Does final energy consumption in Portugal exhibit long memory?

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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.

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 stationary, although the mean reversion process will be slower than in the typical short run processes. In addition, our findings also indicate that there is clear seasonal long memory evidence for all the Portuguese components of final energy demand.

These results have important implication for the design of environmental policies. First, despite the effects of a policy shock on energy consumption will tend to disappear slowly, they preserve their temporary nature. This is good news for the success of the Portuguese green tax reform since fiscal neutrality may be achieved earlier and cause temporary budget imbalances for a smaller period.

Second, given the temporary nature of the effects of the policy shock, long lasting effects on the final energy consumption will be achieved by means of a more permanent policy stance.

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 energy production and consumption as well as the effectiveness of energy and environmental policies. This paper aims to contribute to these discussions by testing for the presence of long memory in final energy demand in Portugal.

Understanding final energy consumption persistence is crucial for governmental agencies because it might have strong implications for the design, the implementation and the effectiveness of the energy and environmental public policies. In particular if energy consumption and/or production is stationary, then public policies that promote energy efficiency, fuel switching or reductions in GHG emissions, will tend to have transitory effects, thereby requiring a permanent policy stance [Lean and Smyth (2009), Gil-Alana et al. (2010), Pereira and Belbute (2014) and Apergis and Tsoumas (2012)]. Furthermore, 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 transitory but last long 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)]. Third, a low degree of persistence means that energy consumption and/or production will eventually returns to its trend path after a shock so that past behavior can fairly be used to predict future energy consumption or production [see, for example, Lean and Smyth (2009) or Smyth, R. (2012)]. Finally, the issue of whether or not energy consumption is stationary has important implications for modelling purposes. For example, the Granger causality between energy consumption, GGE emissions or the GDP depends on whether these variables are stationary or not.

Understanding final energy consumption persistence in the final energy consumption is also imperative because the European Union (EU hereafter) is now resuming in its policies the longer term perspectives which were temporarily sidelined by the turmoil of the financial, budgetary and sovereign debt crises [see the Energy Efficiency Plan and the White Paper on Transport and the roadmap for moving to a competitive low carbon economy in 2050]. At the core of this renewed policy framework 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 onto a more sustainable path and reduce the European energy dependence.
Accordingly, understanding final energy consumption persistence in the final energy consumption is crucial for Portugal because the Portuguese government is now preparing an important environmental fiscal reform aligned with both the European 2020 strategy and the implementation of the United Nations green economy guidelines. The green fiscal reform embraces the fiscal neutrality principle in order to both promote a shift in consumption and production patterns to a more sustainable path, and provide the appropriate incentives for the efficient use of resources. The fiscal intervention should leave unchanged the tax burden through fully recycling of the environmental tax revenues back into the economy. In particular, the tax system should be redesigned by broadening tax bases and shifting the tax burden away from labor revenues on to tax bases linked to consumption, property and pollution.

The key question is how long does it take until the environmental tax revenues increase enough to fully offset the loss of tax the revenues on labor or property. Since the reduction of the labor tax revenues is almost instantaneous the effectiveness of the green fiscal neutrality crucially depends on how energy consumption and/or production react to the fiscal stimulus. Furthermore, even if the environmental tax reform is optimal in the sense that it minimizes the economic costs, it remains the question of how effective it will be. Persistence reflects strong habit formation mechanisms and technological rigidities. Accordingly, if final energy consumption is a pure stationary process (that is a short memory process) then it will tend to move away from and revert to its trend more quickly than when in presence of a strong dependence from its distant past values after a policy shock. Therefore, fiscal neutrality will be achieved later and cause temporary budget imbalances for a larger period. This is not careless (despicable?) since Portugal is subject to the fiscal conditionalities imposed by the European fiscal stability treaty.

There is an vast literature using univariate 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 (2014)]. The main results of this literature can be summarized as follows. First the univariate unit root tests without structural breaks suggest that the energy variables have a unit root in a majority of cases. Secondly, in the presence of one or two breaks the unit root null hypothesis is rejected in most cases. Third, panel tests without structural breaks have not provided much additional evidence in favor of stationarity over univariate unit root tests.
without structural breaks. However, panel tests that accommodate structural breaks provide strong support in favor of energy consumption and production being stationary [for a detailed survey of the literature on the integration properties of energy consumption and production see Smyth (2012)].

