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Does Final Energy Demand in Portugal Exhibit Long Memory? A Fractional Integration Analysis (*)

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Abstract

In this paper, we measure the degree of fractional integration in final energy demand in Portugal using an ARFIMA model with and without adjustments for seasonality. We consider aggregate energy demand as well as final demand for petroleum, electricity, coal, and natural gas. Our findings suggest the presence of long memory in all of the energy demand variables. All fractional-difference parameters are positive and lower than 0.5 indicating that the series are stationary, although the mean reversion process will be slower than in the typical short run processes. These results have important implications for the design of energy policies. The effects of temporary policy shocks on final energy demand will tend to disappear slowly as a result of the long-memory process. This means that even transitory shocks have long lasting effects. Given the temporary nature of these effects, however, permanent effects on final energy demand require permanent policies. This is unlike what would be suggested by the more standard but much more limited unit root approach, which would incorrectly indicate that even transitory policies would have permanent effects.

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

JEL Codes: C22, O13, Q41.

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1. Introduction

Understanding persistence in final energy demand is crucial for the design, the implementation, and the effectiveness of the energy and environmental policies. First, if energy consumption is stationary, then public policies that promote energy efficiency, fuel switching or reductions in greenhouse gas emissions, will tend to have transitory effects, thereby requiring a permanent policy stance [see, Lean and Smyth (2009), Gil-Alana et al. (2010), and Apergis and Tsoumas (2012)]. Second, a low degree of persistence means that energy consumption returns to its trend path after a shock so that past behavior can appropriately be used to predict future energy consumption [see Lean and Smyth (2009) and Smyth (2012)]. Finally, given the strong connection of the energy sector to the rest of the economy, if the effects of shocks to energy consumption are transitory but last long then such effects may be transmitted to other sectors of the economy as well as to macroeconomic variables [see Lean e Smyth (2009), Gil-Alana et al. (2010)].

There is a vast literature using traditional autoregressive univariate unit roots methods to test the stationary properties of energy variables [see, for example, Altinay and Karagol (2004), Lee and Chang (2005, 2008), Narayan and Smyth (2005, 2007), Hsu and Lee (2008), Lee and Lee (2009), Narayan et al. (2008) and Smyth (2012)]. Recent evidence with panel data tests that accommodate structural breaks provide strong support for the stationarity of energy consumption and production.

Traditional autoregressive univariate unit root tests, however, are limited to the stationary/non-stationary dichotomy. Their power to reject the null hypothesis depends on several factors such as structural breaks, non-linearities, and the existence of long memory or fractional integration, all of them likely to affect energy variables [see, for example, Narayan and Smyth (2007), Hasanov and Telatar (2011), Apergis and Payne (2010), Narayan et al. (2010), Aslan and Kum (2011)]. More importantly from our perspective, the unit root tests only provide evidence about the existence or absence of a permanent component but not its extent. That is, 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.

There is now a growing literature on fractional integration going beyond the stationary/non-stationary dichotomy to consider the possibility that variables may follow a long memory process [see, for example, Palma (2007)]. This long range dependence is characterized by a hyperbolically decaying autocovariance function and by a spectral density that tends to infinity as frequency tends to zero. The intensity of this phenomena can be measured by a differencing parameter "d", which includes the stationary case ($d = 0$) and the non-stationary case ($d = 1$) as particular cases. When $d < 1$ the process is mean reverting. For $0.5 < d < 1$, the process is not covariance stationary thought mean reverting. When $-0.5 < d < 0.5$ the process is said to be covariance stationary and ergodic with a bounded and positively value spectrum at all frequencies. When $-0.5 < d < 0$ the process is called intermediate memory or over differenced. In turn, when $0 < d < 0.5$, the process is stationary but displays long memory in the sense that its autocorrelation function decay exponentially, rather than geometrically as in the case of short memory ($d = 0$).

In this context, long memory represents an important and nuanced situation that goes beyond the stationary/non-stationary paradigm. It reflects a significant dependence between observations widely separated in time. Therefore, the effects of shocks, although mean reverting, tend to decay slowly. From a policy perspective, the existence of long memory implies that the effects of transitory policies are long-lasting. It also implies that such effects are transitory and, therefore, that the only way to achieve permanent effects is to adopt permanent policies. By contrast, the traditional stationary/non-stationary dichotomy would suggest that the effects of transitory policies are either short-lived (stationary case) or permanent (non-stationary case). This more rigid approach is bound to lead to misleading policy implications by either identifying short lived effects where the effects may actually be long lasting or by identifying as permanent, effects that may actually be mean reverting.

Despite its widespread use in the general economics literature[1], only recently has the presence of long range dependence been tested in the energy literature [see for example, Elder and Serletis (2008), Gil-Alana et al. (2010), Apergis and Tsoumas (2011 and 2012), Barros et al. (2012a and 2002b), and Belbute and Pereira (2015a and 2015b]]. The results from these fractional integration tests generally confirm that energy variables are stationary but exhibit long term memory, with the resulting implications for policy suggested above.

