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The Study on the Stationarity of Energy Consumption in US States: Considering Structural Breaks, Nonlinearity, and Cross-Sectional Dependency

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***Abstract*—**This study applies the sequential panel selection method (SPSM) procedure proposed by Chortareas and Kapetanios (2009) to investigate the time-series properties of energy consumption in 50 US states from 1963 to 2009. SPSM involves the classification of the entire panel into a group of stationary series and a group of non-stationary series to identify how many and which series in the panel are stationary processes. Empirical results obtained through SPSM with the panel KSS unit root test developed by Ucar and Omay (2009) combined with a Fourier function indicate that energy consumption in all the 50 US states are stationary. The results of this study have important policy implications for the 50 US states.

***Keywords*—**Energy Consumption, Panel Unit Root, Sequential Panel Selection Method, Fourier Function, US states.

I. Introduction

RESEARCH in energy economics has long focused on the time-series properties of energy consumption, with particular interest in whether energy consumption can be described as a random walk (unit root) or mean reverting (trend stationary) process. Nelson and Plosser (1982) pointed out that modeling of energy consumption as a trend-stationary or difference-stationary process has important implications vis-à-vis modeling, testing, and forecasting. Shocks in energy consumption will have permanent effects if energy consumption follows a unit root process; this condition is consistent with path dependency or hysteresis in energy consumption (Agnolucci et al., 2004). Path dependency of energy consumption implies that innovations in world energy markets will have permanent effects. However, if energy consumption is a stationary process, then shocks in energy consumption will have only temporary effects; a subsequent major shock in the energy market will allow energy consumption to return to its original equilibrium level. When energy consumption deviates from the trend because of a shock in the energy market, then governments should not adopt unnecessary targets.

The stationarity properties of energy consumption also have several important implications. Properly modelling the relationship between energy consumption and other macroeconomic variables is important because of its crucial policy implications. Many recent empirical studies in the field of energy economics have focused on the analysis of the relationship between energy consumption and real output (for a recent survey on this issue, see Ozturk, 2010 and Payne, 2010). Given the importance and policy implications of the results of these studies, the stochastic behavior of energy consumption must be considered and a proper modeling approach must be adopted to obtain statistically valid results. The stationary behavior of energy consumption also has important implications on energy consumption forecasting. Energy consumption forecasts are crucial for the formulation of energy policies. Given the importance of having a safe energy supply for economic growth, reliable forecasts of energy demand should be obtained to formulate future energy policies. If energy consumption is a stationary process, then future energy demand can be forecasted based on past observations. However, if energy consumption is characterized by a stochastic trend, then past observations would not be useful in forecasting future trends in energy demand.

Serveral empirical studies in the field of energy economics have focused on the examination of the stationary properties of the energy consumption. Earlier studies on the stationary properties of energy consumption failed to reject the null hypothesis of unit root. Previous studies reported that conventional unit root tests not only fail to consider information across regions, thereby leading to less efficient estimations, but also have lower power compared with near-unit-root but stationary alternatives (Maddala and Wu, 1999; Levin et al., 2002; Im et al., 2003; Pesaran, 2007). These factors have shed considerable doubt on many of the earlier findings, which were based on a unit root in energy consumption (see, for instance, Soytas and Sari, 2003; Lee, 2005). Many researchers have employed panel data to increase testing power for a unit root. For instance, Levin et al. (2002) and Im et al. (2003) developed asymptotic theory and the finite-sample properties of augmented Dickey-Fuller (ADF) tests for use with panel data. These two tests have significantly improved testing power even in relatively small panels. Narayan and Smyth (2007) applied panel data unit root tests to the annual data of 182 countries to examine the stationarity of

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per capita energy consumption. The researchers first applied a conventional ADF test and reported that a univariate unit root test results in the rejection of the null hypothesis of unit root in 56 countries or 31% of the sample. They attributed this result to the low power of the conventional ADF test. The researchers then applied panel unit root tests to overcome this problem. When the panel unit root test proposed by Im et al. (2003) was applied, strong evidence in favor of panel stationarity of energy consumption was obtained.

Although panel unit root tests have good small-sample properties and high power compared with time series unit root tests, the use of panel data techniques requires careful treatment. Chen and Lee (2007) argued that ignoring cross-sectional dependency and structural breaks in panel unit root tests can result in severe size biases and loss of power. The researchers first applied conventional panel unit root tests and found that per capita energy consumption in 104 countries categorized into seven geographical groups is not stationary even after controlling for cross-sectional dependence. The test procedure proposed by Carrion-i-Silvestre et al. (2005), which allows for multiple structural breaks, was then applied. The application of this test procedure revealed that energy consumption is panel stationary in all groups of countries. Mishra et al. (2009) also applied the panel unit root test proposed by Carrion-i- Silvestre et al. (2005) to examine the stationarity properties of per capita energy consumption in 13 Pacific Island countries. Mishra et al. (2009) first applied conventional panel stationarity and unit root tests that ignore structural breaks, and found that energy consumption in the sample countries contains a unit root. However, after allowing for multiple structural breaks in the data, the researchers found that per capita energy consumption in only five out of the 13 countries. Mishra et al. (2009) thereby concluded that countries whose energy consumption is non-stationary are the largest energy consumers in the region, and have the most volatile energy consumption.

Another issue in a panel unit analysis is related to the interpretation of the null hypothesis in panel unit root tests. Taylor and Sarno (1998), Breuer et al. (2001, 2002), and Taylor and Taylor (2004) showed that the recent methodological refinements to the Levin-Lin-Chu test fail to address fully the “all-or-nothing” nature of the test. Given that they are joint tests of the null hypothesis, they are not informative with regard to the number of series that are stationary processes when the null hypothesis is rejected. Breuer et al. (2001, 2002) further claimed that when an F-statistic rejects the null hypothesis that a vector of coefficients is equal to zero by simple regression, each coefficient is not necessarily non-zero. When the unit-root null hypothesis is rejected, concluding that all series in the panel are stationary is erroneous. Breuer et al. (2001, 2002) developed panel seemingly unrelated regression ADF (panel SURADF) test, which allows one to account for possible cross-sectional effects and identify how many and which members of the panel contain a unit root. Hsu et al. (2008) applied the panel SURADF test developed by Breuer et al. (2001, 2002) to examine the stationarity of energy consumption in 84 countries in five regions. The researchers found that although the stationarity properties of energy consumption are affected by regions, most of the investigated series follow unit root processes. Results revealed that conventional panel unit root tests can lead to misleading inferences that are biased toward stationarity even if only one series in the panel is strongly stationary.

A common feature of previous studies is that none of them considered possible nonlinearities in the data-generating process. Many economic time series are known to follow nonlinear processes (Granger and Tervasvirta, 1993). Therefore, possible nonlinearities in the data-generating process should be explicitly considered in analyzing time series to avoid spurious results. Kapetanios et al. (2003) argued that conventional unit root tests have low power when the true data-generating process is subjected to regime changes. If the process is globally stationary but exhibits unit root or explosive behavior in one of the regimes, then test procedures that ignore regime-dependent dynamics and nonlinearities might be biased against stationarity (Kapetanios et al., 2003).

However, Lundbergh et al. (2003) argued that time series could be described more appropriately by simultaneous structural change and nonlinearities. Sollis (2004), Telatar and Hasanov (2009), and Hasanov and Telatar (2011) proved that considering structural changes and nonlinearity in the models is more appropriate for economic modeling. The researchers also reported that failure to consider both structural changes and nonlinearities in the data-generating process may seriously reduce the power of unit root tests. Nonlinearity and structural breaks are well-studied issues in empirical energy economics literature (Hamilton, 2003; Huang et al., 2008; Gabreyohannes, 2010). However, to the best of our knowledge, only a few researchers have simultaneously considered possible nonlinearities and structural changes in testing the stationarity of energy consumption. [1] This study attempts to fill a gap in existing empirical literature by testing the stationarity properties of energy consumption in consideration of both nonlinearities and structural breaks in the data-generating process.

