hyperbolically as a result of the strong dependence of past values. In this case the spectral density function (6) is unbounded at the origin and the time series x_t is said to exhibit long memory behavior, i.e. the effect of a given random shock in the innovations will be transitory and the series will eventually revert to its trend. Nevertheless, the effects will last longer than in the pure stationary case ($d = 0$).

[5] It should be noted that the properties (5) and (7) are equivalent only under specific conditions. See, for example, Yong (1974) and Zygmung (1995).

When $0{,}5 < d < 1$ the process becomes more non-stationary in the sense that the variance of the partial sums (5) increases, but the series retains its mean-reverting property. Finally, if $d > 1$, the process is non-stationary and non-mean-reverting[6], i.e. the effects of random shocks are permanent. Therefore, the larger the value for fractional-difference parameter d, the greater will be the degree of persistence.

A process like (1) with a non-integer d is called fractionally integrated or order d and when u_t in (1) is an $ARMA(p,q)$, then x_t is called an ARFIMA (AutoRegressive Fractionally Integrated Moving Average) process. Thus the model becomes,

$$\phi(L^p)(1-L)^d x_t = \theta(L^q)e_t \tag{8}$$

where $\phi(L^p)$ and $\theta(L^q)$ are the polynomials of order p and q respectivelly, with all zeroes of $\phi(L^p)$ and $\theta(L^q)$ given, respectively, by,

$$\phi(z) = 1 - \phi_1 z - \phi_2 z^2 - \ \dots \ - \phi_p z^p = 0 \tag{9}$$

$$\theta(z) = 1 + \theta_1 z + \theta_2 z^2 + \ \dots \ + \theta_p z^q = 0 \tag{10}$$

lying outside the unit circle, and e_t is a white noise. The process is stationary and invertible for $-0{,}5 < d < 0{,}5$.

ARFIMA models were first introduced by Granger and Joyeux [1980], Granger [1980, 1981] and Hosking [1981 e 1984]. Its use was justified by the problems caused to the tests of unit roots by aggregation (see, for example, Robinson, 1978 and Granger, 1980) and more recently by the problem of the duration of the shocks (Parke, 1999). Diebold and Rudebusch (1989), Sowell (1992a), Sowell (1992b), Baillie (1996) and Palma (2007), among others, provide a good review of the literature about these models.

The estimation of all the parameters of the ARFIMA model is done by the method of maximum likelihood. The log Gaussian likelihood was established by Sowell (1992b) and is

$$\ell\big((y|\hat{\eta})\big) = -\frac{1}{2}\Big\{\boldsymbol{T}\log(2\pi) + \log\big|\widehat{\boldsymbol{V}}\big| + \big(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}\big)'\ \widehat{\boldsymbol{V}}^{-1}\big(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}\big)\Big\} \tag{11}$$

The covariance matrix $\boldsymbol{V}$ has a Toeplitz structure:

[6] In the specific case of $-0{,}5 < d < 0$, the autocorrelation function also decays at a slower hyperbolic rate but the process is called anti-persistent (or, alternatively, to have rebounding behavior or negative correlation) because the autocorrelations for lags greater than zero are negative.

$$
\boldsymbol{V} = \begin{bmatrix} \gamma_0 & \gamma_1 & \gamma_2 & \cdots & \gamma_{T-1} \\ \gamma_1 & \gamma_0 & \gamma_1 & \cdots & \gamma_{T-2} \\ \gamma_2 & \gamma_1 & \gamma_0 & \cdots & \gamma_{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{T-1} & \gamma_{T-2} & \gamma_{T-3} & \cdots & \gamma_0 \end{bmatrix} \tag{12}
$$

where $\gamma_0 = Var(y_t)$ and $\gamma_j = Cov(y_t, y_{t-1})$ for $j = 1, 2, \dots t-1$ and $t = 1, 2, \dots T$.

