Sharp and Smooth Breaks in Unit Root Testing of Renewable Energy Consumption: The Way Forward

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Abstract: This study proposes a flexible unit root test that detects sharp and smooth breaks simultaneously. Most unit root tests are not general enough to capture different dynamics, such as smooth structural breaks, sharp structural breaks, state-dependent nonlinearity or a mixture of them. Therefore, considering all these data structures in one unit root process is important, and the results produced with this type of test structure do not face misspecification problems. We test 9 countries' historical renewable energy consumption covering the period of 1800-2008 with traditionally used structural break unit root tests and a newly proposed test. The newly proposed test performs better than the traditional ones. The reason is that renewable energy consumption has sharp and smooth breaks in its data generating process which are not captured simultaneously by any other traditional unit root test. The empirical results indicate that renewable energy consumption contains stationary process in the presence of sharp and smooth structural breaks.

Keywords: Unit Root Testing, Sharp and Smooth Break, Renewable Energy Consumption
JEL Classification: C12, C22, Q43, Q47

1. Introduction

Energy demand has increased rapidly as a result of globalization, urbanization and industrialization in emerging and developing economies (Ozcan and Ozturk 2016, Shahbaz et al. 2017). This has led researchers, academicians and practitioners to investigate the unit root properties of energy consumption in a new research area pioneered by Narayan and Smyth 2007) in energy economies. Testing the unit root properties of energy consumption is important, as energy consumption is closely linked with economic growth and environment (Ozcan and Ozturk, 2016). A plethora of empirical studies have investigated whether energy consumption contains a unit root process, but they provide conflicting empirical findings (Shahbaz et al. 2014, Ozturk and Aslan 2015, Ozcan and Ozturk 2016). Understanding the unit root properties of energy consumption is crucial for researchers, practitioners and policy makers to maintain the energy supply by designing comprehensive energy policies for sustainable economic development over a long time span (Ozturk and Aslan, 2015).

The testing of the time series stationary properties of energy consumption has many policy implications for the design of energy policy: (i) if energy consumption follows a stationary process, then shocks to the global energy market will have temporary or transitory effects on energy consumption. In such circumstances, a shock to energy consumption results in a temporary deviation from the long-run path, and energy consumption returns to its trend path after a certain time (Hsu et al. 2008, Kula et al. 2012). This suggests that governments should avoid the unnecessary adoption of energy targets, as energy consumption deviates from the long-run path temporarily. In such situations, the implementation of energy conservation and energy management policies for reducing energy intensity or consumption is meaningless in the long run (Kum 2012, Ozturk and Aslan 2015, Shahbaz et al. 2016). Apergis and Payne (2010) explain that energy conservation and management policies, i.e., fuel economy standards, tariffs on imported fuel and vehicles, and carbon taxes on transportation, will have transitory effects, as oil consumption contains a stationary process, and oil consumption will revert to the mean. If energy consumption contains a unit root or random walk process, then shocks to the global energy market will have permanent and long-run effects on energy demand or energy consumption. This is termed the hysteresis hypothesis in energy consumption or energy demand (Narayan and Smyth 2007, Barros et al. 2013, Shahbaz et al. 2016). In such circumstances, shocks to energy consumption affect economic activity permanently and, energy exploring and energy management policies designed for energy supply will be effective.

Based on the close linkage between energy demand and real economy, the presence of structural breaks, i.e., the outcomes of government policies in energy markets, may cause fluctuation in macroeconomic variables. In such circumstances, permanent shocks to energy consumption may cause a unit root process in other macroeconomic variables, such as domestic production, employment, inflation, trade and the exchange rate via the transmission mechanism (Narayan and Smyth 2007, Mishra et al. 2009, Shahbaz et al. 2014). Hendry and Juselius (2000) argue that "*variables related to the level of any variables with a stochastic trend will inherit that nonstationary and transmit to it other variables in turn*". This invalidates some economic theories. For instance, real business cycle theory implies that the real output contains a stationary process that indicates the transitory shocks to real output (Hamilton 1996, Sardosky, 1999, Hasanov and Telatar 2011)[1]. Similarly, permanent shocks to the unit root process in oil consumption transmit to economic activity, which invalidates the empirical support of oil price shocks and real business cycle theories (Ozcan and Ozturk 2015). In international trade, the law-of-one-price theory accepts exchange rates as stationary, and conventional sticky price models developed by Dornbusch (1976) and Taylor (1979) assume that the price level contains a stationary process. The presence of a random walk

[1] Narayan et al. (2010) report that if energy consumption contains a unit root process via a transmission mechanism, real output also contains a unit root problem due to the close relationship between energy consumption and economic growth, i.e., real output growth.

process in energy consumption may invalidate these economic theories as we use transmission mechanisms to explain direct and indirect linkages between energy and macroeconomic variables.

Testing the unit root properties of energy consumption is crucial for forecasting future energy demand. The forecasting of energy consumption is considered a basic tool for formulating policy on energy management and planning (Chen and Lee 2007, Mishra et al. 2009, Aslan 2011). The mean contains a reverting process to the trend path if energy consumption contains a stationary process. In such a situation, the past trend of energy consumption might be used to forecast energy demand (Chen and Lee 2007, Apergis et al. 2010, Shahbaz et al. 2014). The past behaviour of energy consumption is useless for forecasts of future energy demand if energy consumption has a unit root problem, i.e., energy consumption does not return to the trend path. This shows that other macroeconomic variables explaining energy consumption are important for generating forecasts of future energy consumption (Shahbaz et al. 2014, Ozcan and Ozturk 2015).

Last but not least, testing the unit root properties of energy consumption will be helpful in applying time series approaches, such as cointegration and causality tests, for empirical analysis (Shahbaz et al. 2013). Furthermore, the stationary properties of energy consumption play an important role in modelling the association between energy consumption and macroeconomic variables, such as output growth (Hasanov and Telatar 2011, Liu 2013, Smyth 2013, Yilanci and Tunali 2014, Wang et al. 2016). If all variables contain a stationary process, then a vector autoregressive (VAR) model is suitable to empirically examine the long-run relationships between the variables[2]. If the variables contain a unit root process, we have three options: (i) The VAR model in differences is a suitable way to model the relationships between the variables, as there is an absence of cointegration between the series

[2] There is no need to apply a cointegration approach as all the variables are found to be stationary at the level.

(Hendry and Juselius 2000, Hasanov and Telatar 2011, Liu 2013). (ii) The vector error correction (VEC) is applicable as variables are integrated at I(I). For example, Granger (1969) argues that if the variables are integrated at I(1), then the VECM Granger causality version of unrestricted VAR is suitable to examine the long-run and short-run causal associations between the variables. (iii) If the variables contain a unique order of integration, the Johansen and Juselius (1990) cointegration approach is suitable to examine the cointegration relationships between the variables. The bounds testing approach to cointegration developed by Pesaran et al. (2001) is also suitable if the variables have a mixed order of integration, i.e., I(1)/I(0)[3]. Additionally, modelling the association between energy consumption and economic growth shows the vital role of energy consumption in economic growth (Oh and Lee, 2004). For instance, causality runs from energy consumption to economic growth, which indicates that energy consumption leads to economic growth or that energy consumption is a driver of economic growth. In such a situation, the implementation of energy conservation policies would impede economic growth by de-fuelling economic activity.

Following conflicting empirical results as reported in Table-1, this paper consequently contribute to the existing energy economics by two major folds: (i), This paper uses long historical data for the period of 1800-2008 in order to examine the unit root properties of renewable energy consumption for Canada, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK[4]. (ii), This study also enriches by means of a unit root test which accounts potential sharp shifts and smooth breaks stemming in renewable energy consumption. It is documented that the persistence parameter of a process may be overestimated if structural breaks are omitted or disregarded from unit root analysis, subsequently decreasing the explanatory power to reject a unit root when the stationarity alternative is true (Perron, 1989). Therefore, we model breaks in our unit root testing process,

[3] The bounds-testing approach to cointegration is applicable even if variables are integrated at I(0) or I(1).
[4] The selection of sample countries is based on data availability

with the structure changes being both smooth and sharp, given that we use very long historical yearly data, and hence, both types of structural breaks are possibly to co-exist. Our procedure also allows us to model sharp breaks endogenously, unlike standard dummy variable unit root tests which only permit exogenous determination. Therefore, our methodology allows more flexible testing structure when there is no sharp break available in the data, thereby the methodology does not account for sharp break. While at the same time, we have the same flexibility in the smooth structural break methodology. The Fourier function parameters are not significant when there is no smooth break is available, hence, the testing procedure does not account for smooth break, as well. Thus these features make our testing procedure more general and flexible. Moreover, our methodology is also efficient (powerful) in which the data generating process (DGP) is containing sharp structural break in isolation or any other features of DGP such as state dependent nonlinearity, smooth shifts and/or linear DGP. These properties of our unit root testing procedure give opportunity to a researcher to safely analyse wide variety of datas' stationarity features in more flexible and general setting.