The energy literature on long memory properties has focused almost invariably on total energy consumption and on the case of the United States. The absence of evidence on the degree of long range dependence in other advanced countries and on the relative levels of persistence among different forms of final energy demand is an important void in the literature. This is a void that we intend to start filling 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.

Indeed, in this paper we measure the degree of fractional integration in final energy demand in Portugal considering both aggregate final energy demand and its four main components – petroleum and its derivatives, electricity, coal, and natural gas. We use an autoregressive moving average fractionally integrated, ARFIMA, model approach. An ARFIMA model is a generalization of the ARIMA model which frees it from the stationary versus non-stationary dichotomy. We consider monthly data starting in early 1985 and use both the original data and its seasonally adjusted version to test for fractional integration.

This paper is not the first looking into the general issue of persistence in energy demand in Portugal. A previous, albeit tentative, analysis can be found in Belbute and Pereira (2014). There, the issue is approached in very general terms using annual energy consumption data and a non-parametric approach. The present paper brings much greater focus and clarity to the issue both in scope and in approach and,

[1] See, for example, Diebold and Rudebush (1989), Lo (1991), Backus and Zin (1993); Cheung (1993), Willinger, Taqqu and Teverovsky (1999), Gil-Alana (2002), Dijk, Hans, and Paap (2002), Caporale and Gil-Alana (2004), Sinclair (2005), Yoon, G (2009), Gil-Alana (2010), Aloy, Boutahar, Gente and Feissolle (2011), Bos, C. S. Koopman and M. Ooms (2014), for applications in the area of GDP, unemployment, inflation, exchange rates, and stock market prices.

therefore, to the meaning and precision of the findings. It does so, first, by using a much expanded monthly data set which allows for a deeper, more nuanced and more robust analysis. Second, it uses a fractional integration approach, which by its very nature, allows for a clear identification of the type of memory that characterizes the different types of energy demand going well beyond the traditional stationary/non-stationary dichotomy.

The paper is organized as follows. Section 2 presents the data set. Section 3 provides a brief technical description. Section 4 discusses the empirical evidence. Finally, section 5 provides a summary of the results and discusses their policy implications.

2. Data: Sources and Description

This work uses monthly data for gross inland energy consumption (GIEC, hereafter). According to the Eurostat, GIEC is the total energy demand and it represents the quantity of energy necessary to satisfy consumption of the geographical entity under consideration. It covers four components; a) consumption by the energy sector itself; 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). Eurostat computes GIEC as the sum of primary production, recovered products, net imports and variations of stocks, minus bunkers. Moreover, consumption by the energy sector includes the energy consumption by the sector itself in refineries, in electric power plants, transport losses and the consumption with hydroelectric pumping.

All data comes from the Eurostat’s web site which, in turn, are based on data from the Portuguese Department of Energy. They clearly reflect the distinction between primary and final energy demand. Primary energy is defined as 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.

GIEC for Portugal includes four energy components: petroleum and its derivatives, electricity, natural gas and coal. GIEC data for Portugal covers the period from February 1985 until December 2011 (which corresponds to 232 observations). In the case of natural gas, the starting date is February 1997 (which corresponds to 179 observations), the date when the necessary distribution infrastructure was completed thereby allowing natural gas to become an important component of the Portuguese energy system. All variables are expressed in 10^3 tons of oil equivalent (ktoe hereafter), and were converted into natural logarithms for the empirical analysis. The original data are not seasonally adjusted. See Table 1 for details.

Final demand of petroleum and derivatives includes crude oil and all derivatives that are used exclusively as a primary energy source such as diesel, fuel oil, gasoline, liquefied petroleum gas, naphtha, kerosene, and petroleum coke. Petroleum and its derivatives used as raw materials in the production of, for example, lubricants, of asphalt, paraffin, solvents and propylene are not considered in our data. Petroleum and its derivatives account for 66.0% of total energy demand in Portugal, although this share showed a declining trend over the sample period. In 2011 the final demand of petroleum and derivatives represented 53.7% of total energy demand.

Final demand for electricity does not distinguish among production technologies or the raw material used in electricity generation, with the exception of co-generation (that is, combined heat and power stations) and heat (that is, electricity produced by plants which are designed to produce heat only), which are accounted for separately by Eurostat. It represents 13.0% of total final energy demand for the entire sample period but has increased consistently in the last part of the sample period. In 2011 the final demand for electricity represented 15.6% of total energy demand.

Final demand for coal includes domestic production and imports of hard coal, anthracite and coke coal. It constitutes 14.1% of total final energy demand for the sample period but with a decreasing trend over the last part of the sample period. It represented 10.2% of total energy demand in 2011.