Nonetheless, traditional autoregressive univariate unit root tests are typically limited to the stationary/non-stationary dichotomy. Furthermore, their power to reject the null hypothesis depends on several factors such as structural breaks, non-linearities and fractional integration (or long memory), all of them affecting most of the energy variables [see, among others, Narayan and Smyth (2007), Hasanov and Telatar (2011), Apergis and Payne (2010), Narayan et al. (2010), Aslan and Kum (2011), Choi and Moh (2007), Diebold and Rudebush (1989) and Lee and Schmidt (1996)]. Finally, the unit root tests only provide evidence about the existence (or absence) of a permanent component but not its extent. In other words, 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 [see Diebold and Rudebush (1989)].

There is now an emerging literature which considers the possibility that energy variables may follow a long memory process. 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 this phenomena can be measured by a differencing parameter “d.” When $-0.5 < d < 0.5$ then the process is said to be covariance stationary and ergodic with a abounded and positively value spectrum at all frequencies. When $-0.5 < d < 0$ the process is called intermediate memory or over differenced. For $0 < d < 0.5$, 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 ($d = 0$). Long memory means a significant dependence between observations widely separated in time and therefore the effects caused by shocks tend to decay slowly, thought mean reverting. When $d < 1$ the process is mean reversing while for $d = 1$ the process is a random walk. Accordingly, for $0.5 < d < 1$, the process is not covariance stationary thought mean reverting.


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), Breitung and Hassler (2002) and Gil-Alana (2003)] 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 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)]. The results from these fractional integration tests generally confirm that energy variables are stationary process, but where the autocorrelations take longer to decay than the exponential rate associated with ARMA processes.

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 given the Portuguese commitments with the European strategy 2020 and the Green Economy Initiative.

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. 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; 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, 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.

Aggregate final gross inland energy consumption 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 (ktoe hereafter), and were converted into natural logarithms for the empirical analysis. The original data are not seasonally adjusted.

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 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.
Table 1 – Decomposition of the aggregate inland energy consumption

<table>
<thead>
<tr>
<th>Year</th>
<th>Aggregate inland energy consumption: monthly average (ktoe)</th>
<th>Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Petroleum (%)</td>
<td>Coal (%)</td>
</tr>
<tr>
<td>1985</td>
<td>6.810</td>
<td>0.744</td>
</tr>
<tr>
<td>1986</td>
<td>6.864</td>
<td>0.747</td>
</tr>
<tr>
<td>1987</td>
<td>6.947</td>
<td>0.736</td>
</tr>
<tr>
<td>1988</td>
<td>7.033</td>
<td>0.711</td>
</tr>
<tr>
<td>1989</td>
<td>7.223</td>
<td>0.723</td>
</tr>
<tr>
<td>1990</td>
<td>7.251</td>
<td>0.701</td>
</tr>
<tr>
<td>1991</td>
<td>7.257</td>
<td>0.709</td>
</tr>
<tr>
<td>1992</td>
<td>7.360</td>
<td>0.712</td>
</tr>
<tr>
<td>1993</td>
<td>7.333</td>
<td>0.693</td>
</tr>
<tr>
<td>1994</td>
<td>7.329</td>
<td>0.703</td>
</tr>
<tr>
<td>1995</td>
<td>7.414</td>
<td>0.701</td>
</tr>
<tr>
<td>1996</td>
<td>7.355</td>
<td>0.699</td>
</tr>
<tr>
<td>1997</td>
<td>7.417</td>
<td>0.704</td>
</tr>
<tr>
<td>1998</td>
<td>7.512</td>
<td>0.712</td>
</tr>
<tr>
<td>1999</td>
<td>7.635</td>
<td>0.649</td>
</tr>
<tr>
<td>2000</td>
<td>7.622</td>
<td>0.634</td>
</tr>
<tr>
<td>2001</td>
<td>7.625</td>
<td>0.650</td>
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<tr>
<td>2002</td>
<td>7.651</td>
<td>0.653</td>
</tr>
<tr>
<td>2003</td>
<td>7.633</td>
<td>0.621</td>
</tr>
<tr>
<td>2004</td>
<td>7.650</td>
<td>0.618</td>
</tr>
<tr>
<td>2005</td>
<td>7.718</td>
<td>0.595</td>
</tr>
<tr>
<td>2006</td>
<td>7.629</td>
<td>0.580</td>
</tr>
<tr>
<td>2007</td>
<td>7.592</td>
<td>0.603</td>
</tr>
<tr>
<td>2008</td>
<td>7.538</td>
<td>0.593</td>
</tr>
<tr>
<td>2009</td>
<td>7.533</td>
<td>0.546</td>
</tr>
<tr>
<td>2010</td>
<td>7.527</td>
<td>0.569</td>
</tr>
<tr>
<td>2011</td>
<td>7.498</td>
<td>0.537</td>
</tr>
</tbody>
</table>