Finally, increasing economic activity boosts energy demand and the environmental constraints such as increasing CO_2 emissions restricts energy consumption. Therefore, in a long span data, this dynamic may create a sharp break which cannot be captured by smooth shifts. When we looked at the 9 developed countries data from 1800s until 1940s there occur a smooth, nearly horizontal trend which can be captured by simple linear trend, however, after the Second World War renewable energy consumption is triggered and the trend become nearly vertical until 1980. This sharp shift cannot be captured by simple linear trend or any other function which can captured smooth structural break, hence, this period dynamics can be classified as sharp structural break or shift. The recovery period of the world economy after Second World War is slowdown in 1980s which we can be classified as the liberalization and globalization period. In this period, energy consumption of developed countries decreases and the slope of energy consumption becomes more horizontal relatively to recovery period, but steeper than before the Second World War era. In the meanwhile, we also see some smooth breaks in all 9 countries renewable energy consumption. For example in between 1940-1945 nearly all countries energy demand falls for a short period due to Second World War and similar short period decrease is also seen in 1973 oil crises. These, short period swings are also occurred due to business cycles as we have mentioned before and has seen in renewable energy consumption data of 9 developed countries. Finally, after 1990s depending on environmental pollutions and deterioration most of developed countries shift their industrial production to less developed areas which is also cause a decline in energy demand thereby creates small breaks in renewable energy consumption data of sampled countries.

These stylized facts which we have documented show that renewable energy consumption follows some deterministic pattern. Therefore, if these deterministic patterns can be captured with unit root testing procedures, then we prevent our self to accepting wrong non-stationarity hypothesis of renewable energy consumption. The numerous dynamics which are explained in the previous paragraph cannot be captured by a linear or state dependent or structural break unit root tests in isolation. Therefore, our hybrid, flexible and more general approach is the only right procedure to capture these varieties of dynamics to lead us for making correct decision on stationary properties of renewable energy consumption for sampled countries, otherwise, we may accept the unit root hypothesis and give rise to policy makers to take wrong policy actions.

The rest of the paper structured as follows. Section 2 presents the literature review, section 3 introduces the new unit root test, section 4 outlines the empirical study, and section 5 concludes.

2. Literature review

Narayan and Smyth (2007) started the debate on testing the unit root properties of energy consumption. Subsequently, researchers have focused on investigating the stationary properties of energy variables, such as energy consumption. Table-1 contains a summary of studies in the literature that have investigated unit root testing of energy consumption. Most of the studies have produced mixed results regarding stationary and unit root processes in energy consumption. These conflicting results are the outcome of the samples, countries and unit root tests chosen. These unit root tests are not free from criticism. For example, Narayan and Smyth (2007) applied the ADF unit root test to examine the unit root properties of energy consumption. This test provides ambiguous empirical findings as it ignores the role of structural breaks in the series, which may be the cause of the unit root problem. This test has low explanatory power and thus is not suitable for small data sets (Ng and Perron, 2001). These disadvantages of the ADF unit root test call into question the empirical findings of Narayan and Smyth (2007) and Hasanov and Telatar (2011). The Langrage Multiplier (LM) was developed by Schmidt and Phillips (1992) and has been applied by numerous researchers, such as Aslan and Kum (2011), Ozturk and Aslan (2015), Kum (2012), Bolat et al. (2013), Ozcan (2013), Lean and Smyth (2014), Shahbaz et al. (2015) and Wang et al. (2016), to examine the unit root properties of energy consumption; however, the results are ambiguous. This test is suitable for restricted and linear models, imposing a significant demand on parameter estimations. The LM unit root test requires accurate estimates of parameter covariance, which is a main disadvantage of it. Therefore, the empirical findings on the LM unit root test are doubtful. The minimum LM unit root test by Lee and Strazicich (2003), which accommodates two unknown structural breaks in the time series, has been employed by Apergis and Payne (2010), Narayan et al. (2010), Aslan (2011), Kula et al. (2012) and Gozgor (2016) to examine the stationary properties of energy consumption. The Lee and Strazicich

(2003) test is superior to the ADF and LM unit root test, but its issue is that the economic implications of two structural breaks in a time series are difficult to identify while testing the unit root process. Similarly, Chen and Lee (2007), Hsu et al. (2008), Mishra et al. (2009), Liu (2013) and Magazzino (2016) applied the C-S (Carrion i Silvestre et al. 1999), SURADF (Breuer et al. 2001), KSS (Kapetanios et al. 2003) and IPS (Im et al. 2003) unit root tests to investigate whether shocks to energy consumption are temporary or permanent. These unit root tests are also not free from criticism and provide vague empirical results.

Table-1: Summary of Studies on Unit Root Analysis

No.	Author(s)	Time Period	Unit Root Test	Conclusion
1	Narayan and Smyth (2007)	1979-2000	ADF	Unit root process.69% count.
2	Chen and Lee (2007)	1971-2002	C-S	Stationary
3	Hsu et al. (2008)	1971-2003	SURADF	Mixed Evidence
4	Mishra et al. (2009)	1980-2005	C-S	Mixed Evidence
5	Apergis and Payne (2010)	1960-2007	LS	Mixed Evidence
6	Narayan et al. (2010)	1973-2007	LS	Stationary
7	Aslan (2011)	1960-2008	LS	Mixed Evidence
8	Aslan and Kum (2011)	1970-2006	LM	Unit Root Process
9	Hasanov and Telatar (2011)	1980-2006	ADF. KSS. ST-TAR	Stationary
10	Kula et al. (2012)	1960-2005	LS	Mixed Evidence
11	Kum (2012)	1971-2007	LM	Stationary
12	Bolat et al. (2013)	1971-2010	LM	Stationary
13	Liu (2013)	1963-2009	KSS	Stationary
14	Ozcan (2013)	1980-2009	LM	Stationary
15	Ozturk and Aslan (2015)	1970-2006	LM	Mixed Evidence
16	Yilanci and Tunali (2014)	1960-2011	FLM	Mixed Evidence
17	Lean and Smyth (2014)	1975-2008	LM	Mixed Evidence
18	Shahbaz et al. (2015)	1965-2010	LM	Mixed Evidence
19	Wang et al. (2016)	1965-2011	LM	Mixed Evidence
20	Gozgor (2016)	1971-2014	LS	Mixed Evidence
21	Magazzino (2017a)	1960-2013	IPS	Unit Root Process
22	Magazzino (2017b)	1971-2013	CADF	Mixed Evidence
23	Edmir and Gozgor (2017)	1971-2016	N-P	Unit Root Process

Note: ADF, SURADF, C-S, W, LS, LM, FLM, KSS, ST-TAR, and IPS refer to Augmented Dickey-Fuller, Seemingly Unrelated Regressions ADF, Carrion i Sivestre, Westerlund, Lee and Strazicich, Langrage Multiplier, Fourier LM, Kapetanios, Shin and Shell, Stationary Smooth Transition Threshold Autoregressive, and Im, Pesaran and Shin, Cross-sectional ADF, Narayan and Popp (2010) respectively.

The most important thing to do while performing a unit root test is to employ a true data-generating process in the unit root-testing process. The studies shown in Table-1 aimed to employ true unit root tests for a true sample period with true country groups, which means that they restrict themselves to finding consistent stationarity results. However, most of the unit root tests are not general enough to capture different dynamics, such as smooth structural breaks, sharp structural breaks, state-dependent nonlinearity or a mixture of them. The available tests in the literature target these data-generating processes one at a time. For example, the KSS test considers only state dependent nonlinearity. The LS test considers only multiple smooth structural breaks. The ST-TAR considers one smooth break and the TAR type of state-dependent mixed nonlinearity; although the ST-TAR unit root test is the most general one, it still includes one smooth structural break and a very restricted type of state-dependent nonlinearity. Therefore, considering all these data structures in one unit root process is important, and the results produced by this type of test structure do not face misspecification problems. As indicated by Table-1, energy consumption has different dynamics in different countries and different samples. Therefore, it is better to understand the historical perspective of renewable energy consumption.