3. Data: sources and description

This work uses monthly data for gross inland energy consumption (GIEC hereafter) from February 1985 until December, 2011 (which corresponds to 232 observations). In the particular case of natural gas, the starting date is February 1997 (which corresponds to 179 observations) as it was only then that Portugal developed the necessary distribution infrastructure which allowed natural gas to become an important component of the Portuguese energy system.

According to the Eurostat, GIEC is the total energy demand of a country or region and it represents the quantity of energy necessary to satisfy inland consumption of the geographical entity under consideration. It covers four components; a) consumption by the energy sector itself[7]; b) distribution and transformation losses; c) final energy consumption by end users and d) “statistical differences" (not already captured in the figures on primary energy consumption and final energy consumption)[8].

Aggregate final demand for energy in Portugal is defined here as the sum of four components: petroleum and its derivatives, electricity, natural gas and coal. All variables are expressed in 10^3 tons of oil equivalent (toe hereafter), and were converted into natural logarithms for the empirical analysis[9].

All data were extracted from the Eurostat’s web site which in turn are based on data from the Direcção Geral de Energia e Minas (Portuguese Department of Energy and Mines, DGEM hereafter). They clearly reflect the distinction between primary[10] and final energy demand.

Petroleum and its derivatives can be used as raw material in the production of, for example, lubricants, of asphalt, paraffin, solvents and propylene, and as an energy source. Petroleum

[7] Eurostat computes GIEC as follows:

primary production + recovered products + net imports + variations of stocks – bunkers

[8] The consumption of the energy sector includes the energy consumption by the sector itself in refineries, in all kind of electric power plants, transport losses and the consumption with hydroelectric pumping.

[9] The original data are not seasonally adjusted.

[10] Primary energy is the energy found in nature that has not been subjected to any conversion or transformation process but it is used to produce other forms of energy.

and its derivatives used as raw materials are not considered in our data. Therefore the final demand of petroleum and derivatives includes crude oil and all derivatives that are exclusively used as a primary energy source (referred to as "energetic oil") like diesel, fuel oil, gasoline, liquefied petroleum gas, naphtha, kerosene and petroleum coke. Petroleum and derivatives account for 66.03% of total energy demand in Portugal, although this share showed a declining trend for the sample period. In December 2011 the share of petroleum and derivatives in total energy demand was 45.64%.

Final demand for electricity does not distinguish among production technologies nor the raw material used in electricity generation, with the exception of co-generation[11] and heat[12], which are accounted for separately by Eurostat. It represents 12.99% of total final energy demand for the entire sample period but has increased consistently, especially in the last five years. In 2011 the final demand for energy represented 15.56% of total energy demand compared to a share of 11.87% five years before. In 2011 45.4% of total electricity consumption in Portugal was produced by renewable sources (hydro, wind, photovoltaic, geothermal, solid biomass, biogas, liquid biofuels and municipal solid waste), which exceeds the goal set for the country by EU policy on renewable energy.

Final demand for coal includes domestic production and imports of hard coal, anthracite and coke coal. It constitutes 14.08% of total final energy demand for the sample period. The coal share in final energy demand has consistently decreased after 1995. In annual average it represented 10.17% of total energy demand in 2011. However, by the middle of this year its relative importance began to rapidly increase, reaching 15.95% in December as a result of the change of the relative prices in the international energy markets.

Final demand for natural gas consists of the imports of both natural gas transported by pipeline and liquefied natural gas shipped by vessels. In 1997 the country began an important program devoted to the development of a natural gas distribution infrastructure which rapidly stimulated its consumption. After its introduction, the consumption of natural gas grew at an average monthly rate of 14.08% during 1998 and its share in final energy demand was 2,7%. In December 2011 it accounts for 19.62% of final energy demand in Portugal.

[11] Also known as "combined heat and power (CHP) stations.

[12] That is, electricity produced by plants which are designed to produce heat only.