Sample descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>μ</th>
<th>σ_μ</th>
<th>σ_μ/μ</th>
</tr>
</thead>
<tbody>
<tr>
<td>µ</td>
<td>7.408</td>
<td>0.660</td>
<td>0.130</td>
</tr>
<tr>
<td>σ_μ</td>
<td>0.015</td>
<td>0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>σ_μ/μ</td>
<td>0.20%</td>
<td>0.59%</td>
<td>0.88%</td>
</tr>
</tbody>
</table>

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

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 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 (also known as “combined heat and power (CHP) 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 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.

3. Fractional Integration

3.1 Fractionally integrated processes

A fractionally integrated process is a process whose degree of integration is a fractional number - the so called $d$ parameter, - and whose autocorrelation function exhibits persistence that is neither an I(0) nor an I(1) process. Nevertheless, the extent of the persistence is consistent with a stationary process but where the autocorrelations decay hyperbolically.
Because the autocorrelations die out so slowly the fractionally integrated processes display a type of long-run dependency, rather than short-run dependence, and for that reason are also known as long memory processes.

A time series \( x_t = y_t - \beta z_t \) - where \( \beta \) is the coefficients vector, \( z_t \) represents all deterministic factors of the process \( y_t \) and \( t = 1, 2, \ldots n \) - is said to be fractionally integrated of order \( d \) (\( x_t \sim I(d) \)) if it can be represented by

\[
(1 - L)^d x_t = u_t, \quad t = 1, 2, 3, \ldots
\]

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,

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

and thus (1) can be written as:

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

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,

\[
\gamma_j = \alpha_1^j, \quad \text{for } j = 1, 2, \ldots \text{ and } |\alpha_1| < 1
\]

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

\[
\gamma_j \approx c_1 j^{2d-1}, \quad \text{for } j = 1, 2, \ldots \text{ and } 0 < |c_1| < \infty
\]

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

(6)

than for low frequencies as \( \lambda \to 0^+ \) we get

\[ f(\lambda) \approx c_2\lambda^{-2d} \]  

(7)

where \( c_2 = \left( \frac{\sigma^2}{2\pi} \right) \theta (1)^2 > 0 \) and “\( \approx \)" means that the ratio between the two sides of (7) will tend to unity as \( \lambda \to 0^+ \). However, 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 \( 0 < d < 0.5 \), 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 \( (d = 0) \).

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\(^1\), 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.

### 3.2 ARFIMA processes

An auto regressive fractionally integrated moving average (ARFIMA, hereafter) process is an extension of the traditional ARMA process in that the autocorrelations decay in a slower rate than the exponential rate associated with the ARMA process and, generally, than with short memory processes. The ARFIMA model provides a more parsimonious parameterization of long memory processes than the ARMA models. Moreover, by allowing for fractional degrees of integration, the ARFIMA model also generalizes the usual autoregressive integrated moving-average (ARIMA) model with integer degree of integration.

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 called an ARFIMA process and the model becomes,

\(^1\) 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.
\[
\phi(L^p)(1 - L)^d x_t = \theta(L^q)e_t
\]

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

\[
\phi(z) = 1 - \phi_1 z - \phi_2 z^2 - \ldots - \phi_p z^p = 0
\]

\[
\theta(z) = 1 + \theta_1 z + \theta_2 z^2 + \ldots + \theta_q z^q = 0
\]

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

ARFIMA models were first introduced by Granger and Joyeux (1980) and Granger (1980, 1981) and 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

\[
\ell((y|\hat{\eta})) = -\frac{1}{2}\left\{ T \log(2\pi) + \log|V| + (y - X\hat{\beta})' V^{-1} (y - X\hat{\beta}) \right\}
\]