We know that renewable energy consumption has faced various types of structural breaks in the course of its history, starting with the Industrial Revolution, due to technological improvements or the dynamics of the business cycle, which directly affect the use of energy. It is important to understand historical data in order to understand the stochastic properties of energy use. Many studies use a short data timespan to analyse the stochastic properties of energy use, but this approach gives a very limited picture of the real data-generating process of energy consumption. Therefore, in this study, we use a very long historical data period, starting from 1820, which can be classified as the start of the Industrial Revolution. This novel data set can foster our understanding of the stochastic behaviour of energy use. However, to understand this long-span data, we must have very flexible method that can detect smooth and sharp breaks in the data-generation process. Plenty of studies have proposed the unit root test for sharp and smooth breaks. Furuoko (2016) uses a dummy variable for sharp breaks and Fourier transforms for smooth breaks. His way of detecting sharp breaks is problematic in two ways. First, the exogenous determination of structural breaks requires another method or visual inspection, which limits the power of the test. Second, using a dummy variable creates discontinuity in de-trending data or nonlinear trends, which may be other important problem. Moreover, he does not use trend breaks in his modelling, which is also another limitation in his modelling of sharp breaks. In our modelling, we eliminate all of these problems. The other strand of literature on Fourier transforms claims to detect sharp and smooth breaks in the data by increasing the number of Fourier transforms, N (Enders and Holt, 2012). This methodology has its own problems, as documented by the same authors (Becker et al. 2006, Enders and Lee, 2012a, b). They note that the increasing number of Fourier transforms (cumulative) captures sharp breaks, but this process also creates a problem: the newly added Fourier function over-fits the data and induces an over-filtration problem, especially in the stochastic part of the series. Thus, we propose a more flexible method that solves all the mentioned problems in two steps.

3. Methodological Framework

3.1 The model and testing framework

Let y_t be a changing trend function with a smooth transition on the time domain $t = 1, 2, ..., T$.

Model A: $y_t = \alpha_1 + \alpha_2 F_t(\gamma, \tau) + \varepsilon_t$ (1)

Model B: $y_t = \alpha_1 + \beta_1 t + \alpha_2 F_t(\gamma, \tau) + \varepsilon_t$ (2)

Model C: $y_t = \alpha_1 + \beta_1 t + \alpha_2 F_t(\gamma, \tau) + \beta_2 F_t(\gamma, \tau) t + \varepsilon_t$ (3)

where ε_t is a zero mean $I(0)$ process, and $F_t(\gamma,\tau)$ is the following the LST function, based on a sample of size *T*:

$$F_t(\gamma,\tau) = 1/1+\exp\left[-\gamma(t-\tau T)\right],\ \gamma>0 \tag{4}$$

In this modelling strategy, the structural change is modelled as a smooth transition between different regimes[5]. In these specifications, no change and one instantaneous and, sharp structural change are limiting cases[6]. Following Leybourne et al. (1998), the test statistics proposed here are calculated with a two-step procedure:

Step 1. Using constrained nonlinear optimization algorithm via Genetic[7], we estimate only the deterministic component of the preferred model and compute its residuals.

$$\text{Model A}: \hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 F_t(\hat{\gamma},\hat{\tau}) \tag{6}$$

$$\text{Model B}: \hat{\varepsilon}_t = y_t - \hat{\alpha}_1 + \hat{\beta}_1 t - \hat{\alpha}_2 F_t(\hat{\gamma},\hat{\tau}) \tag{7}$$

$$\text{Model C}: \hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 F_t(\hat{\gamma},\hat{\tau}) - \hat{\beta}_2 F_t(\hat{\gamma},\hat{\tau}) t \tag{8}$$

Step 2. Compute the Enders and Lee (2012) (Henceforth, EL test) statistic, which is the *t* ratio associated with $\hat{\phi}$ in the ordinary least squares regression:

$$\hat{\varepsilon}_t = d(t) + \phi_1 \hat{\varepsilon}_{t-1} + \upsilon_t \tag{9}$$

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[5]For details, see Omay and Emirmahmutoglu (2017).
[6] For further discussion and possible extensions, see Leybourne et al. (1998).
[7]We use the genetic algorithm in our estimation process of the smooth transition trend since it is shown to be the best performing algorithm in estimating LST types of equations. For details, see Omay and Emirmahmutoglu (2017).

where υ_t is a stationary disturbance with variance σ^2, and $d(t)$ is a deterministic function of t. We note that the initial value is assumed to be a fixed value, and ε_t is weakly dependent. If the functional form of $d(t)$ is known, it is possible to estimate equation-9 directly and to test the null hypothesis of a unit root (i.e. $\phi_1 = 1$). When the form of $d(t)$ is unknown, any test for $\phi_1 = 1$ is problematic if $d(t)$ is mis-specified. This unit root test is based on the fact that it is often possible to approximate $d(t)$ using the Fourier expansion:

$$d(t) = \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\pi kt}{T}\right), \; n \leq T/2 \tag{10}$$

where n represents the number of cumulative frequencies contained in the approximation, k represents a particular frequency, and T is the number of observations. In the absence of a nonlinear trend, all values of $\alpha_k = \beta_k = 0$ so that the LNV (1998) specification emerges as a special case. There are several reasons why it is inadvisable to use a large value for n. As we demonstrate below, the presence of many frequency components uses degrees of freedom and can lead to an over-fitting problem. As evidenced by Gallant (1981), Davies (1987), Gallant and Souza (1991) and Bierens (1997), a Fourier approximation using a small number of frequency components can often capture the essential characteristics of an unknown functional form smooth break. Moreover, n should be small since[8] it is important to allow the

[8]As indicated in Becker, Enders and Hurn (2004), structural change can be captured by the relatively low frequency components of a series since breaks shift the spectral density function towards zero. Becker et al. also show that the higher frequency components of a series are most likely to be associated with stochastic parameter variation. When the sample size gets very large, it will be natural to expect that the number of frequencies (n) will also increase accordingly. In the limit, we may let n = n (T)→∞ as T→∞. However, as n increases, the tests lose power. As such, in finite samples, it is sufficient to treat n as a finite value (n_T), and the test depends on n.

evolution of the nonlinear trend to be gradual. There is little point in claiming that a series reverts to an arbitrarily evolving mean. The testing equation is finally as follows:

$$\Delta\hat{\varepsilon}_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\pi kt}{T}\right) + \phi_1\hat{\varepsilon}_{t-1} + \sum_{i=1}^{p} \varphi_k \Delta\hat{\varepsilon}_{t-i} + \upsilon_t \tag{11}$$

where the common practice is to augment the dependent variables' lag value in testing the equation to account for any stationary dynamics in $\hat{\varepsilon}_t$. Therefore, we denote value of this EL test statistic as $s\tau_\alpha$ if Model A is used to construct $\hat{\varepsilon}_t$, $s\tau_{\alpha(\beta)}$ if Model B is used, and $s\tau_{\alpha,\beta}$ if model C is used.

One key issue for our test is whether a small number of frequency components can replicate the types of breaks typically observed in economic data. To keep the problem tractable, we begin by considering a Fourier approximation using a single frequency component so that k represents the single frequency selected for the approximation, and α_k and β_k measure the amplitude and displacement of the sinusoidal component of the deterministic term. Thus, even with a single frequency $\mathrm{k} = 1$, we can allow for multiple smooth breaks. The established hypotheses of unit root testing based on models A, B and C with the Fourier transforms are as follows:

$$\begin{aligned} &H_0 : Unit\ Root && (\text{Linear Nonstationary}) \\ &H_1 : Nonlinear\ Stationary && \begin{pmatrix} \text{Nonlinear and Stationary around} \\ \text{simultenously changing sharp and smooth trend} \end{pmatrix} \end{aligned} \tag{12}$$

The critical values for the newly proposed test with trends in the Fourier function are not tabulated because Models B and C of the LNV type of trend already consist of trend functions. Therefore, including trends in the second step is useless. However, we include the trend in the Fourier function for Model Abecause there is no trend variable in Model A of the smooth transition trend. This model is probably a competitor of Model B. We tabulate the value of Model A* in Appendix A.2 with Fourier transforms, which also includes trend functions. Additionally, we do not generate the critical values for the cumulative Fourier function because the LNV function captures the sharp breaks without including any other term. Table-2 consists the critical values for Model A ($s\tau_{\alpha}$), B ($s\tau_{\alpha(\beta)}$) and C ($s\tau_{\alpha,\beta}$).