4. Results

Table 1, presents the main results of the estimation of the several $ARFIMA(p, d, q)$ models using the natural logarithm of the raw data and tables 2 and 3 do the same but with seasonality corrections using two distinct methodologies. In all cases, we present the results of the two ARMA components, if present, as well as of the estimated parameter d. We used the Schwartz Bayesian Information Criterion (BIC) as the model selection criteria for the "best" model specification but in some cases, especially with gas, the decision has been complemented with the Akaike information criterion (AIC). For each estimated parameter we present the corresponding standard errors, p-values and 95% confidence intervals.

4.1 Data in natural logarithms

Results presented in table 1 suggest that there is statistically significant evidence for the non-rejection of the presence of long memory in aggregate energy demand in Portugal as well as in its four components. All parameters are statistically significant at the 5% level and lie within the interval (0, 0.5). The confidence intervals are wide but with the exception of natural gas, the upper limits of the fractional-difference parameters are greater than 0.5 suggesting that the series may be non-stationary, though mean reverting. Nevertheless we proceed as if the series were stationary and considered that the wide confidence interval for parameter d reflects the difficulty of fitting a complex dynamic model with only 232 observations.

For the case of final demand for gas, the value of the fractional-difference parameter is lower than for the other final energy demand variables ($d = 0.2814$), suggesting a weaker intensity of persistence for this component, though stronger than the pure stationary case. Furthermore, the upper limit of the coefficient interval is lower than 0.5.

Table 1 – Fractional integration results (natural logs)

		Constant	AR( )		FI( )	MA( )	
			p	$\hat{\rho}$	$\hat{d}$	q	$\hat{\theta}$
Final aggregate energy demand		7.1348	12	0.9524	**0.4913**	12	-0.7852
	Standard error	*1.5475*		*0.0237*	***0.0117***		*0.0527*
	p-value	*0.000*		*0.000*	***0.000***		*0.000*
	Conf. Interval (95%)	[4,1017; 10,1679]		[0,9059 ; 0,9988]	**[0,4685 ; 0,5141]**		[-0,8884 ; -0,6819]
	BIC			-638.975			
Petroleum and derivatives		6.8700	12	0.3107	**0.4875**	0	
	Standard error	*0.4436*		*0.05916*	***0.016***		
	p-value	*0.000*		*0.000*	***0.000***		
	Conf. Interval (95%)	[6,0005 ; 7,7395]		[0,19448 ; 0,4267]	**[0,4562 ; 0,5187]**		
	BIC			-600.474			
Electricity		5.328	12	0.2744	**0.4803**	0	
	Standard error	*0.3464*		*0.0634*	***0.0256***		
	p-value	*0.000*		*0.000*	***0.000***		
	Conf. Interval (95%)	[4,6491 ; 6,0069]		[0,1502 ; 0,3986]	**[0,4301 ; 0,5305]**		
	BIC			-560.339			
Coal		5.049	12	0.8674	**0.4233**	12	-0.7155
	Standard error	*0.7616*		*0.092*	***0.0428***		*0.1323*
	p-value	*0.000*		*0.000*	***0.000***		*0.000*
	Conf. Interval (95%)	[3,5560 ; 6,5415]		[0,6870 ; 1,0478]	**[0,3393 ; 0,5073]**		[-0,9749 ; -0,4562]
	BIC			296.287			
Gas			1	0.7598	**0.2814**		
	Standard error			*0.1137*	***0.0956***		
	p-value			*0.000*	***0.003***		
	Conf. Interval (95%)			[0,5369 ; 0,9827]	**[0,0942 ; 0,4686]**		
			3	0.2255			
				0.1083			
				0.037			
				[0,0132 ; 0,4379]			
	BIC			130.148			

Note: $\hat{\rho}$ stands for the estimated value of the parameter associated with x_{t-p} of the AR component and $\hat{\theta}$ stands for the estimated value of the stochastic term of order q (e_{t-q}) of the MA component.
For all parameters estimates we reject the null for a test of 5% level of significance

4.2 Seasonally adjusted data

Given the monthly nature of the data, we also consider the presence of a strong seasonal effects, particularly detectable by visual inspection of both the autocorrelation and partial autocorrelation functions of electricity, gas and coal.