The covariance matrix \( V \) has a Toeplitz structure:

\[
V = \begin{bmatrix}
\gamma_0 & \gamma_1 & \gamma_2 & \ldots & \gamma_{T-1} \\
\gamma_1 & \gamma_0 & \gamma_1 & \ldots & \gamma_{T-2} \\
\vdots & \vdots & \ddots & \cdots & \vdots \\
\gamma_{T-1} & \gamma_{T-2} & \gamma_{T-3} & \ldots & \gamma_0
\end{bmatrix}
\]

where \( \gamma_0 = \text{Var}(y_t) \) and \( \gamma_j = \text{Cov}(y_t, y_{t-j}) \) 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-Hudack (1990) who considers a simple seasonally fractionally differenced process as

\[
(1 - L^s)^d x_t = u_t, \quad t = 1, 2, 3, \ldots
\]

where \( s \) is the seasonal period and \( (L^s)x_t = x_{t-s} \). Analogously to Eq.(2), the process also will have an infinite-order \( L^s \) polynomial with slowly and monotonically declining weights,
\[(1 - L^s)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^{sj} = 1 - dL + \frac{d(d - 1)}{2!} L^{2s} - \frac{d(d - 1)(d - 2)}{3!} L^{3s} + \ldots \quad (14)\]

A more general seasonal ARFIMA model (the so called ARFISMA model, where \(S\) stands for accounting the seasonal effect) can be rewritten as

\[\phi(L^p)(1 - L^s)^d x_t = \theta(L^q) e_t \quad (15)\]

The spectrum of the ARFISMA model is given by [see, Porter-Hudak (1990) or Ray (1993)]

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

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 components. Hence the ARFISMA process shows a behavior at seasonal frequencies similar to that of the ARFIMA process at zero frequency (Eq. 6).

In particular, we will use the twelfth seasonal difference \((S12 y_t = y_t - y_{t-12} = (1 - L^{12}) y_t)\) of the natural logs of the series \((y_t = ln(x_t))\) and the SARFIMA model can be written as

\[\phi(L^p)(1 - L^{12})^d y_t = \theta(L^q) e_t \quad (17)\]

Accordingly, seasonality is long memory when \(0 < d_s < 0.50\) and the short run dynamics are described through the estimation of the \(\rho\) parameter of the usual non-seasonal \(AR(p)\) part of Eq. (17). Furthermore, this procedure will allow the SARFIMA model to parameterize the short-run effects via the estimated \(AR\ \rho\) coefficient, along with the long-run effect via the estimated “d” parameter.

### 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 in tables 2 and 3 we show the results for correction of the seasonality 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 (or the confidence intervals of the non-rejection values of “d” at the 5% level of significance).
4.2 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 test and lie
within the interval (0, 0.5). Note that the all the seasonal AR coefficient estimates are large,
suggesting strong influence of this component. 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)

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>AR( )</th>
<th>FI( )</th>
<th>MA( )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{p}$</td>
<td>$\hat{d}$</td>
<td>$\hat{q}$</td>
<td>$\hat{\theta}$</td>
</tr>
<tr>
<td>Aggregate energy consumption</td>
<td>7.1348</td>
<td>0.9524</td>
<td>0.4913</td>
<td>-0.7852</td>
</tr>
<tr>
<td>Standard error</td>
<td>1.5475</td>
<td>0.0237</td>
<td>0.0117</td>
<td>0.0527</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>BIC</td>
<td>-638.975</td>
<td>[0.9059 ; 0.9988]</td>
<td>[0.4685 ; 0.5141]</td>
<td>[-0.8884 ; -0.6819]</td>
</tr>
<tr>
<td>Petroleum and derivatives</td>
<td>6.8700</td>
<td>0.3107</td>
<td>0.4675</td>
<td>0.000</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.4436</td>
<td>0.05916</td>
<td>0.016</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>BIC</td>
<td>[0.19448 ; 0.4267]</td>
<td>[0.4562 ; 0.5187]</td>
<td>[-0.600 ; -0.474]</td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td>5.328</td>
<td>0.2744</td>
<td>0.4803</td>
<td>0.000</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.3464</td>
<td>0.0634</td>
<td>0.0256</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>BIC</td>
<td>[0.1502 ; 0.3986]</td>
<td>[0.4380 ; 0.5305]</td>
<td>[-0.560 ; -0.339]</td>
<td></td>
</tr>
<tr>
<td>Coal</td>
<td>5.049</td>
<td>0.8674</td>
<td>0.4233</td>
<td>0.7155</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.7616</td>
<td>0.092</td>
<td>0.0428</td>
<td>0.1323</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>BIC</td>
<td>[0.0870 ; 1.0478]</td>
<td>[0.3993 ; 0.5073]</td>
<td>[-0.9749 ; -0.4562]</td>
<td></td>
</tr>
<tr>
<td>Gas</td>
<td>1.000</td>
<td>0.7538</td>
<td>0.2614</td>
<td>0.2814</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.1137</td>
<td>0.0956</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>BIC</td>
<td>[0.05369 ; 0.9827]</td>
<td>[0.0942 ; 0.4686]</td>
<td>[0.0132 ; 0.4379]</td>
<td></td>
</tr>
</tbody>
</table>