Table-2: Critical Values for FLST Models only Intercept Included in Fourier Function[9]

	$s\tau_{\alpha}$			$s\tau_{\alpha(\beta)}$			$s\tau_{\alpha,\beta}$		
T	1%	5%	10%	1%	5%	10%	1%	5%	10%
k=1									
25	-5.658	-4.777	-4.323	-6.085	-5.184	-4.747	-6.794	-5.596	-5.150
50	-5.288	-4.484	-4.139	-5.515	-4.804	-4.450	-5.826	-5.127	-4.788
100	-4.926	-4.394	-4.081	-5.189	-4.625	-4.354	-5.549	-4.965	-4.670
200	-4.941	-4.323	-4.037	-5.138	-4.585	-4.317	-5.405	-4.859	-4.579
500	-4.807	-4.281	-4.007	-5.129	-4.513	-4.273	-5.345	-4.810	-4.518
k=2									
25	-5.955	-4.985	-4.554	-6.530	-5.506	-5.061	-6.885	-5.871	-5.412
50	-5.453	-4.730	-4.389	-5.705	-5.079	-4.751	-6.040	-5.373	-5.016
100	-5.206	-4.614	-4.312	-5.459	-4.892	-4.567	-5.726	-5.141	-4.851
200	-5.065	-4.528	-4.233	-5.369	-4.788	-4.522	-5.587	-5.031	-4.750
500	-4.997	-4.480	-4.192	-5.227	-4.711	-4.436	-5.563	-5.020	-4.704
k=3									
25	-6.048	-4.990	-4.527	-6.677	-5.631	-5.149	-7.076	-6.081	-5.599
50	-5.450	-4.743	-4.368	-5.870	-5.187	-4.828	-6.240	-5.497	-5.175
100	-5.206	-4.614	-4.262	-5.583	-4.976	-4.661	-5.889	-5.276	-4.974
200	-5.104	-4.476	-4.185	-5.396	-4.866	-4.582	-5.697	-5.124	-4.827
500	-5.029	-4.484	-4.172	-5.330	-4.821	-4.540	-5.607	-5.073	-4.792
k=4									
25	-5.884	-4.870	-4.365	-6.637	-5.507	-5.016	-7.072	-6.022	-5.526
50	-5.398	-4.614	-4.209	-5.919	-5.125	-4.737	-6.234	-5.515	-5.131
100	-5.183	-4.504	-4.156	-5.587	-4.917	-4.590	-5.860	-5.255	-4.939
200	-5.042	-4.435	-4.099	-5.401	-4.847	-4.533	-5.670	-5.110	-4.816
500	-4.995	-4.419	-4.094	-5.309	-4.762	-4.492	-5.610	-5.081	-4.770
k=5									
25	-5.655	-4.624	-4.138	-6.509	-5.322	-4.844	-6.926	-5.841	-5.317

[9]The critical values for FLST models with trends in the Fourier function are not tabulated because Models B and C of the LNV type of trend already consist of trend functions. Therefore, including trends in the second step is useless.

50	-5.308	-4.506	-4.114	-5.797	-5.006	-4.611	-6.109	-5.388	-5.028
100	-5.113	-4.410	-4.051	-5.491	-4.844	-4.498	-5.773	-5.138	-4.820
200	-5.019	-4.370	-4.045	-5.298	-4.735	-4.423	-5.663	-5.045	-4.738
500	-4.987	-4.342	-4.019	-5.237	-4.673	-4.389	-5.563	-4.998	-4.722

2.2 Small sample properties of the test statistics

For the small sample[10], we use the data-generating process below:

$$y_t = \alpha_1 + \alpha_2 F_t(\gamma,\tau) + \varepsilon_t \qquad 13$$

$$F_t(\gamma,\tau) = 1/1 + \exp\left[-\gamma(t - \tau T)\right].\ \gamma > 0 \qquad 14$$

$$\hat{\varepsilon}_t = d(t) + \phi_1 \hat{\varepsilon}_{t-1} + \upsilon_t \qquad 15$$

$$\hat{\varepsilon}_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\pi kt}{T}\right) + \phi_1 \hat{\varepsilon}_{t-1} + \upsilon_t \qquad 16$$

For the α_2 sharp break parameter, we use $\alpha_2 = \{10, 20\}$. For the slope parameter gamma $\gamma = \{5,10\}$, we select a relatively high speed of transition. For the threshold parameter, $\tau = \{0.2, 0.5\}$ are selected for the beginning of the sample and the middle of the sample, respectively. For the smooth structural break, we select $\{\alpha_k, \beta_k\} = \{0.30, 0.00\}, \{0.30, 0.10\}, \{0.00, 0.10\}, \{0.70, 0.30\}, \{0.30, 0.70\}$ and $\{0.00, 0.70\}$ and finally n=1 as it is recommended in the previous literature.

[10] For the size analysis, we obtain a good nominal size for the 1%, 5%, and 10% significance levels. The results are available upon request.

Figure 1: Comparison of STR and Fourier Parameters

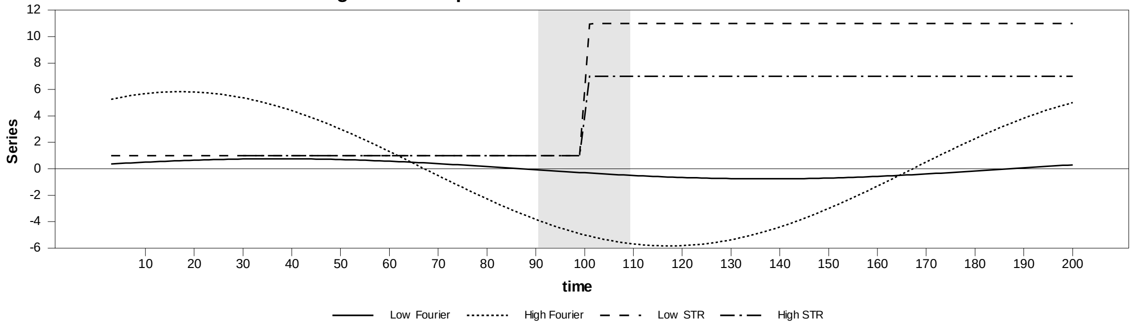


Figure-1 displays the different forms of the smooth transition and the Fourier function, which we use in the power analysis. A high Fourier form parameter is observed to be in the range of a relatively low STR function. This indicates that if we use high values of the Fourier function, it will dominate the sharp break, and the form of the high speed slope parameter of the smooth transition cannot be sustained in the DGP. Therefore, we use relatively small values of α_k and β_k, which measure the amplitude and displacement of the sinusoidal component of the deterministic term in the Fourier function. The Fourier function only mimics the smooth breaks with a single cumulative function; hence, it is better to choose the Fourier function to detect smooth breaks. The STR model can easily imitate TAR type of behaviour as well as smooth breaks depending on γ transition speed.

Table-3 shows that our proposed test has significant superiority in all of the parameter regions. For sharp breaks, we usethe logistic function, whichcan easily capture sharp breaks; hence, the most important parameters for sharp breaks are γ gamma and intercept parameter α_2. For the slope parameter, we use the relatively fast transitions of 5.0 and 10.0. Therefore, as in Figure-1, we obtain moderate and very high speeds of transition from one intercept to another, which leads to moderate and high sharp breaks. For high break parameter α_2, we use 10 and 20, which seem to be sufficient for the second intercept parameter. For the smooth break parameters, we use the Fourier function; α_k and β_k measure the amplitude and displacement of the sinusoidal component of the deterministic term. Therefore, to prevent the domination of the Fourier function parameters, we give low values to a low sharp break and high values to a high sharp break.[11] Asmentioned above, one of the most important parameters in DGP is the speed of transition (gamma, γ). Therefore, we explain the effects of gamma in the power simulation study. When gamma increases from 5 to 10, our newly proposed test gains power in all parameter settings, which shows us that the test works better in sharp break cases. We seesimilar effects in the LNV test, whereas the EL test behaves oppositely. For the second important parameter intercept α_2, we see that our newly proposed test and the LNV test are not affected too much; however, the EL test totally loses its power when it increases from 10 to 20. For threshold location parameter τ, we see that the magnitude of the power properties of the newly proposed test changes depending on Fourier parameters α_k and β_k. When the magnitude of α_k and β_k is low, changing the break point from the beginning of the sample to the middle decreases the power of the test and vice versa. Moreover, increasing the magnitude of α_k and β_k leads to a power decline in the newly proposed test; however, the power loss of this parameter change is vast in the LNV model. In contrast, in this modelling structure, the Fourier form of the unit root testing does not appear to be a competitor without using cumulative n forms. However, as noted in the introduction, using the cumulated frequency has some drawbacks, as extensively explained in Becker et al. (2006) and Enders and Lee (2012a, b).