To take this effect into consideration we adopted two distinct strategies. First, for each final energy demand component, we model the twelfth seasonal difference ($S12y_t = y_t - y_{t-12} = (1-L^{12})y_t$)[13] of the natural logs of the series and then (re)estimated the ARFIMA model.

It should be noted that the ARFIMA model for this case is

$$\phi(L^p)(1-L^{12})^{d_s}y_t = \theta(L^q)e_t \tag{13}$$

Therefore, seasonality is long memory $d_s > 0$ and the short run dynamics are described through a non-seasonal $AR(p)$ process.

Results are presented in Table 2. The second strategy consisted in removing the seasonal pattern of each variable by applying the seasonal adjustment methodology X12 ARIMA,

[13] Where $y_t = ln(x_t)$.

proposed by US Census Bureau. We then estimated the ARFIMA model whose results are presented in table 3. In both cases we used BIC as the selection criterion.

It should be noted that these two strategies are not substitutes, and therefore the results should be interpreted differently. Indeed in the first case we explicitly consider the presence of a seasonal pattern of energy consumption due, for example, to the seasons of the year. In the second case, we removed this seasonal effect and got a smooth time series for each final energy demand.

Nevertheless, both strategies shows that there is statistical evidence of long memory in aggregate and disaggregate final energy demand. Moreover, the estimated d is lower than 0.5 and statistically significant for α = 1%. Again, natural gas has the lowest degree of fractional integration.

Overall, the upper limits of the confidence intervals are slightly above 0.5 which may be due to both the sample size and the complexity of the implicit dynamics of the models used.

Table 2 – Fractional integration results with seasonality adjusted ($ln(x_t/x_{t-12})$)

		Constant	AR( )		FI( )	MA( )	
			p	$\hat{\rho}$	$\hat{d}$	q	$\hat{\theta}$
Final aggregate energy demand			12	-0.3436	**0.4217**		
	Standard error			*0.058*	***0.042***		
	p-value			*0.000*	***0.000***		
	Conf. Interval (95%)			[-0,4576 ; -0,2300]	**[0,3393 ; 0,5041]**		
	BIC	-547.927					
Petroleum and derivatives			4	0.1589	**0.3647**	5	0.1587
	Standard error			*0.5945*	***0.0487***		*0.0667*
	p-value			*0.007*	***0.000***		*0.017*
	Conf. Interval (95%)			[0,04430 ; 0,2734]	**[0,2692 ; 0,4602]**		[0,0279 ; 0,2895]
	BIC	-482.315					
Electricity			1	-0.4199	**0.4264**	1	0.7397
	Standard error			*0.1576*	***0.0588***		*0.1139*
	p-value			*0.008*	***0.000***		*0.000*
	Conf. Interval (95%)			[-0,7288 ; -0,1111]	**[0,3112 ; 0,5415]**		[0,5164 ; 0,9631]
			4	0.2357		4	-0.26
	Standard error			*0.1066*			*0.1124*
	p-value			*0.027*			*0.021*
	Conf. Interval (95%)			[0,0268 ; 0,4445]			[-0,4803 ; -0,0398]
	BIC	-661.329					
Coal					**0.4062**	12	-0.7765
	Standard error				***0.0448***		*0.0608*
	p-value				***0.000***		*0.000*
	Conf. Interval (95%)				**[0,3184 ; 0,4941]**		[-0,8957 ; -0,6574
	BIC	292.881					
Gas			1	0.6316	**0.3787**		
	Standard error			*0.1317*	***0.1098***		
	p-value			*0.000*	***0.001***		
	Conf. Interval (95%)			[0,3735 ; 0,8897]	**[0,1634 ; 0,5939]**		
			2	-0.0729			
	Standard error			*0.0924*			
	p-value			*0.430*			
	Conf. Interval (95%)			[-0,2539 ; 0,1081]			
			3	0.0335			
	Standard error			*0.1193*			
	p-value			*0.779*			
	Conf. Interval (95%)			[-0,003 ; 0,2673]			
			4	0.3658			
	Standard error			*0.1131*			
	p-value			*0.001*			
	Conf. Interval (95%)			[0,1440 ; 0,5875]			
	BIC	144.966					