Note: $\hat{p}$ 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.

In short, for all parameters estimates we reject the null ($d = 0$) for a test of 5% level of
significance and are inside the stationary region (0, 0.5). Furthermore, all the estimates of the
fractional parameter “d” are in the range (0, 1) thus rejection both the pure stationary case ($d = 0$) and the unit root model ($d = 1$). All the variables are mean reverting and there is a strong probability of the overall ad its four types of final consumption in Portugal exhibit long memory. This implies that the effects of a policy shock will be temporary.

### 4.3 Seasonally adjusted data

Monthly data are often affected by seasonality which may by itself be determined by inertial factors caused by the calendar seasons. The presence of this seasonal effect is particularly detectable by visual inspection of both the autocorrelation and the partial autocorrelation functions of electricity, gas and coal final gross inland consumption in Portugal.

We use two distinct strategies to correct for the seasonality. First, for each final energy demand component, we model the twelfth seasonal difference ($S^{12}y_t = y_t - y_{t-12} = (1 - L^{12})y_t$) of the natural logs of the series and then (re)estimate the ARFIMA model. Accordingly, seasonality is long memory when $0 < d_s < 0.50$ and the short run dynamic is described through the estimation of the AR $\rho$ coefficient. 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, 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 twelfth seasonal pattern of energy consumption. In the second case, we removed this seasonal effect to get a smoother 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 $\alpha = 1\%$. 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.

<p>| Table 2 – Fractional integration results with seasonality adjusted ($ln(x_t/x_{t-12})$) | 14 |</p>
<table>
<thead>
<tr>
<th>Energy Demand</th>
<th>Constant</th>
<th>AR(1)</th>
<th>AR(1)</th>
<th>MA(1)</th>
<th>MA(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate energy consumption</td>
<td></td>
<td>1</td>
<td>0.1245</td>
<td>0.3345</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Petroleum and derivatives</td>
<td></td>
<td>4</td>
<td>0.1589</td>
<td>0.3647</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td></td>
<td>1</td>
<td>0.3413</td>
<td>0.3208</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coal</td>
<td></td>
<td></td>
<td></td>
<td>0.4062</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gas</td>
<td></td>
<td></td>
<td></td>
<td>0.6316</td>
<td>0.3787</td>
</tr>
</tbody>
</table>

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. The wide confidence interval for parameter d reflects the difficulty of fitting a complex dynamic model with a short sample size (232 observations for aggregate final energy consumption and only 179 observations for the case of gas).

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

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. All values of the parameter \( d_s \) are in the range (0, 1) thereby rejecting the seasonal unit root model. Evidence of stationary seasonality (that is \( d < 0.5 \)) is obtained for all variables. Furthermore, the confidence interval for the aggregate final energy consumption is very narrow ([0.4149 ; 0.4165] and with parameter \( d = 0.4157 \), while for natural gas it is...
larger ([0.0280 ; 0.2734]. The final consumption for gas is still the final energy component with the smallest degree of persistence \( d = 0.1508 \).

The first order short run seasonal AR coefficient estimates are all statically significant for a 5% test. For the aggregate energy and for gas the upper limit of the confidence interval is greater the one suggesting that non-stationarity should not be exclude for these two series.