This study aims to determine whether shocks in energy consumption in the US economy are permanent or temporary. The stationarity properties of energy consumption in 50 US states were tested by applying the newly developed sequential

[1] With the exception of Hasanov and Telatar (2011) who re-examined the stochastic behavior of per capita total primary energy consumption in 178 countries around the world. In addition to conventional unit root tests, they applied newly developed tests that allow for nonlinear adjustments and structural breaks in the data-generating process. The results of the unit root tests show that allowing for structural breaks and nonlinearity results in more frequent rejection of the null hypothesis of unit root, suggesting that most of the series under consideration follow a stationary process. These findings imply that both energy economists and policy makers must be careful and consider possible nonlinearities and structural breaks in their analyses of energy consumption.

panel selection method (SPSM) combined with panel nonlinear unit root test with a Fourier function. The results suggest that proper modeling of structural breaks and nonlinearities results in the rejection of the null hypothesis of unit root.

This study contributes to literature from different perspectives. First, this paper is the first to test the stationarity properties of energy consumption by considering both nonlinearities and structural breaks in the data-generating process. Second, to the best of our knowledge, this study is the first to utilize panel KSS unit root test with a Fourier function through SPSM to determine whether energy consumption in 50 US states is stationary. Third, independence is not a realistic assumption in that the energy consumption of different states may be contemporaneously correlated. We approximate the bootstrap distribution of the tests to control any cross-section dependence among the data sets. This procedure, which involves the assumption that individuals are cross-section independent, has not been performed in previous studies. O'Connell (1998) reported that the true size of both tests can be far greater than the normal size when the underlying data-generating process is characterized by cross-section dependence. Hence, the current research hopes to fill the existing gap in the literature. Our empirical results indicate that energy consumption series are stationary in all the 50 US states during the sample period. Heterogeneity among the members of the panel is considered in panel unit root analysis rather than assuming that homogeneity exists in the entire panel. Clearly, every country moves from past to present based on its own features and dynamics; the consideration of cross-country heterogeneity is therefore required in panel data analysis. Given that the US economy consists of state economies, a state-specific approach is helpful in understanding the dynamics of the overall economy.

The remainder of this paper is organized as follows. Section II describes the utilized data. Section III outlines the methodology employed. Section IV discusses the empirical findings and then provides several economic and policy implications. Section V presents the conclusions.

II. DATA

Annual data of 50 US states from 1963 to 2009 were utilized in this study. The variables in this study include total energy consumption in each state. Energy consumption is expressed in terms of trillions of BTU. Data were obtained from the US Energy Information Administration. Table I provides a summary of the statistics for energy consumption in the 50 US states. Texas and Vermont have the highest and lowest mean energy consumption of 9,212 and 134 trillion BTUs, respectively.

TABLE I
SUMMARY OF THE STATISTICS OF ENERGY CONSUMPTION BY STATE (IN TRILLION BTUS)

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J.B. test
Alabama	1677	2180	916	336	-0.36	2.44	1.63
Alaska	456	798	81	238	-0.19	1.53	4.51
Arizona	917	1571	349	357	0.25	2.00	2.43
Arkansas	881	1164	486	191	-0.16	2.13	1.69
California	6745	8451	3932	1208	-0.52	2.45	2.68
Colorado	954	1491	467	285	0.36	2.24	2.13
Connecticut	758	923	548	83	-0.52	3.23	2.21
Delaware	246	312	173	39	0.02	2.04	1.82
Florida	2869	4580	998	1112	-0.05	1.79	2.88
Georgia	2074	3161	804	724	-0.02	1.74	3.09
Hawaii	249	341	114	56	-0.63	2.87	3.12
Idaho	393	536	213	92	-0.01	2.01	1.93
Illinois	3733	4222	2728	326	-1.16	4.24	13.56***
Indiana	2466	2936	1641	325	-0.61	2.97	2.89
Iowa	1005	1419	645	182	0.25	2.92	0.52
Kansas	987	1135	642	125	-1.30	3.91	14.90***
Kentucky	1487	2018	894	347	-0.05	1.85	2.61
Louisiana	3297	3968	1682	621	-1.39	3.88	16.57***
Maine	410	519	232	84	-0.77	2.44	5.25*
Maryland	1226	1557	778	195	-0.29	2.53	1.10
Massachusetts	1414	1584	1085	116	-1.00	3.36	8.08**
Michigan	2850	3256	2085	270	-0.90	3.59	6.97**
Minnesota	1393	1937	777	319	0.05	2.04	1.81
Mississippi	927	1232	474	218	-0.28	2.09	2.23
Missouri	1532	1975	961	261	-0.18	2.41	0.94
Montana	355	465	253	47	-0.29	3.18	0.70
Nebraska	550	784	336	107	0.12	2.69	0.30
Nevada	392	772	123	199	0.48	1.94	4.05
New Hampshire	244	339	131	59	-0.24	2.07	2.15
New Jersey	2251	2714	1528	309	-0.60	2.59	3.11
New Mexico	538	714	354	104	0.11	1.76	3.09
New York	3926	4440	3314	278	-0.41	2.41	2.02
North Carolina	1938	2720	932	558	-0.09	1.77	3.04
North Dakota	289	440	170	86	0.18	1.63	3.96
Ohio	3900	4305	3120	281	-0.78	3.23	4.90*
Oklahoma	1248	1621	747	248	-0.66	2.36	4.24
Oregon	933	1160	528	162	-0.82	2.91	5.31*
Pennsylvania	3856	4299	3388	234	-0.33	2.59	1.19
Rhode Island	214	257	174	22	-0.26	2.49	1.03
South Carolina	1170	1731	556	369	-0.10	1.77	3.05
South Dakota	215	360	140	54	0.89	3.35	6.44**
Tennessee	1808	2439	1072	366	-0.19	2.30	1.22
Texas	9212	12108	4837	2220	-0.30	2.05	2.45
Utah	550	801	312	141	0.22	1.93	2.60
Vermont	134	170	72	25	-0.66	2.79	3.51
Virginia	1804	2605	944	486	0.02	1.80	2.81
Washington	1732	2317	901	376	-0.57	2.34	3.39
West Virginia	811	919	716	53	0.27	2.27	1.61
Wisconsin	1511	1899	941	263	-0.20	2.27	1.34
Wyoming	358	541	163	96	-0.35	2.51	1.45

Notes:
Sample period is from 1963 to 2009.
J.B. test is Jarque-Berra normality test.
*, **, and *** indicate significance at 10%, 5%, and 1% level, respectively.

III. Methodology

The consensus that economic time series data exhibit nonlinearities continues to grow. Consequently, conventional unit root tests such as the augmented Dickey–Fuller (ADF) test have low power in detecting the mean reversion of data series. Many studies provided empirical evidence on the nonlinear adjustment of economic series. However, nonlinear adjustment in these studies does not necessarily imply nonlinear mean reversion (stationarity). Therefore, stationarity tests based on a nonlinear framework must be applied. Ucar and Omay (2009) proposed a nonlinear panel unit root test by combining the nonlinear framework proposed by Kapetanios et al. (2003, KSS) with the panel unit root testing procedure developed by Im et al. (2003); this procedure has been proven useful in testing the mean reversion of data series. Perron (1989) argued that in cases where a structural break exists, the power to reject a unit root decreases when the stationary alternative is true and the structural break is ignored. The structural changes present in the data-generating process are neglected, swaying the analysis toward accepting the null hypothesis of a unit root. Therefore, the SPSM proposed by Chortareas and Kapetanios (2009) and panel KSS unit root tests with a Fourier function were utilized in the present study to investigate the time-series properties of energy consumption in 50 US states.