Table-3: The Power Comparison of Alternative Tests: FKSS DGP with KSS 1^{st} μ

K	α_k	β_k	τ	γ	α_2	$s\tau_{\alpha}$	τ_{DF_C}	s_{α}	$s\tau_{\alpha}$	τ_{DF_C}	s_{α}
							T=100			T=200	
1.0	0.30	0.0	0.5	10.0	10.0	**0.289**	0.017	0.261	**0.723**	0.072	0.721
1.0	0.30	0.10	0.5	10.0	10.0	**0.301**	0.012	0.257	**0.774**	0.087	0.689
1.0	0.0	0.10	0.5	10.0	10.0	**0.383**	0.010	0.311	**0.839**	0.088	0.823

[11]We have used the other parameter regionsand found that the newly proposed test is superior. The results of the power analysis are available upon request.

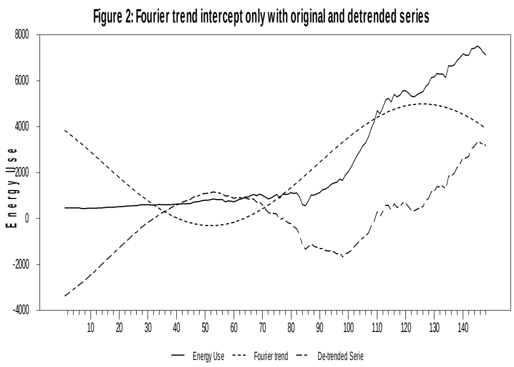
1.0	0.70	0.30	0.5	10.0	10.0	**0.160**	0.025	0.080	**0.451**	0.087	0.125
1.0	0.30	0.70	0.5	10.0	10.0	**0.137**	0.050	0.007	**0.335**	0.102	0.042
1.0	0.0	0.70	0.5	10.0	10.0	**0.157**	0.057	0.005	**0.358**	0.062	0.037
1.0	0.30	0.0	0.2	10.0	10.0	**0.347**	0.002	0.100	**0.952**	0.002	0.585
1.0	0.30	0.10	0.2	10.0	10.0	**0.329**	0.002	0.092	**0.964**	0.002	0.629
1.0	0.0	0.10	0.2	10.0	10.0	**0.395**	0.002	0.281	**0.972**	0.002	0.945
1.0	0.70	0.30	0.2	10.0	10.0	**0.127**	0.002	0.002	**0.596**	0.005	0.002
1.0	0.30	0.70	0.2	10.0	10.0	**0.077**	0.002	0.005	**0.506**	0.012	0.057
1.0	0.0	0.70	0.2	10.0	10.0	**0.140**	0.002	0.005	**0.538**	0.020	0.100
1.0	0.30	0.0	0.5	5.0	10.0	**0.269**	0.022	0.265	**0.929**	0.137	0.925
1.0	0.30	0.10	0.5	5.0	10.0	**0.255**	0.007	0.234	**0.881**	0.185	0.861
1.0	0.0	0.10	0.5	5.0	10.0	**0.317**	0.017	0.253	**0.937**	0.132	0.915
1.0	0.70	0.30	0.5	5.0	10.0	**0.122**	0.017	0.065	**0.669**	0.233	0.355
1.0	0.30	0.70	0.5	5.0	10.0	**0.105**	0.075	0.005	**0.413**	0.378	0.035
1.0	0.0	0.70	0.5	5.0	10.0	**0.157**	0.082	0.007	**0.438**	0.384	0.025
1.0	0.30	0.0	0.2	5.0	10.0	**0.323**	0.002	0.072	**0.957**	0.002	0.571
1.0	0.30	0.10	0.2	5.0	10.0	**0.301**	0.002	0.110	**0.943**	0.002	0.661
1.0	0.0	0.10	0.2	5.0	10.0	**0.341**	0.002	0.240	**0.969**	0.002	0.929
1.0	0.70	0.30	0.2	5.0	10.0	**0.137**	0.005	0.007	**0.604**	0.005	0.005
1.0	0.30	0.70	0.2	5.0	10.0	**0.097**	0.005	0.007	**0.453**	0.012	0.057
1.0	0.0	0.70	0.2	5.0	10.0	**0.152**	0.005	0.022	**0.571**	0.012	0.120
1.0	0.30	0.0	0.5	10.0	20.0	**0.257**	0.001	0.255	**0.761**	0.001	0.759
1.0	0.30	0.10	0.5	10.0	20.0	**0.281**	0.001	0.244	**0.751**	0.001	0.702
1.0	0.0	0.10	0.5	10.0	20.0	**0.321**	0.001	0.234	**0.844**	0.001	0.812
1.0	0.70	0.30	0.5	10.0	20.0	**0.125**	0.001	0.062	**0.488**	0.001	0.109
1.0	0.30	0.70	0.5	10.0	20.0	**0.426**	0.001	0.002	**0.842**	0.001	0.003
1.0	0.0	0.70	0.5	10.0	20.0	**0.523**	0.001	0.002	**0.876**	0.001	0.007
1.0	0.30	0.0	0.2	10.0	20.0	**0.357**	0.001	0.092	**0.929**	0.001	0.583
1.0	0.30	0.10	0.2	10.0	20.0	**0.307**	0.001	0.090	**0.935**	0.001	0.607
1.0	0.0	0.10	0.2	10.0	20.0	**0.361**	0.001	0.222	**0.963**	0.001	0.913
1.0	0.70	0.30	0.2	10.0	20.0	**0.182**	0.001	0.002	**0.747**	0.001	0.015
1.0	0.30	0.70	0.2	10.0	20.0	**0.087**	0.001	0.002	**0.610**	0.001	0.022
1.0	0.0	0.70	0.2	10.0	20.0	**0.165**	0.001	0.005	**0.807**	0.001	0.015
1.0	0.30	0.0	0.5	5.0	20.0	**0.297**	0.001	0.259	**0.901**	0.001	0.899
1.0	0.30	0.10	0.5	5.0	20.0	**0.249**	0.001	0.232	**0.913**	0.001	0.901
1.0	0.0	0.10	0.5	5.0	20.0	**0.305**	0.001	0.246	**0.947**	0.001	0.919
1.0	0.70	0.30	0.5	5.0	20.0	**0.117**	0.001	0.057	**0.650**	0.001	0.294
1.0	0.30	0.70	0.5	5.0	20.0	**0.421**	0.001	0.005	**0.946**	0.001	0.002
1.0	0.0	0.70	0.5	5.0	20.0	**0.518**	0.001	0.002	**0.972**	0.001	0.005
1.0	0.30	0.0	0.2	5.0	20.0	**0.305**	0.001	0.080	**0.949**	0.001	0.621
1.0	0.30	0.10	0.2	5.0	20.0	**0.351**	0.001	0.100	**0.941**	0.001	0.639
1.0	0.0	0.10	0.2	5.0	20.0	**0.375**	0.001	0.295	**0.951**	0.001	0.917
1.0	0.70	0.30	0.2	5.0	20.0	**0.165**	0.001	0.002	**0.714**	0.001	0.007
1.0	0.30	0.70	0.2	5.0	20.0	**0.112**	0.001	0.007	**0.627**	0.001	0.016
1.0	0.0	0.70	0.2	5.0	20.0	**0.152**	0.001	0.007	**0.781**	0.001	0.019

Note: $S\tau_{\alpha}$, τ_{DF_C}, and S_{α} indicate the newly proposed intercept-only test, the Enders and Lee (2012b) intercept-only test, and Leybourne et al. (1998) Model A.

4. Empirical results of renewable energy consumption

We use data from 9 countries with available data covering the longest time span: Canada 1800-2008, France 1800-2008, Germany 1815-2008, Italy 1861-2008, the Netherlands, 1800-2008, Portugal 1856-2008, Spain 1850-2008, Sweden 1800-2008, and the UK 1800-2008. Because these 208 years of data may include different types of structures, such as smooth and sharp breaks, we use different structural break unit root tests to examine whether renewable energy consumption contains unit root problem. The data source is updated from Warde, Paul, Energy Consumption in England & Wales, 1560-2004 (Naples: CNR, 2007).