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 very rapidly. Its share of final energy demand was just 2.8% in 1998 and reached 20.5% in 2011. The average over the sample period was

Table 1 – Aggregate Inland Energy Consumption in Portugal

	Aggregate Inland Energy Consumption: monthly average (ktoe)	Shares			
		Petroleum (%)	Electricity (%)	Coal (%)	Gas (%)
1985	6.810	0.744	0.142	0.114	-
1986	6.864	0.747	0.147	0.106	-
1987	6.947	0.736	0.134	0.131	-
1988	7.033	0.711	0.137	0.151	-
1989	7.223	0.723	0.127	0.149	-
1990	7.251	0.701	0.137	0.163	-
1991	7.257	0.709	0.142	0.149	-
1992	7.360	0.712	0.126	0.161	-
1993	7.333	0.693	0.132	0.175	-
1994	7.329	0.703	0.125	0.172	-
1995	7.414	0.701	0.119	0.179	-
1996	7.355	0.699	0.132	0.169	-
1997	7.417	0.704	0.119	0.173	0.004
1998	7.512	0.712	0.123	0.138	0.028
1999	7.635	0.649	0.120	0.154	0.078
2000	7.622	0.634	0.124	0.157	0.086
2001	7.625	0.650	0.132	0.126	0.091
2002	7.651	0.653	0.123	0.117	0.108
2003	7.633	0.621	0.126	0.147	0.106
2004	7.650	0.618	0.118	0.133	0.131
2005	7.718	0.595	0.111	0.154	0.139
2006	7.629	0.580	0.124	0.149	0.146
2007	7.592	0.603	0.119	0.119	0.159
2008	7.538	0.593	0.115	0.110	0.183
2009	7.533	0.546	0.141	0.126	0.187
2010	7.527	0.569	0.159	0.073	0.199
2011	7.498	0.537	0.156	0.102	0.205
Sample Descriptive Statistics					
μ	7.408	0.660	0.130	0.141	0.069
σ_μ	0.015	0.004	0.001	0.002	0.004
σ_μ/μ	0.20%	0.59%	0.88%	1.68%	3.53%

Note: μstands for the mean, σ_μ stand for the standard deviation of the mean and σ_μ/μstands for the coefficient of variation.

just 6.9% which naturally reflects its total absence in the final energy mix prior to 1997.

Overall, over the sample period, we observe a declining trend in the final demand for petroleum and its derivatives and coal while the opposite is true for electricity and natural gas. Yet, petroleum and its derivatives continue to account for more than half of the final demand for energy.

3. Fractional Integration

3.1 Fractionally integrated processes

A fractionally integrated process is a stochastic process whose degree of integration is a fractional number and whose autocorrelation function exhibits persistence which is neither an I(0) nor an I(1) process. Nevertheless, persistence is consistent with a stationary process where the autocorrelations decay hyperbolically. Because the autocorrelations die out slowly, the fractionally integrated processes display long-run, rather than short-term dependence, and for that reason are also known as long-memory processes [See, for example, Granger and Joyeux (1980), Granger (1980, 1981), Sowell (1992a, 1992b), Baillie (1996) and Palma (2007).

A time series $x_{t,} = y_t - \beta z_t$ - where β is the coefficients vector, z_t represents all deterministic factors of the process y_t and $t = 1, 2, \dots n$ - is said to be fractionally integrated of order 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, d is a real number that captures the long-run effect and u_t is $I(0)$.

Through 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:

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

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

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

Allowing d to be a real number provides a richer degree of flexibility in the specification of the dynamic nature of the series, and depending on the value of the parameter d we can determine different levels of intertemporal dependency. In fact, when d is a non-integer number, each x_t depends on its past values far away back in time. Moreover, the auto-covariance function satisfies the following property

$$\gamma_j \approx c_1 j^{2d-1}, \qquad \text{for} \;\; j = 1, 2, \ldots \;\; \text{and} \;\; 0 < |c_1| < \infty \tag{5}$$

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,

$$f(\lambda) = \left(\frac{\sigma^2}{2\pi}\right) \left|\frac{\theta \;\, (e^{-i\lambda})}{\phi \;\, (e^{-i\lambda})}\right|^2 \; [2(1 - \cos(\lambda)]^{-2d} \tag{6}$$

then for low frequencies as $\lambda \to 0^+$ we get

$$f(\lambda) \approx c_2 \lambda^{-2d} \tag{7}$$

Where $c_2 = \left(\frac{\sigma^2}{2\pi}\right) \left|\frac{\theta(1)}{\phi(1)}\right|^2 > 0$ and "$\approx$ " means that the ratio between the two sides of (7) will tend to unity as $\lambda \to 0^+$.