Similar to that in Kapetanios et al. (2003), the Kapetanios, Shin, and Snell (KSS) unit root test detects the presence of nonstationarity against a nonlinear but globally stationary exponential smooth-transition autoregressive (ESTAR) process. The model is given as

$$\Delta y_t = \gamma y_{t-1}\{1-\exp(-\theta y_{t-1}^2)\} + v_t \qquad (1)$$

where y_t is the data series of interest, v_t is an independent identically distributed error with zero mean and constant variance, and $\theta \geq 0$ is the EATAR transition parameter that governs the transition speed. Under the null hypothesis, y_t follows a linear unit root process; under the alternative, y_t follows a nonlinear stationary ESTAR process. One shortcoming of this framework is that γ is not identified under the null hypothesis. Kapetanios et al. (2003) use a first-order Taylor series approximation for $\{1-\exp(-\theta y_{t-1}^2)\}$ under the null hypothesis $\theta = 0$ and then approximated Equation [1] by using the following auxiliary regression:

$$\Delta y_t = \xi + \delta y_{t-1}^3 + \sum_{i=1}^{k} \theta_i \Delta y_{t-i} + v_t \qquad (2)$$
$$t = 1,2,....,T$$

The null and alternative hypotheses in this framework are expressed as $\delta = 0$ (nonstationarity) against $\delta < 0$ (nonlinear ESTAR stationarity). Ucar and Omay (2009) expand a nonlinear panel data unit root test based on regression [1]. The regression is expressed as follows:

$$\Delta y_{i,t} = \gamma_i y_{i,t-1}\{1-\exp(-\theta_i y_{i,t-1}^2)\} + v_{i,t} \qquad (3)$$

Ucar and Omay (2009) also use first-order Taylor series approximation to the panel ESTAR model around $\theta_i = 0$ for all I and obtain the following auxiliary regression:

$$\Delta y_{i,t} = \xi_i + \delta_i y_{i,t-1}^3 + \sum_{j=1}^{k} \theta_{i,j} \Delta y_{i,t-j} + v_{i,t} \qquad (4)$$

where $\delta_i = \theta_i \gamma_i$ The hypotheses established for unit root testing based on regression [4] are as follows:

$$H_0 : \delta_i = 0 \text{ for all I (linear nonstationarity)}$$
$$H_0 : \delta_i < 0 \text{ for some I (nonlinear stationarity)} \qquad (5)$$

We estimate the following system of the KSS equations with a Fourier function:

$$\Delta y_{i,t} = \xi_i + \delta_i y^3{}_{i,t-1} + \sum_{j=1}^{k1} \theta_{i,j} \Delta y_{i,t-j} + a_{i,1}\sin(\frac{2\pi kt}{T}) + b_{i,1}\cos(\frac{2\pi kt}{T}) + \varepsilon_{i,t} \qquad (6)$$

where $t = 1,2,....,T$, k represents the frequency selected for the approximation, and $[a_i, b_j]'$ is the amplitude and the displacement. Of the frequency component $[\sin(2\pi kt/T), \cos(2\pi kt/T)]$ is selected because a Fourier expression can approximate absolutely integrable functions to any desired degree of accuracy. At least one frequency component must also be present if a structural break[2] exists. Gallant (1981), Becker et al. (2004), Enders and Lee (2011), and Pascalau (2010) observe that a Fourier approximation can often capture the behavior of an unknown function even if the function itself is not periodic. Considering that no a priori knowledge exists on the shape of breaks in the data, we perform a grid search to find the best frequency.

The sequential panel selection method proposed by Chortareas and Kapetanios (2009) is based on the following steps:

1) A panel KSS test with a Fourier function is performed on all (energy consumption) in the panel. If the unit-root null hypothesis cannot be rejected, the procedure is stopped. Therefore, all series in the panel are considered nonstationary. If the null hypothesis is rejected, Step 2 is performed.

[2] Enders and Lee (2011) suggest that the frequencies in equation (6) should be obtained by minimizing the sum of squared residuals. Monte Carlo experiments suggest that only one or two frequencies should be used because of the power loss associated with many frequencies.

2) The series with the minimum KSS statistic is removed because it is identified as stationary.
3) Step 1 is repeated for the remaining series, or the procedure is stopped if all series have been removed from the panel.

The result is a separation of the whole panel into a set of mean-reverting series and a set of nonstationary series.

IV. Empirical Results and Economic and Policy Implications

A. Results from Unit Root Tests

Univariate unit root tests were applied first prior to performing the sequential panel selection procedure. The first and second generation panel unit root tests were then conducted. Table II presents the state-by-state unit root and stationary tests. As shown in Table II, the three univariate unit root tests, namely, augmented Dickey–Fuller (1981, ADF), Phillips and Perron (1989, PP), and Kwiatkowski et al. (1992, KPSS) tests, lead to the conclusion that energy consumption in most of the 50 US states contains unit roots[3]. This result is consistent with that in existing literature and may be due to the low power of the three univariate unit root tests when the series are highly persistent. This result also implies that energy consumption data series are not stationary for most of the 50 US states during the sample period. Another possible reason for the presence of unit roots (possibly spurious) is the recently forwarded argument that energy consumption series are likely to be nonlinear because of the existence of the business cycle and policies implemented for each state. The power of the three tests might be poor in such situations. Furthermore, univariate unit root tests might have low power when they are applied to a finite sample. The panel-based unit tests in this situation are of great help, provided that they allow for an increase in the power of the order of the integration analysis by allowing the cross-sectional and temporal dimensions to be combined.

[3] With some exceptions. We found that unit root null hypothesis was rejected in Kansas, Vermont, and West Virginia when the ADF tests were conducted. The KPSS test also fails to reject the stationary null hypothesis for 33 states (see Table II).

TABLE II
ENERGY CONSUMPTION BY STATE (UNIVARIATE UNIT ROOT TESTS)

State	*Levels*			*First Differences*		
	ADF	PP	KPSS	ADF	PP	KPSS
Alabama	-1.6045 (0)	-1.7443 (3)	0.0865 [4]	-5.1864*** (0)	-5.1568*** (5)	0.0988 [3]
Alaska	-0.4178 (0)	-0.4178 (0)	0.1834** [4]	-7.0792*** (0)	-7.0851*** (2)	0.1384* [2]
Arizona	-2.3142 (1)	-1.9201 (1)	0.1550** [5]	-3.6072** (0)	-3.281* (2)	0.0827 [3]
Arkansas	-1.774 (1)	-1.6459 (2)	0.0722 [5]	-4.7829*** (0)	-4.6968*** (2)	0.1118 [1]
California	-2.4548 (1)	-2.4658 (2)	0.1430* [4]	-5.1923*** (0)	-5.1592*** (3)	0.0702 [1]
Colorado	-1.2974 (0)	-2.6595 (3)	0.1539** [5]	-5.8626*** (0)	-5.8501*** (2)	0.1383* [2]
Connecticut	-2.7391 (0)	-2.6595 (2)	0.0917 [3]	-5.8129*** (1)	-6.9249*** (4)	0.0798 [5]
Delaware	-1.6864 (0)	-1.8777 (1)	0.0845 [4]	-5.6488*** (1)	-5.4933*** (3)	0.10494 [2]
Florida	-2.4909 (1)	-1.6574 (3)	0.0694 [2]	-4.4134*** (0)	-4.003** (7)	0.0971 [4]
Georgia	-0.9902 (0)	-0.9204 (1)	0.0837 [4]	-7.2002*** (0)	-7.2002*** (0)	0.1329* [1]
Hawaii	-1.9223 (0)	-2.0924 (3)	0.1619** [4]	-5.7439*** (0)	-5.6803*** (5)	0.0449 [3]
Idaho	-1.9857 (0)	-2.0785 (1)	0.0695 [5]	-5.9073*** (0)	-5.9075*** (1)	0.0855 [0]
Illinois	-2.7252 (0)	-2.7452 (2)	0.0901 [5]	-4.9134*** (0)	-4.9259*** (1)	0.1359* [2]
Indiana	-1.9975 (0)	-2.0826 (2)	0.0804 [5]	-5.4542*** (0)	-5.4542*** (0)	0.1093 [1]
Iowa	-1.1690 (0)	-1.4961 (4)	0.1192* [5]	-6.6258*** (0)	-6.6834*** (4)	0.1492** [4]
Kansas	-3.2714* (0)	-2.7795 (7)	0.1790** [5]	-6.9226*** (1)	-8.6204*** (19)	0.1807** [18]
Kentucky	-1.6006 (0)	-1.8397 (3)	0.0660 [5]	-5.9724*** (0)	-5.9757*** (3)	0.0834 [3]
Louisiana	-1.60352 (0)	-1.5587 (1)	0.1747 [5]	-7.3067*** (0)	-7.3067*** (0)	0.0615 [1]
Maine	-1.2525 (0)	-0.6576 (12)	0.2042** [5]	-6.1050*** (2)	-17.6746*** (44)	0.3134*** [32]
Maryland	-2.8709 (0)	-2.8585 (2)	0.0760 [4]	-7.4020*** (0)	-7.4063*** (1)	0.0701 [1]
Michigan	-1.7595 (0)	-1.9361 (3)	0.0759 [5]	-5.43241*** (0)	-5.4307*** (1)	0.1194* [2]
Minnesota	-1.9098 (0)	-2.0156 (3)	0.0964 [5]	-5.3604*** (0)	-5.3759*** (1)	0.1133 [2]
Mississippi	-1.8815 (1)	-1.4306 (0)	0.0731 [5]	-4.3763*** (1)	-5.0410*** (4)	0.0894 [1]
Missouri	-2.4140 (1)	-2.2389 (3)	0.0856 [5]	-4.4221*** (0)	-4.4942*** (3)	0.0927 [3]
Montana	-2.8601 (0)	-2.6614 (6)	0.1073 [4]	-6.4126*** (0)	-7.1518*** (14)	0.1379* [15]
Nebraska	-2.1744 (1)	-1.7972 (2)	0.1140 [5]	-4.6975*** (0)	-4.6919*** (2)	0.1352* [1]
Nevada	-2.2832 (1)	-1.7151 (1)	0.2070** [5]	-3.4344* (2)	-2.3469 (5)	0.1106 [1]
New Hampshire	-2.6096 (1)	-1.8012 (0)	0.0646 [4]	-5.4076*** (0)	-5.3392*** (4)	0.0539 [2]
New Jersey	-2.2166 (0)	-1.8406 (2)	0.1497** [4]	-7.9907*** (0)	-8.0196*** (1)	0.0628 [1]
New Mexico	-2.1925 (0)	-2.2352 (1)	0.0983 [5]	-6.7236*** (0)	-6.7228*** (1)	0.0747 [3]
New York	-2.3534 (0)	-2.5038 (3)	0.0946 [5]	-5.3569*** (0)	-5.2988*** (2)	0.1268* [3]
North Carolina	-0.8043 (0)	-1.0236 (1)	0.0825 [4]	-5.2381*** (0)	-5.2458*** (1)	0.1063 [1]
North Dakota	-3.0777 (0)	-3.0191 (3)	0.1525** [4]	-6.71638*** (0)	-7.4508*** (11)	0.1372* [12]
Ohio	-2.3054	-2.3479	0.0815	-5.6666***	-5.6666***	0.0944