When we seasonally adjust the data using the X12 procedure, the basic pattern of our findings do not change. In particular, the degree of fractional integration is below 0.5 for all energy demand. Additionally, the confidence interval for the aggregate final energy demand is very narrow ([0.4149 ; 0.4165] and with parameter d $=0.4157$), while for natural gas it is larger ([0.0280 ; 0.2734], which might be due to the sample size ($n = 179$). The final demand for gas continues to be the final energy demand component with the weaker degree of persistence (d $=0.1508$).

Table 3 – Fractional integration results with seasonality adjusted using X12 procedure

		Constant	AR( )		FI( )	MA( )	
			p	$\hat{\rho}$	$\hat{d}$	q	$\hat{\theta}$
Final aggregate energy demand		7.043	1	0.9851	**0.4157**	1	-0.922
	Erro Padrão	*0.8998*		*0.03991*	***0.00042***		*0.0268*
	p-value	*0.000*		*0.000*	***0.000***		*0.000*
	Interv- Confiaça (95%)	[5,2795 ; 8,8065]		[0,9083 ; 1,0619]	**[0,4149 ; 0,4165]**		[-0,9745 ; -0,8695]
			2	0.0092			
	Erro Padrão			0.0382			
	p-value			0.809			
	Interv- Confiaça (95%)			[-0,0657 ; 0,0842]			
	BIC	-718.068					
Petroleum and derivatives		6.8924			**0.4956**		
	se	*0.4904*			***0.0061***		
	p-value	*0.000*			***0.000***		
	95% Conf. Interval	[5,9314 ; 7,8536]			**[0,4836 ; 0,5075]**		
	BIC	-664.309					
Electricity		5.3187	1	0.332	**0.4856**		
	se	*0.3618*		*0.0604*	***0.0212***		
	p-value	*0.000*		*0.000*	***0.000***		
	95% Conf. Interval	[4,5097 ; 6,0278]		[0,2137 ; 0,4529]	**[0,4441 ; 0,5271]**		
			3	0.1659			
	se			*0.0546*			
	p-value			*0.000*			
	95% Conf. Interval			[0,2137 ; 0,4503]			
	BIC	-880.623					
Coal		5.2126			**0.4449**		
	se	*0.4481*			***0.0348***		
	p-value	*0.000*			***0.000***		
	95% Conf. Interval	[4,3343 ; 6,0910]			**[0,3767 ; 0,5131]**		
	BIC	249.739					
Gas			1	0.9922	**0.1508**		
	Erro Padrão			*0.0078*	***0.0626***		
	p-value			*0.000*	***0.018***		
	Interv- Confiaça (95%)			[0,9770 ; 1,0075]	**[0,028 ; 0,2734]**		
	BIC	104.480					

5. Conclusions and policy implications

This paper tests the presence of long memory in aggregate and disaggregate final energy demand in Portugal. Long range dependence is related to the behavior of the autocorrelation persistence in each series. Contrary to what happens with short memory, long memory means a significant dependence between observations widely separated in time. Therefore the effects caused by shocks tend to decay slowly. In contrast to short memory, the presence of a large permanent component in the series implies that a substantial portion of a given shock would persist through time.

We use the autoregressive fractionally integrated moving average (ARFIMA) model to estimate the fractional-difference parameter d which allows for a parsimonious and flexible parameterization of long memory processes. Moreover, the ARFIMA model generalizes the ARIMA model with integer degrees of integration to non-integer number and provides a solution for the tendency to over-difference stationary series that exhibit long range dependency.

The study uses monthly data on gross inland energy consumption in Portugal from February 1985 until December, 2011, extracted from the Eurostat web site. Aggregate final demand of energy in Portugal is defined as the sum of four components: petroleum and its derivatives, electricity, natural gas and coal.