In general, larger values for the fractional-difference parameter, d, indicate a greater degree of persistence. Specifically, if $-0.5 < d < 0$, the autocorrelation function decays at a slower hyperbolic rate but the process can be called anti-persistent, or, alternatively, to have rebounding behavior or negative correlation. If $0 < d < 0.5$, the process reverts to its mean but the auto-covariance function decreases slowly as a result of the strong dependence on past values. Nevertheless, the effects will last longer than in the pure stationary case ($d = 0$). If $0.5 < d < 1$, the process is non-stationary with a time-dependent variance, but the series retains its mean-reverting property. Finally, if $d \geq 1$, the process is non-stationary and non-mean-reverting, i.e. the effects of random shocks are permanent.

3.2 ARFIMA processes

An auto-regressive fractionally integrated moving average process, ARFIMA, is an extension of the traditional ARIMA model allowing for fractional degrees of integration. The autocorrelations of the ARFIMA process decay in a slower rate than the exponential rate associated with the ARMA process and, generally, with short memory processes. ARFIMA models were first introduced by Granger and Joyeux (1980) and Granger (1980, 1981) to solve problems to unit roots tests caused by either variable aggregation, and more recently, by the duration of shocks [see, for example, Sowell (1992a, 1992b), Baillie (1996) and Palma (2007), for reviews of this literature].

A process like (1) is called fractionally integrated of order d if d is a non-integer. If, in addition, u_t in (1) is an $ARMA(p, q)$, then x_t is an ARFIMA process becomes,

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

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

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

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

lying outside the unit circle, and e_t is white noise. Clearly, the process is stationary and invertible for $-0.5 < d < 0.5$.

The estimation of 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:

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

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

3.3 A seasonal long-memory process

A seasonal white noise parametric long-memory process has been proposed by Porter-Hudak (1990) who considers a simple seasonally fractionally differenced process as

$$(1-L^s)^d x_t = u_t, \qquad t = 1, 2, 3, \ldots \tag{13}$$

where, s is the seasonal period and $L^s x_t = x_{t-s}$. As with (2), the process also will have an infinite-order L^s polynomial with slowly and monotonically declining weights,

$$(1-L^s)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^{sj} = 1 - dL + \frac{d(d-1)}{2!} L^{2s} - \frac{d(d-1)(d-2)}{3!} L^{3s} + \cdots \tag{14}$$

A more general seasonal ARFIMA model, can be written as

$$\phi(L)(1-L^s)^{d_s} x_t = \theta(L) e_t \tag{15}$$

The spectrum of the seasonal ARFIMA model is given by Porter-Hudak (1990) and Ray (1993) as

$$f(\lambda) = \left(\frac{\sigma^2}{2\pi}\right) \left|\frac{\theta\ (e^{-i\lambda})}{\phi\ (e^{-i\lambda})}\right|^2 [2(1-\cos(s\lambda)]^{-2d} \tag{16}$$

The spectrum is unbounded at frequencies $\lambda_j = \frac{(2\pi j)}{s}$, for $j = 0, 1, 2, \ldots\ s/2$, so that the model contains a persistent trend and a (s/2) persistent cyclical component. Hence the seasonal ARFIMA process shows a behavior at seasonal frequencies similar to that of the ARFIMA process at zero frequency (6).

In particular, we will use the twelfth seasonal difference $(S12y_t = y_t - y_{t-12} = (1-L^{12})y_t$ of the natural logs of the series $(y_t = ln(x_t))$ and the seasonal ARFIMA model can be written as

$$\phi(L)(1-L^{12})^{d_s} y_t = \theta(L) e_t \tag{17}$$

Accordingly, seasonality has long memory when $0 < d_s < 0.5$ and the short-run dynamics are described through the estimation of the ρ parameter of the usual non-seasonal $AR(p)$ part of (17).

4. The Empirical Results

In this section, we present the main empirical results. The bulk of this section deals with the estimation of different $\mathrm{ARFIMA}(p, d, q)$ models using natural logarithms of the raw data. We consider three empirical approaches, first using the raw data in logs without any modifications' second, using the raw data in logs but with seasonality filtered out; and third, with the data corrected for seasonality.

As a starting point of reference and for the sake of highlighting the insights brought forth by the fractional integration approach, we begin by considering the results from the standard unit roots tests, i.e., the tests that only consider the dichotomy between stationarity and non-stationarity. The results are traditionally interpreted as suggesting that the effects of one-time shocks to the series are either transitory, if the series is stationary, or permanent if the series is not stationary.

4.1 The Traditional Approach: Standard Unit Roots Tests

We use the Augmented Dickey-Fuller (ADF) t-test to test the null hypothesis of a unit root in aggregate energy consumption and its components in log differences. The optimal lag structure is chosen using the Schwartz Bayesian Information Criterion (BIC) as the model selection criteria, and the deterministic component (DET hereafter) were included if statistically significant.