	(0)	(2)	[5]	(0)	(0)	[1]
Oklahoma	-1.6947	-1.5652	0.1775**	-6.1554***	-6.0406***	0.0727
	(0)	(3)	[5]	(0)	(7)	[7]
Oregon	-2.1372	-2.1522	0.1605**	-6.4560***	-6.4560***	0.0552
	(0)	(1)	[5]	(0)	(0)	[0]
Pennsylvania	-2.6201	-2.7016	0.0914	-5.8457***	-5.8451***	0.1065
	(0)	(2)	[5]	(0)	(1)	[0]
Rhode Island	-2.4977	-2.4872	0.0654	-7.92133***	-7.9213***	0.0562
	(0)	(2)	[5]	(0)	(0)	[2]
South Carolina	-0.8732	-0.8732	0.0887	-6.8334***	-6.8322***	0.1223*
	(0)	(0)	[4]	(0)	(1)	[1]
South Dakota	0.5609	0.7670	0.1803**	-6.37596***	-6.3844***	0.1420*
	(0)	(2)	[5]	(0)	(3)	[3]
Tennessee	-2.0916	-1.7137	0.0892	-3.7235**	-3.5621**	0.0866
	(1)	(1)	[5]	(0)	(3)	[1]
Texas	-1.1365	-1.0922	0.1087	-5.3202***	-5.2361***	0.0989
	(0)	(7)	[4]	(0)	(20)	[10]
Utah	-2.0610	-2.1878	0.1108	-5.67836***	-5.5567***	0.0803
	(0)	(1)	[5]	(0)	(4)	[4]
Vermont	-3.7617**	-2.2630	0.1263*	-6.6706***	-7.2995***	0.3132***
	(1)	(11)	[4]	(1)	(18)	[26]
Virginia	-2.7817	-1.7346	0.0721	-4.9134***	-4.8606***	0.0811
	(1)	(0)	[3]	(0)	(2)	[1]
Washington	-1.8300	-1.5434	0.1857**	-5.0307***	-4.8176***	0.0475
	(1)	(2)	[5]	(0)	(6)	[4]
West Virginia	-3.1960*	-3.1762	0.0920	-6.5522***	-6.5855***	0.1002
	(0)	(3)	[4]	(0)	(7)	[8]
Wisconsin	-1.8703	-1.8492	0.0737	-5.6964***	-5.5884***	0.1053
	(0)	(2)	[5]	(0)	(2)	[2]
Wyoming	-2.5134	-2.5224	0.1376*	-6.7410***	-6.7410***	0.0623
	(0)	(1)	[5]	(0)	(0)	[0]

Notes:
***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The number in parentheses indicates the lag order selected based on recursive t-statistic as suggested by Perron (1989). The number in the brackets indicates the truncation for the Bartlett kernel as suggested by the Newey-West test (1994).

Tables III and IV present the results of the first-generation and second-generation panel-based unit root tests. Three first-generation panel-based unit root tests, namely, Levin–Lin–Chu (Levin et al., 2002), Im–Pesaran–Shin (Im et al., 2003), and Maddala–Wu (Maddala and Wu, 1999) tests, all yield the same results, indicating that energy consumption in all the 50 US states is stationary.

TABLE III
FIRST-GENERATION PANEL UNIT ROOT TESTS

	t_{ρ}^{*}	$\hat{\rho}$	t_{ρ}^{*B}	t_{ρ}^{*C}	
Levin, Lin and Chu (2002)	-17.79*** (0.000)	-0.05*** (0.000)	-17.69*** (0.000)	-17.688*** (0.000)	
	t_bar_{NT}	$W_{t,bar}$	$Z_{t,bar}$	$t\_bar_{NT}^{DF}$	$Z_{t,bar}^{DF}$
Im, Pesaran and Shin (2003)	-2.780	-10.16*** (0.000)	-10.140*** (0.000)	-2.863	-10.84*** (0.000)
	P_{MW}	Z_{MW}			
Maddala and Wu (1999)	273.97*** (0.000)	12.30*** (0.000)			

Notes:

Levin, Lin and Chu (2002): t_{ρ}^{*} denotes the adjusted *t*-statistic computed with a Bartlett kernel function and a common lag truncation parameter given by $\bar{K} = 3.21T^{1/3}$ (Levin et al., 2002). Corresponding *p*-value is in parentheses. $\hat{\rho}$ is the pooled least squares estimator. Corresponding standard error is in parentheses. t_{p}^{*B} denotes the adjusted *t*-statistic computed with a Bartlett kernel function and individual bandwidth parameters (Newey and West, 1994). t_{p}^{*C} denotes the adjusted *t*-statistic computed with a Quadratic Spectral kernel function and individual bandwidth parameters. Finally, t_{ρ}^{*} denotes the adjusted *t*-statistic computed with a Bartlett kernel function and a common lag truncation parameter. Corresponding *p*-values are in parentheses.

Im, Pesaran and Shin (2003): $t\_bar_{NT}^{DF}$ (respectively t_bar_{NT}) denotes the mean of Dickey Fuller (respectively Augmented Dickey Fuller) individual statistics. $Z_{t,bar}^{DF}$ is the standardized $t\_bar_{NT}^{DF}$ statistic and associated p-values are in parentheses. $Z_{t,bar}$ is the standardized t_bar_{NT} statistic based on the moments of the Dickey Fuller distribution. $W_{t,bar}$ denotes the standardized t_bar_{NT} statistic based on simulated approximated moments (Im, Pesaran and Shin, 2003, Table III). The corresponding *p*-values are in parentheses.

Maddala and Wu (1999): P_{MW} denotes the Fisher's test statistic defined as $P_{MW} = -2\sum \log(p_i)$; where p_i are the *p*-values from ADF unit root tests for each cross-section. Under H_0; P_{MW} has χ^2 distribution with 2N of freedom when *T* tends to infinity and N is fixed. Z_{MW} is the standardized statistic used for large *N* samples: under H_0; Z_{MW} has a N(0, 1) distribution when *T* and *N* tend to infinity.