Our findings suggest that the presence of long memory in aggregate and disaggregate energy demand in Portugal cannot be rejected. All fractional-difference parameters are positive and lower than 0.5 which means that the series are both stationary and mean reverting but with the autocorrelations decaying at a hyperbolic rate. The effects of a given random shock will be transitory, but the reversion to the trend will last longer than in the pure stationary case ($d = 0$).

Overall, using aggregate final energy demand as a point of reference, our results indicate that the final demand for gas is the final energy demand component with the weakest degree of long range dependence while the other types of fuel have levels of persistence intensity similar to aggregate final demand. In turn, final demand of petroleum and electricity tend to have levels of persistence similar to aggregate final demand.

Our findings also indicate that there are no clear seasonal effects over the degree of fractional integration. Again, using aggregate final energy demand as a reference, only the twelfth seasonal difference procedure gives significantly lower level of persistence intensity for all types of final energy demand, with the exception of the demand for natural gas. In turn, removing the seasonal pattern by the use of the X12 procedure only produces significantly different estimated value for the fractional-difference parameter d for the final demand for gas.

In some cases, the upper limit of the confidence intervals for the fractional-difference parameters d is greater than 0.5 which suggests that the series might be non-stationary but still mean reverting. Moreover, the confidence intervals are wide which is explained by both the sample size and specially by the complex dynamics of the models fitted.

Our results are in line with recent results in Lean and Payne (2009), Gil-Alana, Payne and Loomis (2010), Apergis and Tsoumas (2011 and 2012) and Barros et al. (2012), that also use fractional integration in the study of United States final energy demand, but using different methodologies.

These findings have important implications for the design and the effectiveness of the energy and environmental policies, especially when these policies have a permanent component. These implications can be considered from both the aggregate demand perspective and from that of the individual fuel types. In general, long range dependence reflects absence of fuel substitutes, technological rigidities and strong consumption habit formation mechanisms. Therefore, positive policy shocks (in the form of improving energy efficiency programs or subsidies for alternative energy sources, among others) are likely to be more effective because they may move energy consumption away from its predetermined target. Moreover, given the long range dependency of aggregate energy demand and its components those policies may cause energy demand to revert to its (new) trend over a long period of time. In the specific case of natural gas, this reversion to the mean value will occur more rapidly.

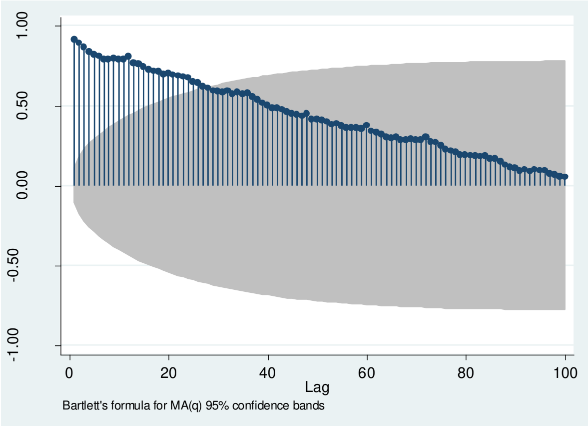
In addition, given that our findings suggest that the estimated fractional-difference parameters d lies within the interval [0 ; 0.5], the effects of an energy policy shock will tend to have temporary effects, but these effects will tend to disappear slowly. Therefore, long lasting effects on the final energy demand will be achieved by means of a more permanently policy stance.