The test results are presented in Table 2 and suggest that all series under consideration are non-stationary in log-levels but stationary in first log-differences, that is, they are I(1). Based on these test results we can conclude that one-time shocks to all of these series have permanent effects on the levels of the different variables. This means that the one-off policy shocks have permanent effects and that maintaining a steady policy stance is not critical, since even one-time shocks will lead to permanent effects. In addition, there is nothing we can say based on these results

Table 2 - Traditional unit root results for energy consumption

Variables	DET	Lag	t	p-value		BIC
In log-levels						
Aggregate energy consumption	Constant and trend	1	0.625	0.851		-614.931
Oil	Constant	2	0.218	0.750		-605.98
Coal	Constant	2	-0.108	0.646		311.39
Gas	Constant and trend	5	0.270	0.765		-85.6854
Electricity	Constant and trend	4	0.702	0.867		-550.573
In log-differences						
Aggregate energy consumption	None	1	-17.714	0.000	***	-620.305
Oil	None	1	-19.179	0.000	***	-611.701
Coal	None	5	-11.621	0.000	***	286.262
Gas	None	4	-8.027	0.000	***	-90.763
Electricity	None	6	-10.046	0.000	***	-606.782

on the relative degree of persistence of the different components of energy consumption.

It is also interesting to note that these results coincide with the directly-related literature on stationarity/non-stationarity in energy consumption to confirm the presence of unit roots. Furthermore, even the evidence using a fractional integration approach suggests that unit roots are prevalent [see, among others Gil-Alana et all (2012) and 2010), Apergis and Tsoumas (2011) or Lean and Smyth (2009)].

4.2 Fractional integration without seasonal adjustments

In all cases that follow, the optimal ARFIMA structure was chosen using the Schwartz Bayesian Information Criterion (BIC) as the model selection criteria. We present the estimation results of the auto-regressive and moving average components that correspond to the optimal specification[2], as well as of the estimated fractional integration parameter d. For each estimated parameter we present the corresponding standard errors, p-values and 95% confidence intervals.

Results for the fractional integration analysis without any consideration of seasonality are presented in Table 3. These results suggest that there is statistically significant evidence for the non-rejection of the presence of long memory in aggregate energy demand as well as in its four components.

[2] Only the parameters corresponding to the optimal ARMA structure are reported. Specifically, if the optimal structure is AR(12) or MA(12) all coefficients will be reported. If, however, only the 12^{th} order coefficients are significant, then only these coefficients are reported.

Table 3 – Fractional integration results without seasonal adjustments

		Constant	AR( )		FI( )	MA( )	
			p	$\hat{\rho}$	$\hat{d}$	q	$\hat{\theta}$
Aggregate energy consumption		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			
	Standard error			0.1083			
	p-value			0.037			
	Conf. Interval (95%)			[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.

All the estimates of the fractional parameter d are in the range $(0, 1)$ thus allowing us to reject both the pure stationary case ($d = 0$) and the unit root model ($d = 1$). More specifically, all estimated parameters d are statistically significant at the 5% level test and lie within the interval (0, 0.5). Petroleum and electricity show the highest degrees of persistence ($d =$ 0.4875 and $d =$ 0.4803) closely followed by coal ($d =$ 0.4233). For the case of final demand for gas, the value of the fractional integration parameter ($d = 0.2814$) is lower than for the other final energy demand variables, suggesting a weaker intensity of persistence for this component, though stronger than the pure stationary case.

Overall, these results mean that the effects of a random shock in the innovations of these series are transitory as the series are mean reverting. Such effects, however, will last longer than in the pure stationary case. These series, therefore, exhibit long-memory behavior.

The confidence intervals for the estimated fractional integration parameters are sometimes wide but always in the positive range. Also, with the exception of natural gas, the upper bounds are slightly greater than 0.5 leaving open the possibility that these series may be non-stationary, though mean-reverting.

Finally, it should be noted that all of the AR coefficient estimates are large and statistically significant, suggesting a strong influence of this short-term component. For coal the upper limit of the confidence interval is greater than one while for aggregate energy demand it is only marginally lower than one. This suggests that non-stationarity cannot be completely ruled out for these series.[3]

4.3 Fractional integration results with seasonally filtered data: the X12 procedure

Monthly data are often affected by seasonality effects, inertial factors related to the calendar. Seasonal effects are particularly clear in the autocorrelation and the partial autocorrelation functions for the final demand for electricity, gas and coal (see Appendix).

To address this issue, we use the seasonal adjustment methodology X-12 ARIMA, adopted by the U.S. Census Bureau [2011]. This strategy removes the seasonal effect to get a smoother time series for each final energy demand. We then estimated the ARFIMA model with the new seasonally adjusted data. Estimation results are presented in Table 4.