*** indicates significance at the 1% level.

A serious drawback of first-generation panel-based unit root tests is that they ignore possible cross-sectional dependencies in the panel-based unit root test procedure. O'Connell (1988) pointed out that failure to consider contemporaneous correlations among data will generate bias toward rejecting the joint unit root hypothesis in panel-based unit root tests. Cross-sectional dependencies are considered in second-generation panel unit root tests. Hence, these tests offer a superior method of studying the long-term behavior of energy consumption. Four second-generation panel-based unit root tests are employed in the present study. These four tests are the tests proposed by Bai and Ng (2004), Choi (2002), Moon and Perron (2004), and Pesaran (2007). Table IV presents the results of these four second-generation panel-based unit root tests. The tests proposed by Bai and Ng (2004) and Choi (2002) provide evidence that energy consumption is stationary, whereas the results from the other two tests indicate that energy consumption is stationary in the 50 US states. Our results therefore indicate that energy consumption in the 50 US states could either be a stationary or non-stationary process.

TABLE IV
SECOND-GENERATION PANEL UNIT ROOT TESTS

Bai and Ng (2004)	$\hat{r}$	$Z_{\hat{e}}^{c}$	$P_{\hat{e}}^{c}$	MQ_c	MQ_f
	2	-1.352 (0.912	80.875 (0.920	2	2
Moon and Perron (2004)	t_a^*	t_b^*	$\hat{\rho}_{pool}^*$	t_a^{*B}	t_b^{*B}
	-12.88***(0.000)	-7.27***(0.000)	0.931	-12.71***(0.000)	-7.24***(0.000)
Choi (2002)	P_m	Z	L^*		
	13.64***(0.000)	-8.670***(0.000)	-9.77***(0.000)		
Pesaran (2003)	P^*	$CIPS$	$CIPS^*$		
	2	-1.730(0.555)	-1.730(0.555)		

Notes:

Bai and Ng (2004): $\hat{r}$ is the estimated number of common factors, based on IC criteria functions. $P_{\hat{e}}^{c}$ is a Fisher's type statistic based on *p*-values of the individual ADF tests. $Z_{\hat{e}}^{c}$ is a standardized Choi's type statistic for large N samples. *P*-values are in parentheses. The first estimated value of $\hat{r}_1$ is derived from the filtered test MQ_f and the second one is derived from the corrected test MQ_c.

Moon and Perron (2004): t_a^* and t_b^* are the unit root test statistics based on de-factored panel data (Moon and Perron, 2004). Corresponding p-values are in parentheses. $\hat{\rho}_{pool}^*$ is the corrected pooled estimates of the auto- regressive parameter. t_a^{*B} and t_b^{*B} are computed with a Bartlett kernel function in spite of a Quadratic Spectral kernel function.

Choi (2002): The P_m test is a modified Fisher's inverse chi-square test (Choi, 2001). The Z test is an inverse normal test. The L^* test is a modified logit test. *P*-values are in parentheses.

Pesaran (2007): $CIPS$ is the mean of individual Cross sectionally augmented ADF statistics (CADF). $CIPS^*$ denotes the mean of truncated individual CADF statistics. Corresponding p-values are in parentheses. P^* denotes the nearest integer of the mean of the individual lag lengths in ADF tests.

Although the second-generation panel unit root tests employed above account for cross-section dependence, they do not consider structural shifts in testing the unit root hypothesis. Thus, we also employed the panel unit root test with multiple structural breaks recently developed by Carrion-i-Silvestre et al. (2005). This test is a panel extension of univariate KPSS test. This test allows for multiple structural breaks in the mean and/or trend and cross-section dependence. This unit root approach to panel unit root analysis involves testing the null hypothesis of stationarity against non-stationarity. The results of the panel unit root test with multiple structural breaks are presented in Table V. When the breaks are ignored in unit root analysis, the null hypothesis of stationarity is strongly rejected irrespective of whether cross-section dependency is controlled. In contrast, the test statistic for structural breaks without cross-section dependence provides evidence for non-stationarity. When cross-section dependency is considered through bootstrapping, the test statistic with the breaks provides evidence for stationarity. Therefore, similar to the first- and second-generation panel unit root tests, the panel stationarity test with structural breaks and cross-section dependence fails to indicate whether a shock in energy consumption in the US economy is permanent or temporary.

TABLE V
PANEL STATIONARY TEST WITH AND WITHOUT BREAKS

Without Breaks		With Breaks	
Asymptotic p-val.	Bootstrap p-val.	Asymptotic p-val.	Bootstrap p-val.
0.000	0.000	0.000	0.956

Note: This table shows the panel stationary test results for each variable. The second and fourth columns contain the asymptotic p-value, and the third and fifth columns contain the bootstrapped p-value. The number of bootstrap replications is 5000.

As mentioned earlier, panel-based unit root tests are joint tests of a unit root for all members of a panel. These tests cannot determine the mix of I(0) and I(1) series in a panel setting. Failure to incorporate the structural breaks in the model would cause low power in detecting the mean reversion of data series. Therefore, we tested energy consumption through SPSM combined with panel KSS unit root test with a Fourier function to investigate the time-series properties of energy consumption in the 50 US states. SPSM classifies the entire panel into a group of stationary series and a group of non-stationary series to clearly identify how many and which series in the panel are stationary processes.

B. SPSM

The results of the panel KSS unit root test without a Fourier function are also reported as a benchmark. Table VI presents the results of the panel KSS unit root test without a Fourier function. A sequence of panel KSS statistics with their bootstrap p-values on a reducing panel, the individual minimum KSS statistic, and the stationary series identified each time through this procedure are also shown. The unit root null hypothesis in is rejected when the panel KSS unit root test is first applied to the entire panel, producing a value of -2.433 with a very small p-value of 0.0002. After implementing SPSM, we found that Vermont is stationary with a minimum KSS value of -4.651. Vermont was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. Afterward, we found that the panel KSS unit root test still rejected the unit root null hypothesis with a value of -2.388 (p-value of 0.0000) and that Kansas is stationary with a minimum KSS value of -4.361. Kansas was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. Again, we found that the panel KSS unit root test still rejected the unit root null hypothesis with a value of -2.346 (p-value of 0.0002) and that New Hampshire is stationary with a minimum KSS value of -3497. New Hampshire was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. The procedure was repeated until the panel KSS unit root test failed to reject the unit root null hypothesis at 10% significance level. The procedure stopped at sequence 41 when the 41 states was removed from the panel. The procedure was performed until the last sequence to verify the robustness of the test. We then found that the panel KSS statistic failed to reject the unit root null hypothesis in the remaining sequences. SPSM combined with panel KSS unit root test and a Fourier function provided strong evidence in favor of stationarity in energy consumption in 41 of the 50 US states studied. This finding leads to the conclusion that stationarity in energy consumption exists in 41 of the 50 US states under study.

TABLE VI
PANEL KSS UNIT ROOT WITHOUT FOURIER FUNCTION

Sequence	OU stat	P-Value	Min KSS	I(0)series
1.0000	-2.4328	0.0002	-4.6523	Vermont
2.0000	-2.3876	0.0000	-4.3609	Kansas
3.0000	-2.3464	0.0002	-3.4966	New Hamspire
4.0000	-2.3220	0.0008	-3.4192	Wyoming
5.0000	-2.2981	0.0004	-3.2699	California
6.0000	-2.2765	0.0002	-3.2582	Maryland
7.0000	-2.2542	0.0002	-3.2279	West Virginia
8.0000	-2.2316	0.0034	-3.2167	Mississippi
9.0000	-2.2081	0.0010	-3.1275	Illinois
10.0000	-2.1857	0.0004	-3.0858	North Dakota
11.0000	-2.1632	0.0024	-2.9781	Oklahoma
12.0000	-2.1423	0.0042	-2.9472	Oregon
13.0000	-2.1211	0.0024	-2.9465	Virginia
14.0000	-2.0988	0.0036	-2.9242	Connecticut
15.0000	-2.0759	0.0050	-2.8839	Montana
16.0000	-2.0528	0.0028	-2.8132	Missouri
17.0000	-2.0304	0.0084	-2.7535	Michigan
18.0000	-2.0085	0.0044	-2.7021	Arkansas
19.0000	-1.9868	0.0042	-2.6603	Pennsylvania
20.0000	-1.9651	0.0120	-2.5807	Hawaii
21.0000	-1.9446	0.0098	-2.4733	Indiana
22.0000	-1.9264	0.0088	-2.4408	Ohio
23.0000	-1.9080	0.0078	-2.4228	Minnesota
24.0000	-1.8889	0.0078	-2.4188	Rhode Island
25.0000	-1.8685	0.0068	-2.4146	New York
26.0000	-1.8467	0.0062	-2.4034	Idaho
27.0000	-1.8235	0.0110	-2.3974	Wisconsin
28.0000	-1.7985	0.0118	-2.3692	New Jersey
29.0000	-1.7726	0.0088	-2.3635	Alabama
30.0000	-1.7445	0.0286	-2.3323	Nebraska