Fourier Intercept only	Fourier Intercept and trend



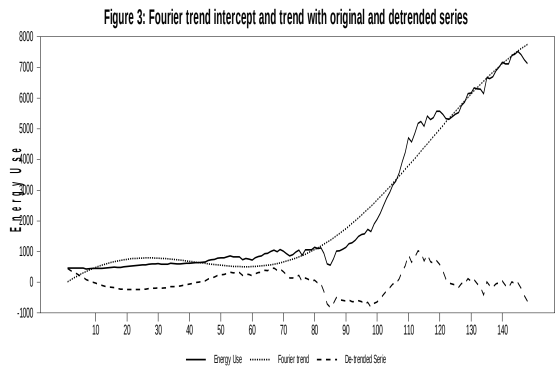


Figure-2 and 3 Fourier Function with Intercept and trend for Italy

As observed in Table-4 and 5, the newly proposed test performs better than the traditionally used LNV and EL tests used in studies on structural break unit root tests. The newly proposed test rejects the null hypothesis of unit root with respect to alternative hypothesis of nonlinear and stationary around simultaneously changing sharp and smooth trend process in all countries at level with Models A and C only. As mentioned before, the LNV test also captures the sharp and smooth breaks. Therefore, we expect better performance; however, out of 9 series, only 4 reject the null hypothesis, again in Models A and C. For the EL test using Fourier methodology, the intercept-only test performs worst as renewable energy consumption is historical data with a sharp trend. However, the intercept and trend cases of the Fourier approach rejectthe null of unit root in two cases. Still, the EL test with the intercept and trend cannot capture the data-generating process of the historical energy use data. As mentioned, the Fourier approach only works in smooth breaks if we do not use the cumulative frequency, and using the cumulative frequency leads to over-filtering the data. Thus, the Fourier approach with this information is the worst performing test under renewable energy consumption DGP.

Table-4: Alternative Break Type of Unit Root Tests

	LNV test			EL	
	Model A	Model B	Model C	Intercept	Int-Trend
Canada	-2.777	-2.474	**-5.060**	-2.079	-2.303
England	-2.755	-3.308	-3.093	-0.901	**-3.239**
France	-3.463	-3.059	**-5.086**	-0.137	-2.855
Germany	-3.241	-2.663	-2.812	-1.492	-2.952
Italy	**-4.107**	-3.120	**-5.794**	-1.089	-1.762
Netherlands	-3.848	-2.914	-3.462	0.035	-2.929
Portugal	-2.334	-2.470	-3.125	0.975	-2.488
Spain	**-3.992**	-3.455	-4.369	0.777	**-3.632**
Sweden	-3.513	-3.011	-3.593	-0.848	-2.229

Note: LNV Model A, 10%, -3.851, -3.909. LNV Model B, 10%, -4.427, -4.337. LNV Model C, 10%, -4.697, -4.572. For the Enders and Lee (2012 b) EL test, Fourier k=1 and 2, 10% critical values are -3.47 and -2.92 for T = 200.

Table-5: Newly Proposed Test

	Model A	Model B	Model C	Model A*
Canada	-3.952	-1.687 k=1 lg=1	**-5.722** k=2 lg=1	-3.952 k=1 lg=1
England	**-4.161**	**-4.785** k=3 lg=1	-4.360 k=3 lg=1	**-4.161 k=2 lg=1**
France	-3.534	-3.226 k=2 lg=3	**-5.379** k=2 lg=1	-3.519 k=3 lg=3
Germany	**-4.056**	-2.913 k=1 lg=1	-4.049 k=3 lg=1	*-4.047 k=3 lg=1*
Italy	-3.565	-2.893 k=2 lg=1	**-5.327** k=4 lg=8	-3.565 k=4 lg=1
Netherland	**-5.176**	-4.260 k=2 lg=1	**-5.835** k=4 lg=1	**-5.176 k=1 lg=1**
Portugal	**-4.526**	-2.737 k=2 lg=1	-3.359 k=3 lg=1	**-4.526 k=1 lg=1**
Spain	**-5.068**	**-4.535** k=2 lg=5	-4.532 k=4 lg=1	***-4.186 k=4 lg=5***
Sweden	**-4.460**	-3.011 k=2 lg=1	-3.718 k=4 lg=1	**-4.460 k=1 lg=1**

Note: Newly proposed test 10% critical values (OS) test: -4.037, -4.317 and -4.579 for Models A, B and C, respectively. The critical values of Model A* for k=3 and 4 are -4.267 and -4.148, respectively. Based on these test results, Germany's values are found to be insignificant and Spain's significant.

Moreover, our methodology clearly identifies sharp and smooth breaks in renewable energy consumption historical data. For Germany, the Netherlands, Portugal and Sweden, other tests conclude as a unit root process i.e. renewable energy consumption is nonstationary at level. However, our newly proposed test clearly identifies stationary process in renewable energy consumption at level with 1 sharp and 3 smooth breaks for Germany, 1 sharp and 4 smooth breaks for the Netherlands with Model C, 1 sharp and 1 smooth break for Portugal and, 1 sharp and 1 smooth break for Sweden. This data structure is not that easy to capture with a simple unit root test procedure. Therefore, we can conclude that tests which do not consider the general data structure may lead to a misspecified model, and the results obtained from these models may be misleading.

Table-6: Parameter Values Obtained for Model A

	Lag order	K	α_2	τ	γ	α_k
Canada	lg=1	k=1	13811.02	0.867	0.053	-0.391
England	lg=1	k=2	16145.45	0.529	0.011	-63.784
France	lg=3	k=3	10209.34	0.844	0.033	4.447
Germany	lg=1	k=3	17336.86	0.692	0.026	50.355
Italy	lg=1	k=4	6458.48	0.738	0.108	-37.219
Netherland	lg=1	k=1	3178.707	0.826	0.069	-3.464
Portugal	lg=1	k=1	1888.655	0.969	0.057	-1.334
Spain	lg=4	k=4	8950.105	0.984	0.051	7.934
Sweden	lg=1	k=1	1494.338	0.765	0.069	-1.163
Average	-	2	8830.32	0.801	0.053	-4.957

Panel B- Empirical Power Analysis Depending on Parameter Values

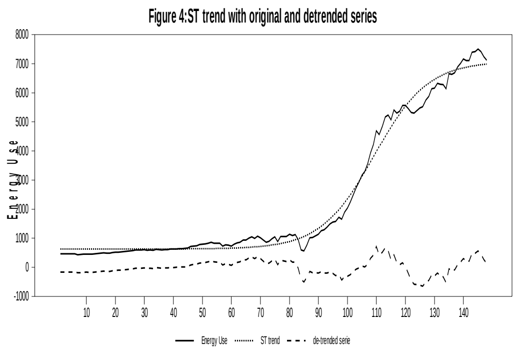
ρ	α_2	τ	γ	α_k	$s\tau_\alpha$	τ_{DF_C}	s_α
0.8	8830.3	0.801	0.053	-4.957	**0,982**	0,003	0,907
0.2	8830.3	0.801	0.053	-4.957	**0,942**	0,003	0,805

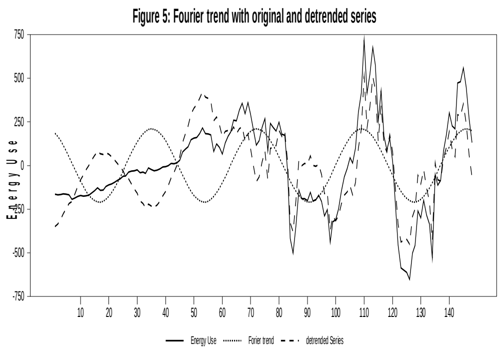
Note: ρ for the first row of Panel B we choose the high persistency parameter like in the power analysis the second one is obtained from the empirical analysis which shows low persistence.