### Table 3 – Fractional integration results with seasonality adjusted using X12 filter

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>AR(1)</th>
<th>FI( )</th>
<th>MA(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aggregate energy consumption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error</td>
<td>0.8998</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[5.2795 ; 8.8065]</td>
<td>[0.9083 ; 1.0619]</td>
<td>[0.4149 ; 0.4165]</td>
<td>[-0.9745 ; -0.8695]</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[-0.0657 ; 0.0842]</td>
<td>[0.4149 ; 0.4165]</td>
<td>[0.4149 ; 0.4165]</td>
<td>[-0.9745 ; -0.8695]</td>
</tr>
<tr>
<td><strong>Petroleum and derivatives</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error</td>
<td>0.4904</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[4.9314 ; 7.8536]</td>
<td>[0.4836 ; 0.5075]</td>
<td>[0.4836 ; 0.5075]</td>
<td>[0.4836 ; 0.5075]</td>
</tr>
<tr>
<td><strong>Electricity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error</td>
<td>0.3618</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[4.5007 ; 6.0278]</td>
<td>[0.2137 ; 0.4529]</td>
<td>[0.4441 ; 0.5271]</td>
<td>[0.4441 ; 0.5271]</td>
</tr>
<tr>
<td><strong>Coal</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error</td>
<td>0.4481</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[4.3343 ; 6.0910]</td>
<td>[0.3767 ; 0.5131]</td>
<td>[0.3767 ; 0.5131]</td>
<td>[0.3767 ; 0.5131]</td>
</tr>
<tr>
<td><strong>Gas</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error</td>
<td>0.0078</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.000</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Conf. Interval (95%)</td>
<td>[0.9970 ; 1.0075]</td>
<td>[0.0282 ; 0.2734]</td>
<td>[0.0282 ; 0.2734]</td>
<td>[0.0282 ; 0.2734]</td>
</tr>
</tbody>
</table>

### 5 Conclusions and policy implications

This paper tests the presence of long memory in aggregate and disaggregate final energy consumption in Portugal. 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 indicating that all the analyzed types of final energy consumption in Portugal are both stationary and mean reverting but with the autocorrelations decaying at a hyperbolic rate. Furthermore, all the estimates of the fractional
parameter “d” are in the range (0, 1) thus rejecting both the pure stationary case (d = 0) and the unit root model (d = 1). In some cases, the upper limit of the confidence intervals for the fractional-difference parameters d is greater than 0.5 suggesting that the series might be non-stationary but still mean reverting. Moreover, the wide level of the confidence intervals in some cases is explained by both the sample size and specially by the complex dynamics of the models fitted. Accordingly, the effects of a given random shock will be transitory, but reverting to the trend slower than in the pure stationary case (d = 0).

Using the aggregate final energy consumption as a 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 final demand of petroleum and electricity tend to have levels of persistence similar to aggregate final demand.

Our findings also indicate that there is evidence of seasonal long memory (d_s < 0.5) for all the Portuguese components of final energy consumption. The estimates range from 0.3345 (for aggregate energy consumption) to 0.4061 (for coal) for the twelfth seasonal differences and from 0.1508 (for gas) to 104956 (for petroleum) in the case of X12 filter. The confidence intervals for fractionally integrated parameter include estimates greater than 0.5, thereby suggesting that the corresponding energy consumption components may be non-stationary, thought mean reverting. Again, this can be attributed to the difficulty of fitting a complex dynamic model with sample size (232 observations for aggregate final energy consumption and only 179 observations for the case of gas). Our results are in line with recent results in Lean and Smyth (2009), Gil-Alana, Payne and Loomis (2010), Apergis and Tsoumas (2011 and 2012) and Barros et al. (2012), which use different methodologies of fractional integration in the study of United States final energy demand.

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 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 and revert to its predetermined target over a long period of time. In the specific case of natural gas, this process will occur more rapidly.
In addition, despite the effects of any active policy on energy consumption tend to disappear slowly, they preserve their temporary nature as the estimated fractional-difference parameters $d$ lies within the interval $[0; 0.5]$. Accordingly, long lasting effects on the final energy consumption will be achieved by means of a more permanently policy stance. This is good news for the success of the Portuguese green tax reform since the presence of long range dependence will tend to move energy consumption away from and revert to its trend more slowly than in the pure stationary process. Therefore, fiscal neutrality will be achieved earlier and cause temporary budget imbalances for a smaller period.

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 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 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.

The main conclusions of the literature on the stationary properties of energy consumption and/or production suggest that allowing for one or more structural breaks in energy consumption or production is important for determining the order of integration of energy variables. Accordingly estimating the ARFIMA/SARFIMA model allowing for structural breaks is a natural extension of our work. In addition, a second research avenue is to extend the test for the presence of long memory in a more disaggregated final energy consumption such us biomass, solar and geothermic.
Appendix - 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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