31.0000	-1.7151	0.0122	-2.3295	Texas
32.0000	-1.6827	0.0248	-2.2840	Utah
33.0000	-1.6493	0.0402	-2.2348	Colorado
34.0000	-1.6149	0.0318	-2.2218	New Mexico
35.0000	-1.5770	0.0208	-2.1349	Louisiana
36.0000	-1.5398	0.0620	-2.0686	Michigan
37.0000	-1.5020	0.0530	-2.0162	Arizona
38.0000	-1.4625	0.0556	-1.9941	Washington
39.0000	-1.4181	0.0768	-1.9303	Delaware
40.0000	-1.3716	0.0854	-1.8687	Iowa
41.0000	-1.3219	0.0568	-1.8044	Georgia
42.0000	-1.2683	0.1202	-1.8016	Tennessee
43.0000	-1.2016	0.1748	-1.7584	Nevada
44.0000	-1.1220	0.1526	-1.5429	Maine
45.0000	-1.0519	0.1532	-1.3800	Kentucky
46.0000	-0.9863	0.2150	-1.3576	Maryland
47.0000	-0.8935	0.1434	-1.2126	Florida
48.0000	-0.7871	0.2030	-0.8707	Alaska
49.0000	-0.7452	0.3820	-0.7595	South Carolina
50.0000	-0.7310	0.3886	-0.7310	South Dakota

As mentioned earlier, Perron (1989) argued that in cases where a structural break exists, the power to reject a unit root decreases when the stationary alternative is true and the structural break is ignored. The structural changes in the data-generating process are neglected, swaying the analysis toward accepting the null hypothesis of a unit root. Therefore, we utilized the panel KSS unit root test with a Fourier function. A grid search was performed to determine the best frequency given that the shape of the breaks in the data is unknown. Equation [6] was also estimated for each integer k = 1, ...5 following the recommendations of Enders and Lee (2011). The residual sum of squares indicates that frequency (k=5) is appropriate for all the 50 US states (refer to the sixth column in Table VII).

Table VII presents the results of panel KSS unit root test with a Fourier function for energy consumption in the 50 US states. A sequence of panel KSS statistics with their bootstrap p-values on a reducing panel, the individual minimum KSS statistic, and the stationary series identified each time through this procedure each time are also shown. As shown in Table VI, the unit root null hypothesis in is rejected when panel KSS unit root test is applied to the entire panel, producing a value of -3.341 with a very small p-value of 0.000. After implementing SPSM, we found that Vermont is stationary with a minimum KSS value of -4.652. Vermont was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. Subsequently, we found that the panel KSS unit root test still rejected the unit root null hypothesis with a value of -3.305 (p-value of 0.000) and that Kansas is stationary with a minimum KSS value of -4.361. Kansas was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. Again, we found that the panel KSS unit root test still rejected the unit root null hypothesis with a value of -3.289 (p-value of 0.000) and that New Hampshire is stationary with a minimum KSS value of -3.735. New Hampshire was then removed from the panel, and the panel KSS unit root test was implemented again for the remaining set of series. The procedure was repeated until the panel KSS unit root test failed to reject the unit root null hypothesis at 10% significance level. The procedure stopped at sequence 50 when the energy consumption for 50 states was removed from the panel. SPSM combined with panel KSS unit root test and a Fourier function provided strong evidence in favor of stationarity in energy consumption in all the 50 US states. This finding leads to the conclusion that stationarity in energy consumption exists in all of the 50 US states. Our empirical findings suggest that allowing for nonlinearities and structural breaks results in further rejection of the unit root null hypothesis. The results reveal the importance of proper modeling of structural breaks and nonlinearities in the data series of the 50 US states. The results are also consistent with that of Apergis and Payne (2010) who found that energy consumption is stationary in most of the US states when structural breaks are incorporated into the testing model.

TABLE VII
PANEL KSS UNIT ROOT TEST WITH THE FOURIER FUNCTION

Sequence	OU stat	P-Value	Min KSS	I(0)series	k
1.0000	-3.3406	0.0000	-4.6523	Vermont	5.0000
2.0000	-3.3047	0.0000	-4.3609	Kansas	5.0000
3.0000	-3.2895	0.0000	-3.7351	New Jersey	5.0000
4.0000	-3.3112	0.0000	-3.5798	Arkansas	5.0000
5.0000	-3.2751	0.0000	-3.5160	Ohio	5.0000
6.0000	-3.2125	0.0000	-3.2699	California	5.0000
7.0000	-3.2090	0.0000	-3.2582	Maryland	5.0000
8.0000	-3.1967	0.0000	-3.2279	West Virginia	5.0000
9.0000	-3.1821	0.0000	-3.1275	Illinois	5.0000
10.0000	-3.1734	0.0000	-3.0858	North Dakota	5.0000
11.0000	-3.1552	0.0000	-2.9781	Oklahoma	5.0000
12.0000	-3.1594	0.0000	-2.9472	Oregon	5.0000
13.0000	-3.1610	0.0000	-2.9242	Connecticut	5.0000
14.0000	-3.1678	0.0000	-2.8839	Montana	5.0000
15.0000	-3.1738	0.0000	-2.7535	Massachusetts	5.0000
16.0000	-3.1731	0.0000	-2.7406	Wyoming	5.0000
17.0000	-3.1782	0.0000	-2.7016	Nebraska	5.0000
18.0000	-3.1902	0.0000	-2.6603	Pennsylvania	5.0000
19.0000	-3.1903	0.0000	-2.6209	Missouri	5.0000
20.0000	-3.1307	0.0000	-2.5807	Hawaii	5.0000
21.0000	-3.1365	0.0000	-2.4733	Indiana	5.0000
22.0000	-3.1214	0.0000	-2.4228	Minnesota	5.0000
23.0000	-3.1062	0.0000	-2.4188	Rhode Island	5.0000
24.0000	-3.0516	0.0000	-2.4146	New York	5.0000
25.0000	-3.0614	0.0000	-2.4034	Idaho	5.0000
26.0000	-3.0099	0.0000	-2.3974	Wisconsin	5.0000
27.0000	-2.9314	0.0000	-2.3738	Nevada	5.0000
28.0000	-2.9656	0.0000	-2.3692	New Jersey	5.0000
29.0000	-2.9666	0.0000	-2.3635	Alabama	5.0000
30.0000	-2.9330	0.0000	-2.2840	Utah	5.0000
31.0000	-2.8880	0.0000	-2.2348	Colorado	5.0000
32.0000	-2.9101	0.0000	-2.2243	Mississippi	5.0000
33.0000	-2.8129	0.0000	-2.2218	New Mexico	5.0000
34.0000	-2.7510	0.0000	-2.1349	Louisiana	5.0000
35.0000	-2.7710	0.0002	-2.0686	Michigan	5.0000
36.0000	-2.7112	0.0002	-2.0162	Arizona	5.0000
37.0000	-2.6884	0.0004	-1.9941	Washington	5.0000
38.0000	-2.7410	0.0004	-1.9694	Virginia	5.0000
39.0000	-2.8198	0.0000	-1.9303	Delaware	5.0000
40.0000	-2.6760	0.0002	-1.8687	Iowa	5.0000
41.0000	-2.6965	0.0000	-1.8044	Georgia	5.0000
42.0000	-2.8163	0.0000	-1.8016	Tennessee	5.0000
43.0000	-2.7873	0.0000	-1.5976	Texas	5.0000
44.0000	-2.8466	0.0000	-1.5429	Kentucky	5.0000
45.0000	-2.7380	0.0002	-1.3800	North Carolina	5.0000
46.0000	-3.0459	0.0000	-1.3576	Maine	5.0000

47.0000	-2.3958	0.0030	-1.2126	Florida	5.0000
48.0000	-2.8438	0.0034	-0.8707	Alaska	5.0000
49.0000	-2.5802	0.0590	-0.7595	South Carolina California	5.0000
50.0000	-3.2785	0.0558	-0.7310	South Dakota	5.0000

Figs. 1 to 6 present the time paths of energy consumption in each state. The structural shifts in the data trend can be clearly observed. Allowing for structural breaks in testing a unit root (and/or stationarity) seems sensible. The estimated time paths of the time-varying intercepts are also shown in Figs. 1 to 6. Further examination of the figures indicates that all Fourier approximations are reasonable and support the notion of long swings in energy consumption processes.