We find, that for all of the seasonally adjusted variables, the estimated fractional integration parameters are again statistically significant and within the interval (0, 0.5). Petroleum and its derivatives ($d = 0.4956$) and electricity ($d = 0.4856$) show the highest degrees of persistence closely followed by coal ($d = 0.4449$). Natural gas, in turn, shows a clearly lower level of persistence ($d = 0.1508$).

The confidence intervals for the fractional integration parameter at the aggregate final energy demand level and for petroleum and derivatives are very narrow while for natural gas it is relatively large. In all cases the lower bound of the confidence interval is positive. For electricity and coal, and more marginally for petroleum and its derivatives, the upper limits of the fractional-difference parameters are greater than

[3] It should be mentioned that in the ARFIMA framework, the short-run behavior of the series can be captured by the ARMA parameters while the long-run behavior can be modeled by the fractional differencing coefficient. Furthermore, the properties of the fractional integration parameter do not depend on the correct specification of the AR or MA terms. [Sowell (1992a and b) and Palma (2007)].

Table 4 – Fractional integration results with seasonality-filtered data: X12 procedure

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

0.5 suggesting that the series may be non-stationary, though mean reverting.

The first order short-run seasonal AR coefficient estimates are all statically significant for a 5% test indicating that adjacent intertemporal dependence is also present. For the aggregate energy and more marginally for gas the upper limit of the confidence interval is greater the one, suggesting that non-stationarity cannot be completely ruled out for these two series.[4]

4.4 Fractional integration with seasonality-adjusted data: the S12 procedure

To directly account for seasonality, for each final energy demand component, we model the twelfth seasonal difference ($S12y_t = y_t - y_{t-12} = (1 - L^{12})y_t$) of the

[4] Refer again to the previous footnote.

Table 5 – Fractional integration with seasonality-adjusted data: the S12 procedure

		Constant	AR( )		FI( )	MA( )	
			p	$\hat{\rho}$	$\hat{d}$	q	$\hat{\theta}$
Aggregate energy consumption			1	0.1245	**0.3345**		
	Standard error			*0.312*	***0.1062***		
	p-value			*0.343*	***0.002***		
	Conf. Interval (95%)			[-0.1326 ; 0.3816]	**[0.1264 ; 0.5426]**		
	BIC				-510.507		
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	0.3413	**0.3208**	1	0.7397
	Standard error			*0.134*	***0.1105***		*0.1139*
	p-value			*0.011*	***0.004***		*0.000*
	Conf. Interval (95%)			[0.0795 ; 0.6031]	**[0.1041 ; 0.5375]**		[0,5164 ; 0,9631]
	BIC				-658.8158		
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]**		
	BIC				144.966		

natural logarithm of the series and then (re)estimate the ARFIMA model.[5] Accordingly, seasonality is long memory when $0 < d_s < 0.50$ and the short run dynamic is described through the estimation of the AR ρ coefficient. Results are presented in Table 5.

All the “d_s” fractional integration parameters range from 0.3345 to 0.4062 thereby rejecting both the pure seasonal stationary case and the seasonal unit root model. With the exception of coal, the confidence intervals are wide. For aggregate final energy consumption, electricity and 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.

[5] A more general approach to seasonality would allow for fractional integration parameters to be different at different seasonal frequencies. See, for example, Hassler (1994) and Robinson (1994). In our case, we would like to argue that the S12 is a perfectly adequate approach. First, there is a clear monthly pattern that repeats itself annually. Second, the argument has been made that for reasons of parsimony the consideration of only one cycle of seasonality is preferable. See, for example, Ferrara and Guégan (2006).

The short-run seasonal AR coefficient estimates are, in general, statistically significant for a 5% test indicating that adjacent intertemporal dependence is also present in final energy consumption. For aggregate final energy consumption the null (that is $\rho = 0$) could not be rejected, suggesting that seasonal short memory is not present.

5. Conclusions and Policy Implications

Our empirical findings suggest that the presence of long memory cannot be rejected for either aggregate final energy demand or for each of its four components – petroleum and its derivatives, electricity, coal, and natural gas. In addition, when we consider the issue of seasonality directly, our findings also indicate annual homologous seasonal long memory for all the components of final energy consumption.[6]

More specifically, all of the estimated fractional-integration parameters are positive and lower than 0.5. We can, therefore, reject both the pure stationary case ($d = 0$) and the unit root case ($d = 1$). All variables are stationary and mean reverting but with the autocorrelations decaying at a hyperbolic rate, that is, they exhibit long-term memory. Accordingly, despite the fact that the effects of temporary shocks tend to disappear only slowly, they preserve a temporary nature. In this sense, our results are in line with the evidence in the recent literature for the United States [see, for example, Lean and Smyth (2009), Gil-Alana, et al. (2010), Apergis and Tsoumas (2011, 2012) and Barros et al. (2012a and 2012b)].