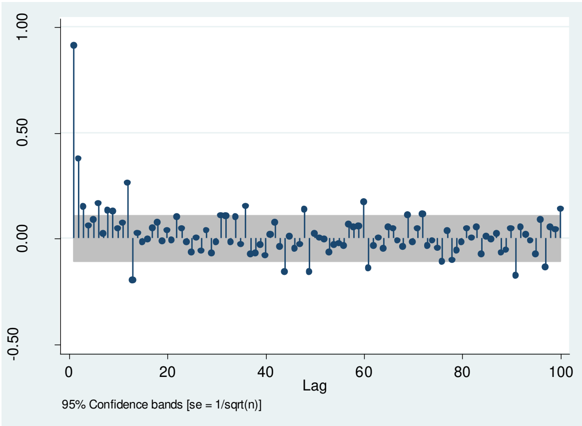
Our results have also implications for fuel switching policies. In general, switching between types of energy with the same level persistence is easier than otherwise. In our case all components of aggregate final energy demand have long range dependency, even though for the case of the demand for natural gas the intensity of persistence is lower than for the other types of fuel.

Furthermore, given the strong connection of the energy sector to the rest of the economy as well as the presence of long memory in aggregate and disaggregate final energy demand, the effect of energy policies may be transmitted to other sectors of the economy and even have impacts on the real economy, such as employment and output. Moreover, positive shocks associated to permanent energy policies stimulating the switch to renewable energy sources may very well contribute to change the energy consumption mix and to reduce carbon dioxide emissions.

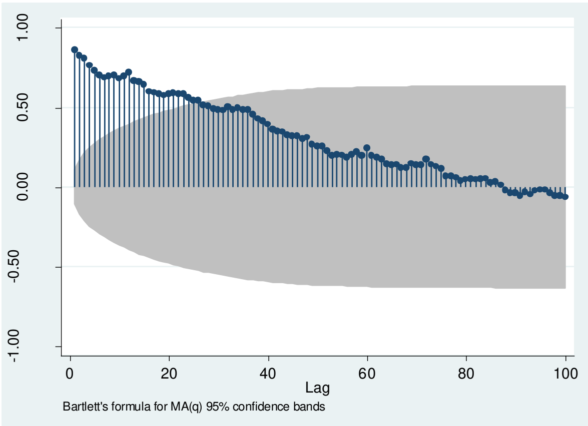
Appendix A - Autocorrelations and partial autocorrelations function (levels)