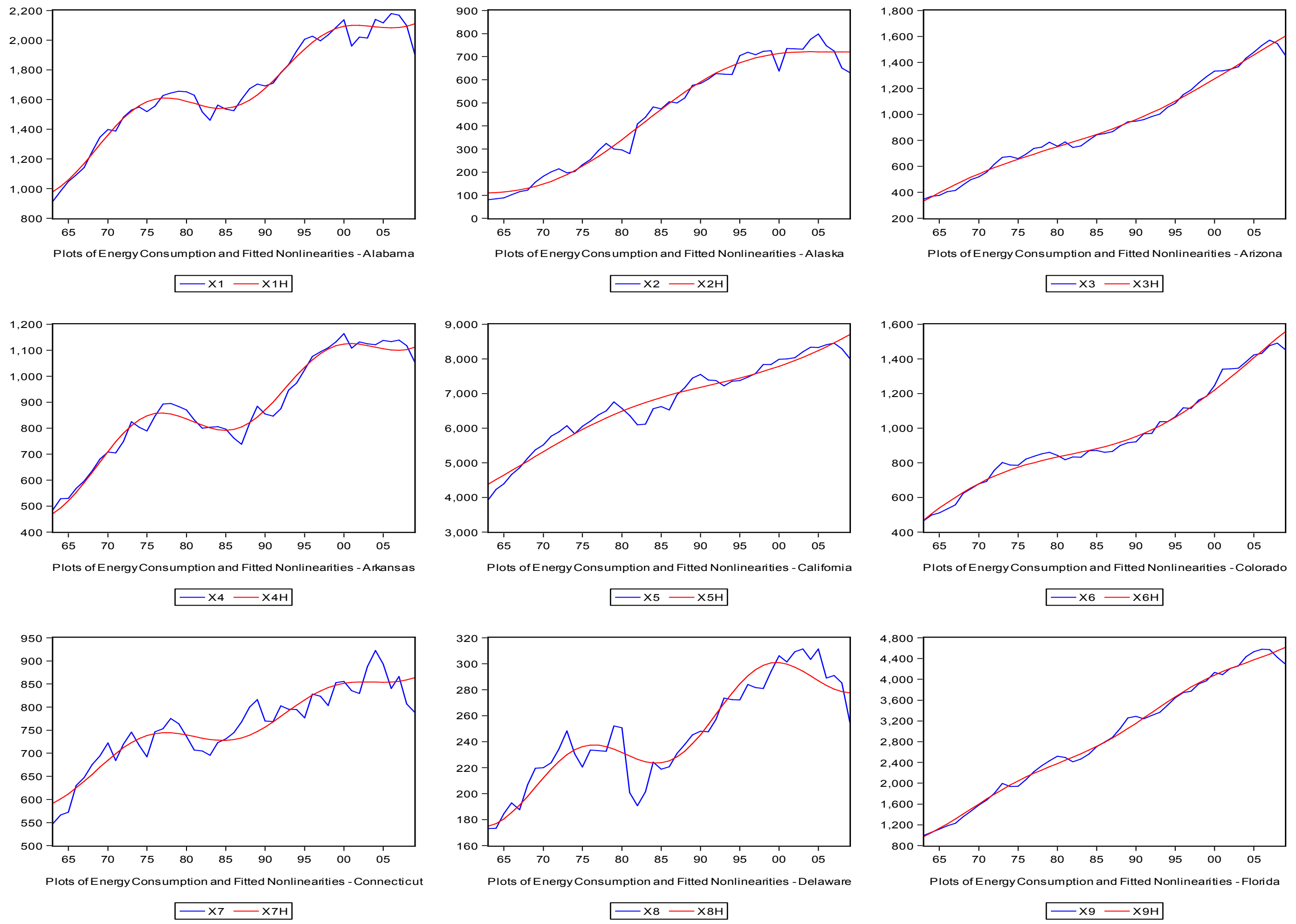


Fig. 1 Plots of Energy Consumption and Fitted Nonlinearities (1 to 9 States)

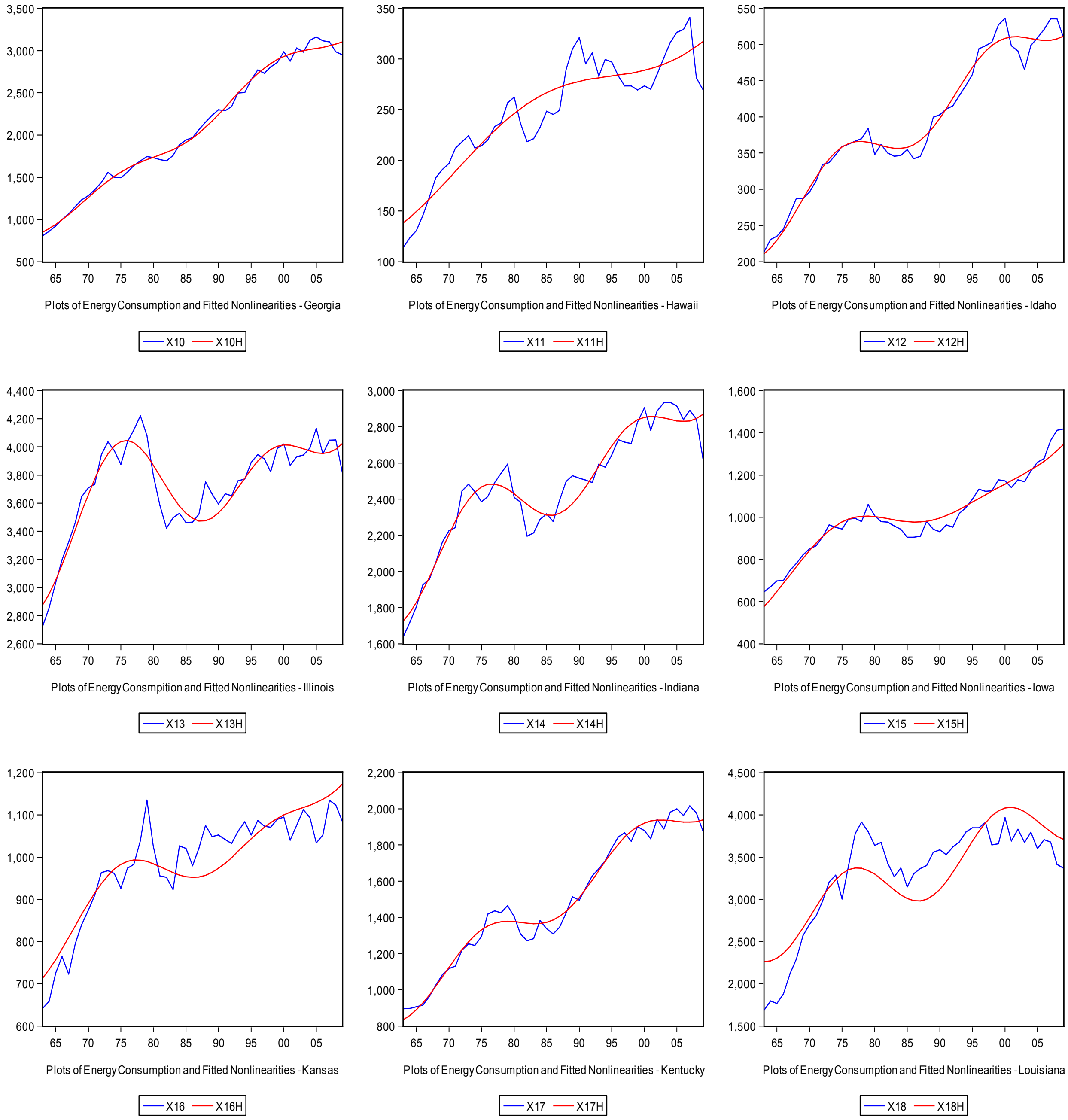


Fig. 2 Plots of Energy Consumption and Fitted Nonlinearities (10 to 18 States)