To frame these results we also use the conventional approach of testing for the dichotomy between stationarity and non-stationarity. In this framework we would invariably conclude in favor of non-stationarity. Therefore, we would conclude that even transitory policy shocks would have permanent effects. Our fractional integration analysis highlights that this is not the case. The effects of transitory shocks are temporary, although long lasting.[7]

Understanding nature of persistence in the final energy consumption is a crucial issue as Portugal embarks work on the implementation of important environmental fiscal

[6] This finding highlights the importance of using monthly data and thereby one way in which this paper goes well beyond Belbute and Pereira (2014).
[7] This is another area in which this paper departs fundamentally from Belbute and Pereira (2014)]

reforms aligned with both the EU strategy and UN green economy guidelines [see, for example, APA (2012) and CRFV (2014)].

Our findings on the long memory nature of final energy demand in Portugal have important implications for the design and the effectiveness of its energy and environmental policies. Persistence reflects strong habit formation mechanisms or technological rigidities. When final energy consumption is a pure stationary process, that is, a short memory process, then after a policy shock it will tend to move away from and revert to its trend more quickly than in presence of long memory, that is, a strong dependence on its past values.

Given the existence of long memory in energy consumption, positive policy shocks in the form, for example, of energy efficiency programs, subsidies for alternative renewable energy sources, or incentives for sustainable electrical mobility, are likely to be more effective because they tend to move energy consumption away from and revert to its predetermined target over a long period of time. This is the good news. The adoption of these programs has the potential to generate effects on energy demand patterns that go beyond the duration of the program.

But there is also bad news. Despite the fact that the effects of any active policy on energy consumption tend to disappear slowly, they preserve, however, their temporary nature. Permanent effects on final energy consumption will require a more permanent policy stance. Simply put, adopting programs only to ignore them or reverse them soon thereafter will not leave a permanent effect on demand patterns. Permanent results require permanent programs.

While it is not in the nature of this approach to make prescriptions about the adoption of any specific policy, our results are very informative in terms of what to expect from any existing or potential policy. On one hand, policies that are designed as temporary or end up being suspended cannot be expected to leave permanent effects. A case in point are the policies for 'green mobility' that pointed to the installation of charging stations for electric and hybrid vehicles and which was in the meantime abandoned without leaving any visible change in energy demand patterns. The same can be said about feed-in tariffs for photovoltaic generation, which had an important effect initially with generous rates but whose effects seem to have now petered out has their generosity has been severely curtailed.

On the other hand, policies that are either permanent or perceived as such will tend to generate strong and permanent effects. To illustrate this case we could consider the recently introduced carbon tax, which is designed as a permanent policy, and which as such has the potential for leading to substantive and permanent changes. Similarly, the long-lived feed in tariff programs for wind energy have left a clear and permanent mark in the sector.

Finally, these results have important implication from a more technical perspective. They suggest the importance of accounting for the energy-economy interactions both in terms of modeling and energy forecasting as shocks in energy demand exhibit long memory and will tend to reverberate throughout the economy. Natural gas seems to be less of an issue in this context given its relatively lower levels of persistence.

Although these are important implications in the Portuguese context, though they are far from parochial. In fact, understanding persistence in final energy consumption is imperative, for example, in the European Union. At the core of the renewed policy focus in the EU is the idea that public policy for a green economy should extend well beyond the usual "getting prices right" in order to shift consumption and production patterns to a more sustainable path of greenhouse gas emissions and reduced energy dependency [see, for example, EC (2011, 2013, 2014a, 2014b].

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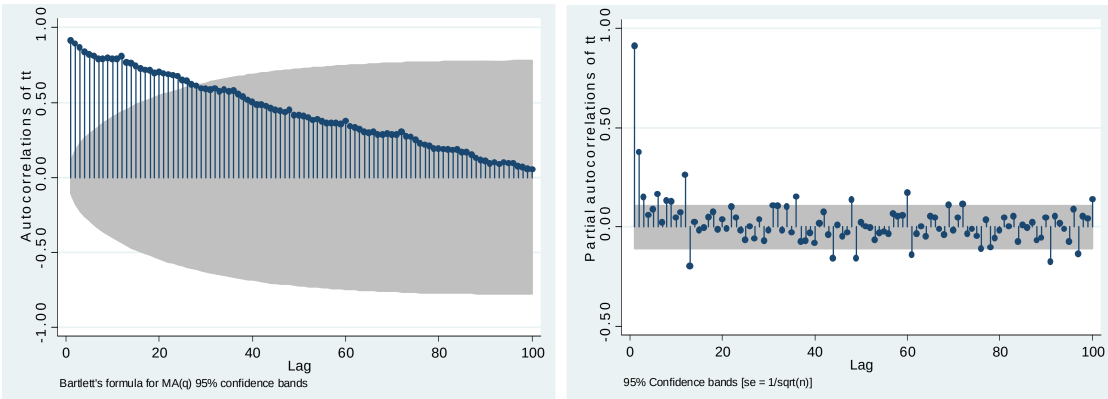
APPENDIX