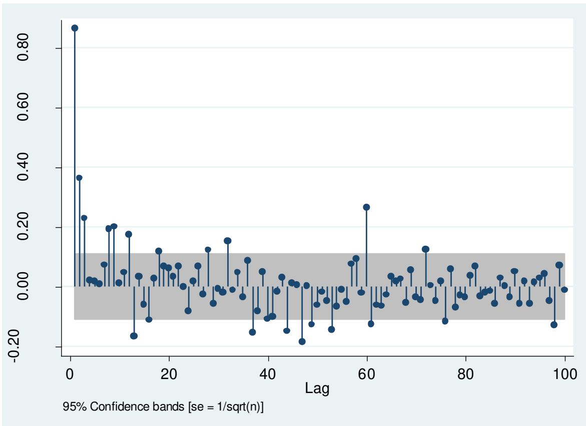
A.1 Aggregate final energy demand



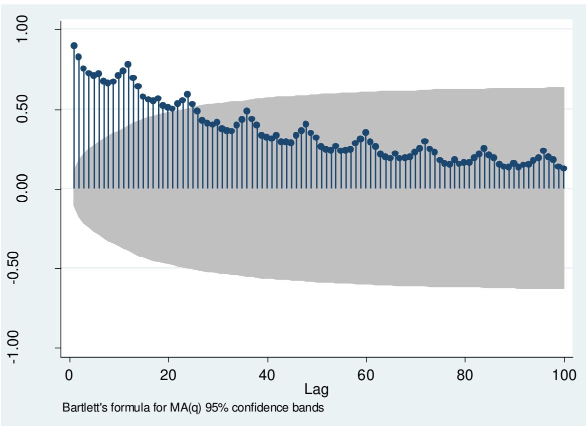


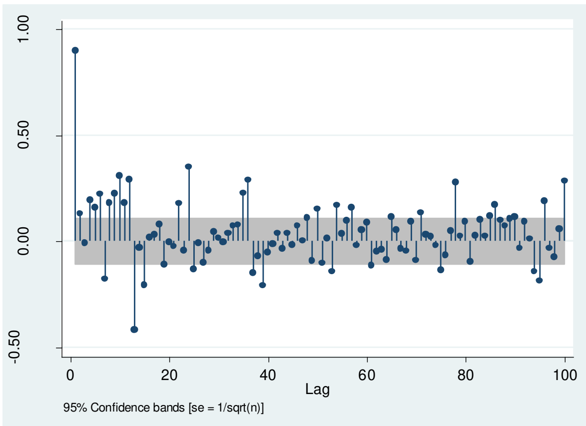
A.2 Petroleum and derivatives



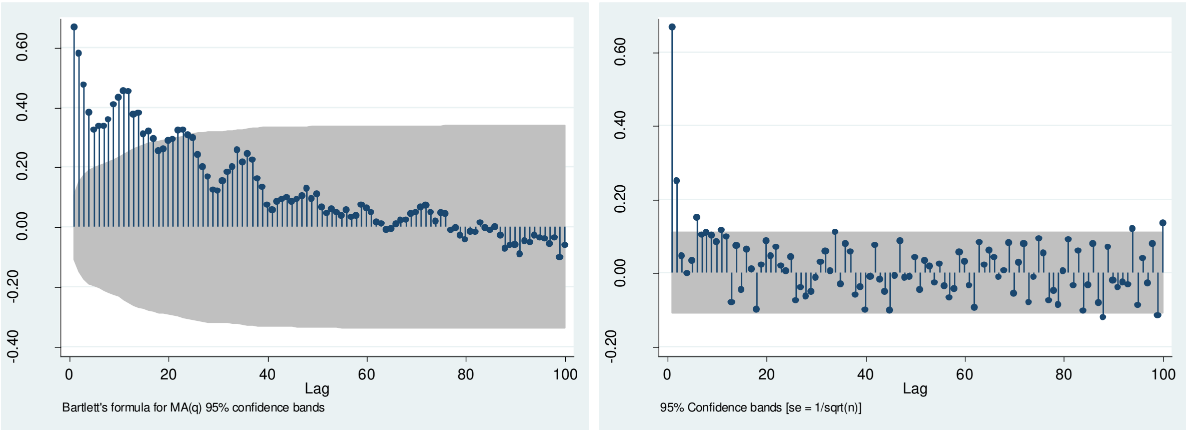


A.3 Electricity

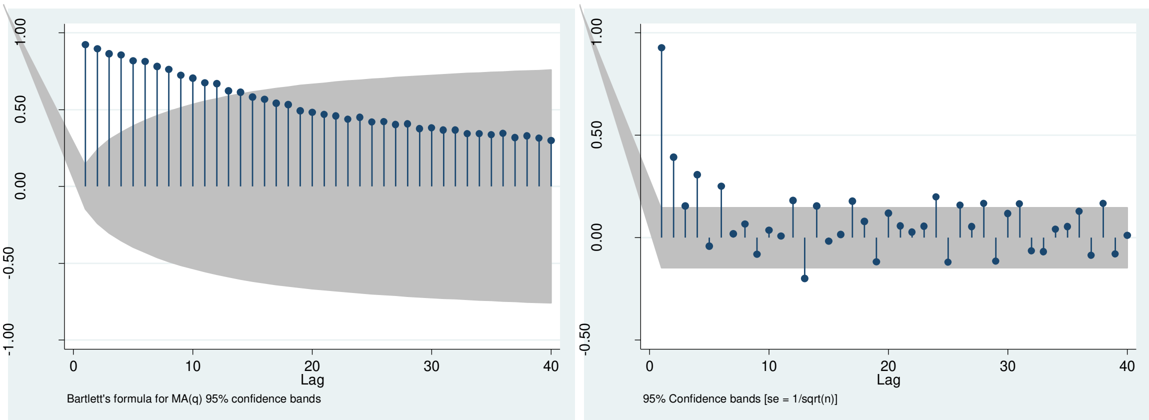




A.4 Coal



A.5 Natural gas



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