We note that Table 6 panel A, provides information of nonlinear parameters from Model A. These parameters indicate that there is a very sharp break in the end of samples for 9 countries which is estimated as the average $\overline{\tau} = 0.801$. This means that renewable energy consumption follows a low mean for a long period nearly ¾ of the sample and starts to change this mean in the beginning of ¾ sample period. On the other hand, break parameter is very high i.e. $\bar{\alpha}_2 = 8830.3$ with average sharp breaks for 9 countries. The gamma parameter indicates that average transition speed between these two means (low and high mean values) is slow i.e. $\bar{\gamma} = 0.053$. Finally, Fourier parameters are estimated to be relatively small with respect to break parameter α_2. In panel B of Table 6, we have used these average parameter values to detect whether newly proposed test well perform under these parameter values. The results obtained in Table 6 from the empirical power analysis indicate the similar conclusion with unit root test results given in Table-4 and 5. Moreover, the empirical power results are also consistent with the power analysis which is given in Table-2. The first best test in this parameter region is newly proposed test i.e. SOR unit root test and second best test is LNV unit root test and finally the Fourier type of unit root test namely EL has nearly no power with these parameter values. Shortly, renewable energy consumption data with these results or parameter values obtained in panel A of Table-6 includes a sharp break which can be captured by logistic smooth transition function and multiple smooth breaks that can be detected by Fourier function. Therefore, testing procedure for the longer period renewable energy consumption data must contain simultaneously these two features. The LNV unit root test only includes the logistic transition function in its testing procedure and EL unit root test Fourier function, hence, these tests make mis-specification error while testing the long span renewable energy consumption stationary properties.

Step 1 STR Trend

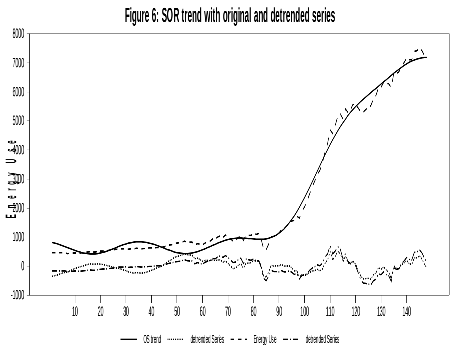
Step 2 Fourier Trend





Step 3 STR-Fourier Trend

Comparison of OS and LNV trends



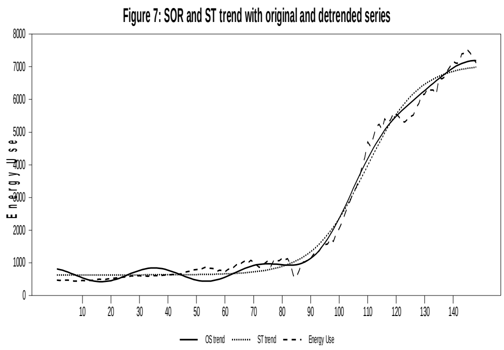


Figure-4, 5, 6 and 7 for Italy data; STR trend; Fourier trend obtained from residuals of STR trend STR + Fourier (SOR trend); comparison of STR and SOR trend

5. Conclusion and Policy Implications

This study proposed a flexible unit root test that detects sharp and smooth breaks simultaneously in time series data. Most of the unit root tests are not general enough to capture different dynamics, such as smooth structural breaks, sharp structural breaks, state dependent-nonlinearity or a mixture of them. Therefore, considering all these data structures in one unit root process is important, and the results produced by this type of test structure do not face misspecification problems. We test stationary properties for 9 countries' historical renewable energy consumption data covering the 1800-2008 period with traditionally used structural break unit root tests and a newly proposed test. The newly proposed unit root test performs better than the traditional ones. The empirical results by SOR unit root test show the presence of stationary process for renewable energy consumption.

Tests of the time-series stationary properties of renewable energy consumption have many implications for the design of energy policy. For example, as mentioned before, if energy consumption follows a stationary process, then shocks to the global energy market will have a temporary or transitory effect on renewable energy consumption. In such circumstances, shocks to energy consumption will result in temporary deviation from the long-run path, and thus, renewable energy consumption returns to its trend path after a certain time. This suggests that governments should avoid the unnecessary adoption of energy targets as renewable energy consumption deviates from long-run path temporarily. In such a situation, the implementation of energy conservation and energy management policies for reducing energy intensity or consumption is meaningless over a long time span. Therefore, our test procedure is the best indicator for policy makers to see the long-run trends and the deviation from this long-run path. The true data generating process of long span renewable energy consumption has two important components: a sharp break and more than one smooth breaks around this sharp break. This means that correctly specified models must include these feature of renewable energy consumption data while testing or estimating renewable energy demand. Any other modelling can lead to wrong results which in turn, misleads the policy makers to adapt appropriate energy policies. Thus, correct polices can be implemented only by using proper modelling or identification of economic environment.

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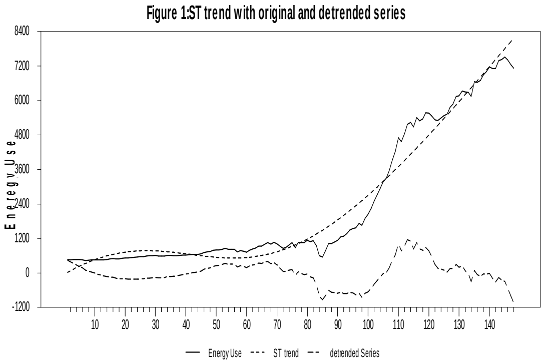
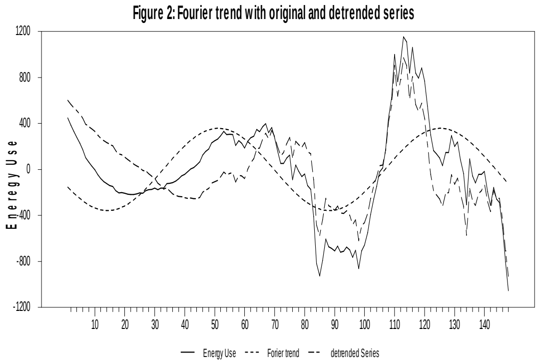
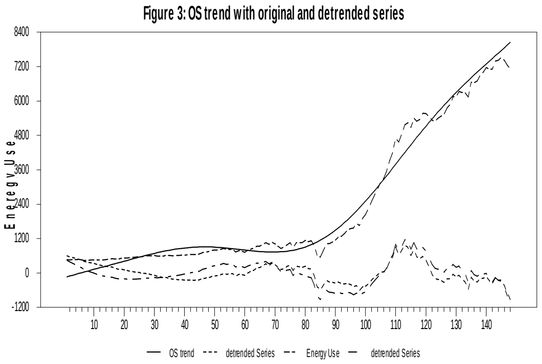
Appendix A1.

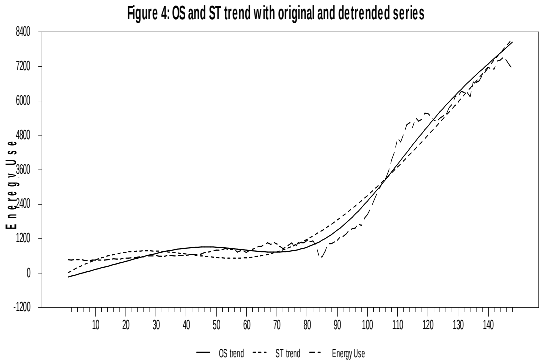
Figures of the rest of de-trending strategies for Italy data