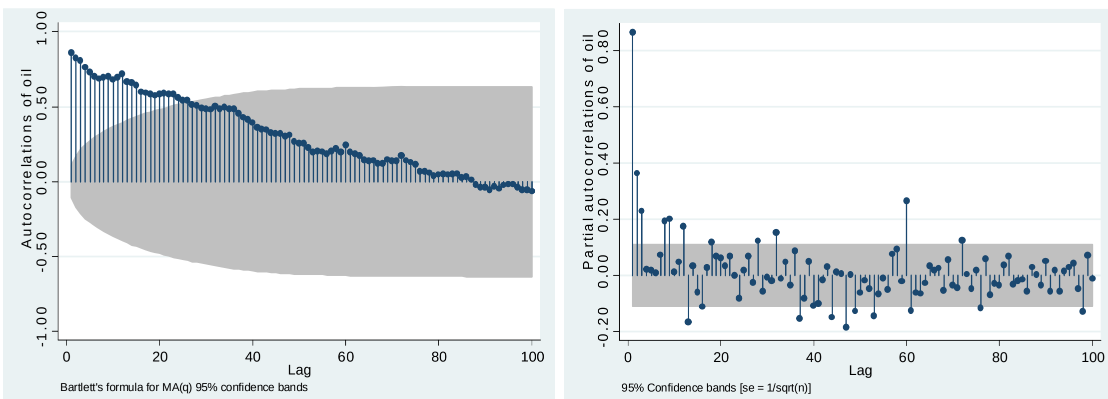
Auto-correlation and partial auto-correlation functions

(log-levels)

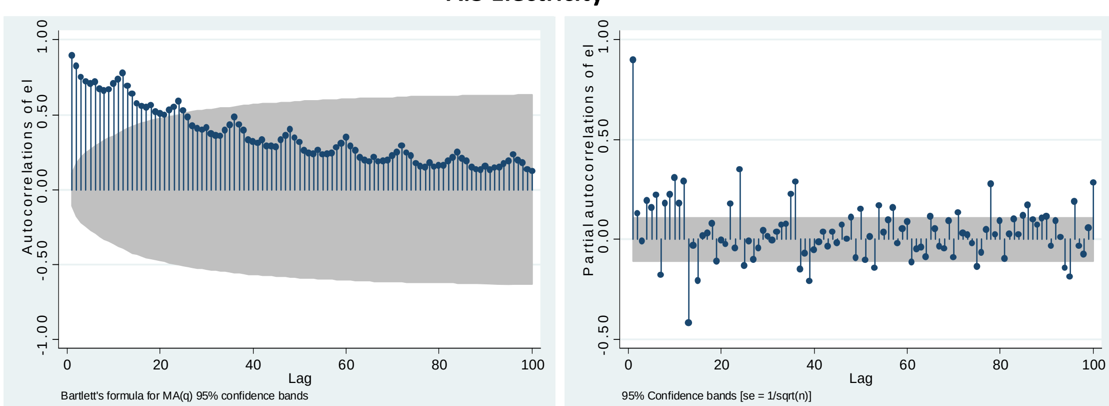
A.1Aggregate final energy demand



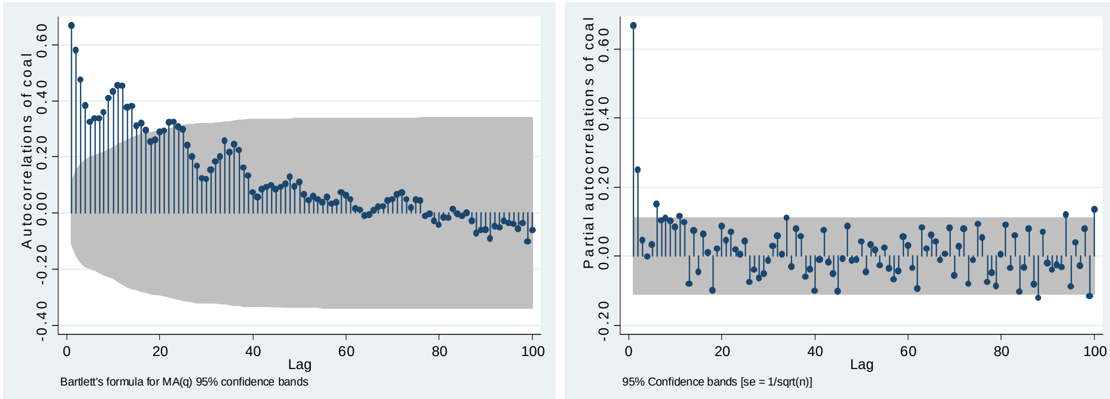
A.2 Petroleum and its derivatives



A.3 Electricity



A.4 Coal



A.5 Natural gas