Model B of Italy

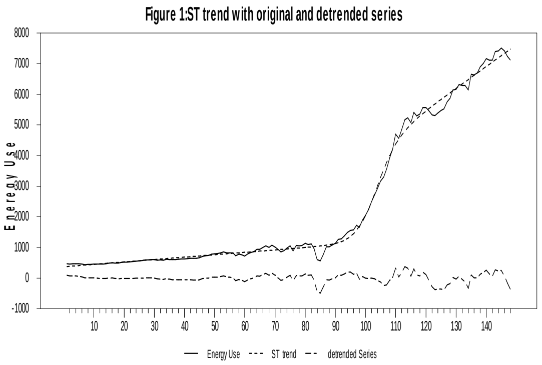








Model C of Italy



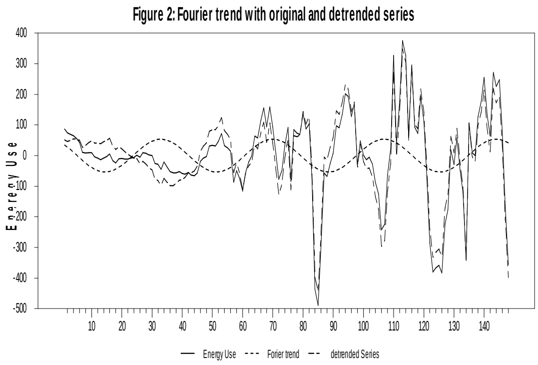


Figure 3: OS trend with original and detrended series

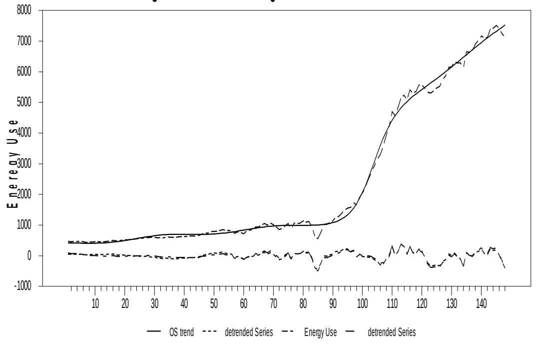
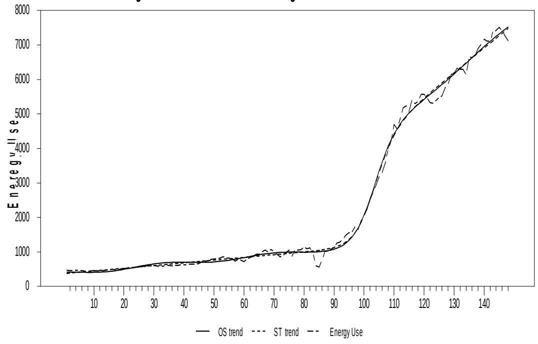


Figure 4: OS and ST trend with original and detrended series



Model A* Italy

Figure 1:ST trend with original and detrended series

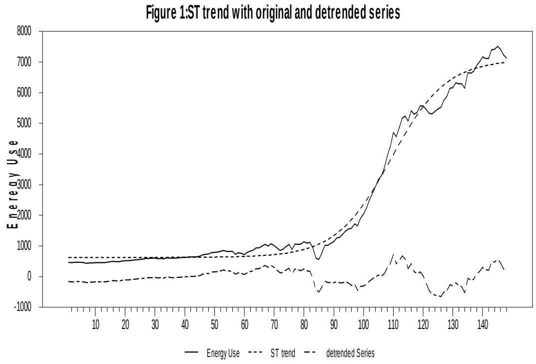


Figure 2: Fourier trend with original and detrended series

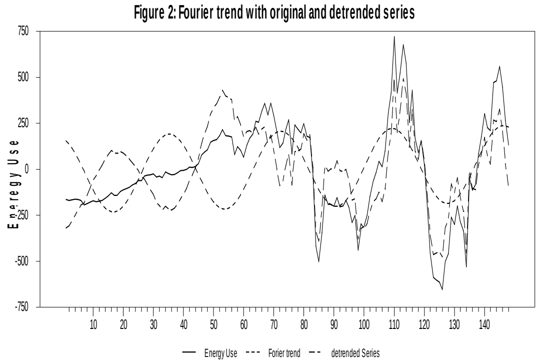


Figure 3: OS trend with original and detrended series

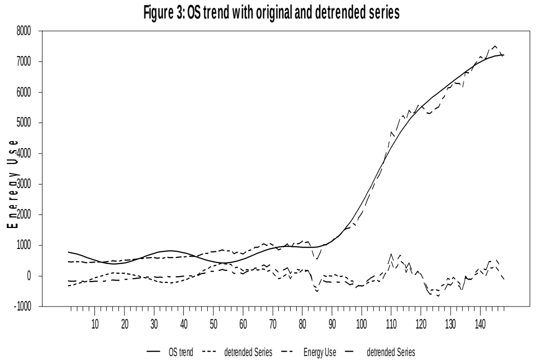
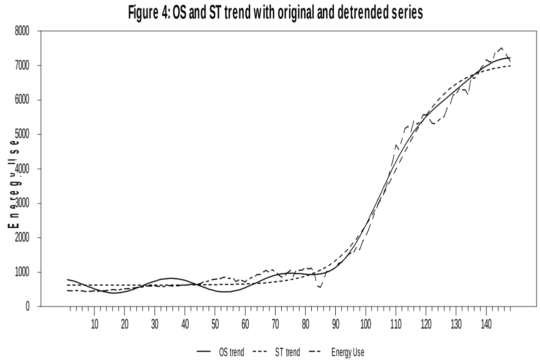


Figure 4: OS and ST trend with original and detrended series



Appendix A2.

Critical values of Model A*

	$s\tau_{\alpha}^{*}$		
T	1%	5%	10%
k=1			
25	-5.925	-4.957	-4.529
50	-5.415	-4.740	-4.408
100	-5.171	-4.566	-4.245
200	-4.970	-4.501	-4.249
500	-4.973	-4.485	-4.241
k=2			
25	-5.923	-5.019	-4.609
50	-5.361	-4.794	-4.450
100	-5.310	-4.590	-4.329
200	-5.149	-4.581	-4.258
500	-5.125	-4.541	-4.218
k=3			
25	-6.264	-5.063	-4.614
50	-5.405	-4.597	-4.216
100	-5.338	-4.629	-4.242
200	-5.227	-4.576	-4.267
500	-5.136	-4.510	-4.204
k=4			
25	-5.840	-4.772	-4.191
50	-5.358	-4.585	-4.180
100	-5.321	-4.464	-4.150
200	-5.071	-4.387	-4.148
500	-4.880	-4.403	-4.113
k=5			
25	-5.449	-4.454	-3.980
50	-5.219	-4.505	-4.096
100	-5.067	-4.426	-4.083
200	-4.987	-4.357	-4.040
500	-4.884	-4.351	-4.051

Appendix A3.

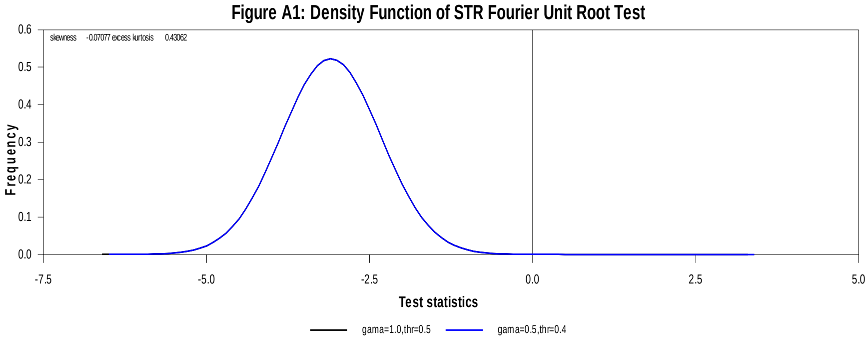
Density functions of the STR-Fourier-type t-statistics and their invariance properties.

Leybourne et al. (1998) showed that the analytical demonstration of the invariance property is difficult under the proposed detrending methods. They made the following modification: As the NLS estimation of parameters γ and τ does not concede closed-form explanations, it would be enormously problematic to consequently create any analytical association between the $\hat{v}$ and y_t. This makes the determination of the null asymptotic distribution of the test statistics s_{α}, $s_{\alpha(\beta)}$ and $s_{\alpha\beta}$ by analytical means more or less intractable. Leybourne et al. (1998) set the initial values for parameters $\hat{\gamma}$ and $\hat{\tau}$ in the NLS iteration at 1.0 and 0.5, correspondingly, and found that the solutions at convergence were not sensitive at all to these selections. Sollis (2004) also used parallel procedures for their proposed unit root tests.

Previous researchers provided only a general description of the insensitivity of the results without providing any proof (Such as Leybourne et al. 1998, Sollis 2004). In contrast, Omay et al. (2017), Omay and Emirmahmutoglu (2017) and Omay et al. (2018) carried out simulation exercises to see whether the derived test statistics obtained after nonlinear de-trending have the invariance properties suggested in Leybourne et al. (1998).

Following Omay et al. (2017), Omay and Emirmahmutoğlu (2017) and Omay et al. (2018) in this appendix, we apply a Monte-Carlo simulation to establish the invariance of the critical values with respect to α, β, γ and τ. For this purpose, we use $\{\gamma,\tau\}$, $\{1.0, 0.5\}$ and $\{0.5, 0.4\}$ to generate the critical values. The density function of the simulated critical values for T=100 and 10000 trials is given below:

Figure A1: Density Function of STR Fourier Unit Root Test



As observed from the generated density functions obtained for different initial values of γ and τ, critical values at convergence are clearly not sensitive to the choices of initial values, as stated by Leybourne et al. (1998). In fact, the density functions of the test statistics with different pairs of transition parameters overlap one another.