Fig. 3 Plots of Energy Consumption and Fitted Nonlinearities (19 to 27 States)

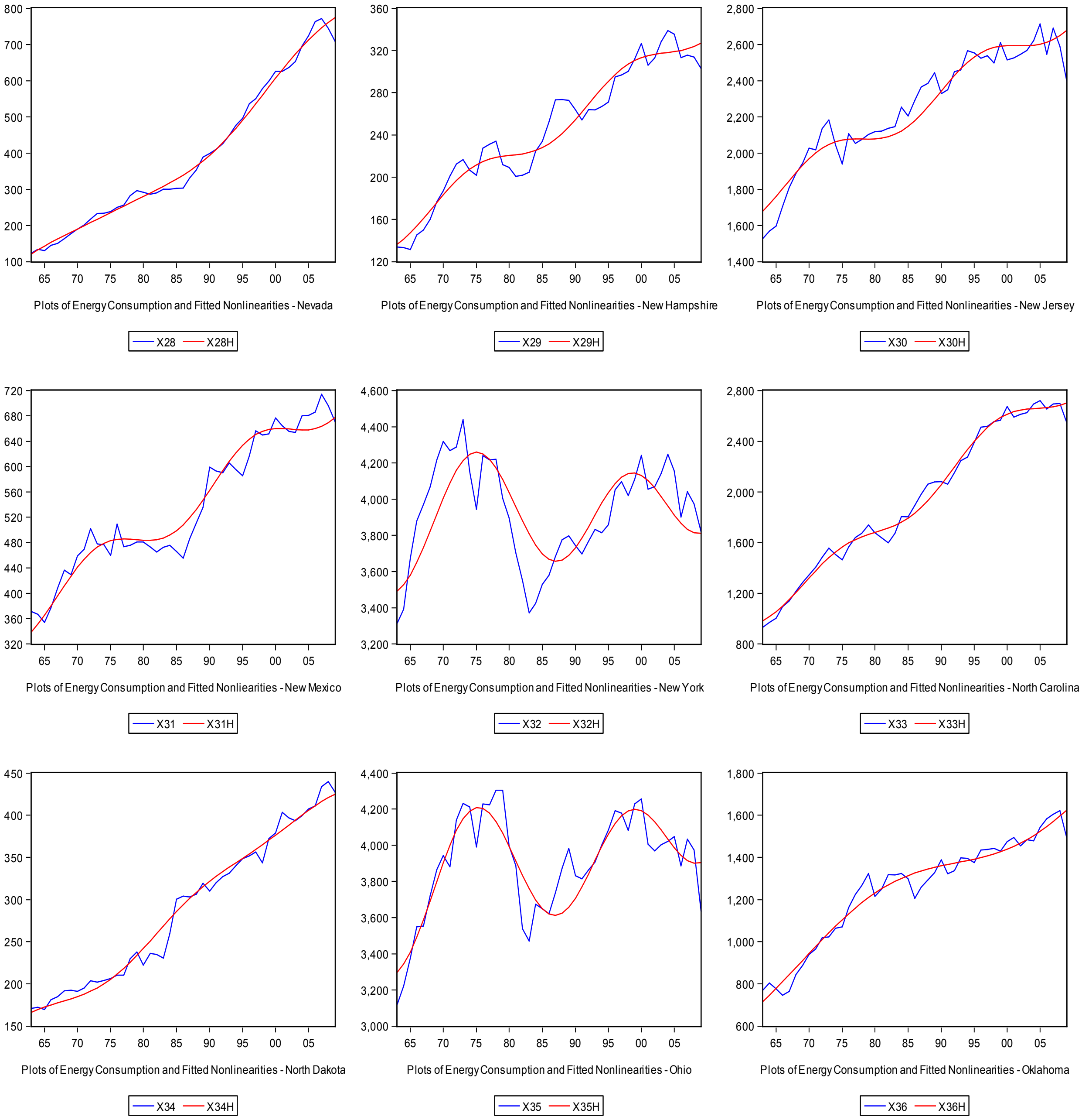


Fig. 4 Plots of Energy Consumption and Fitted Nonlinearities (28 to 36 States)

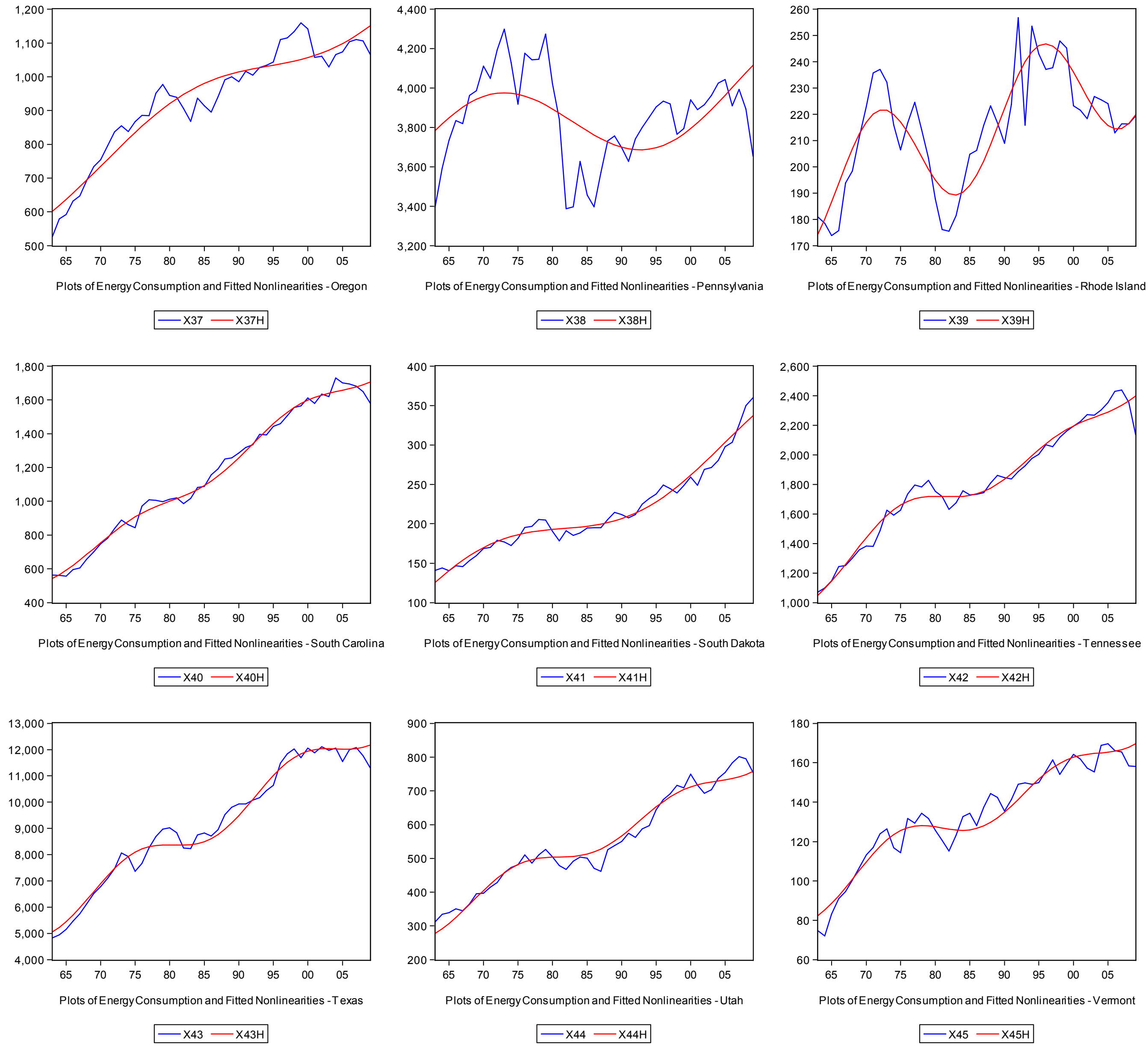
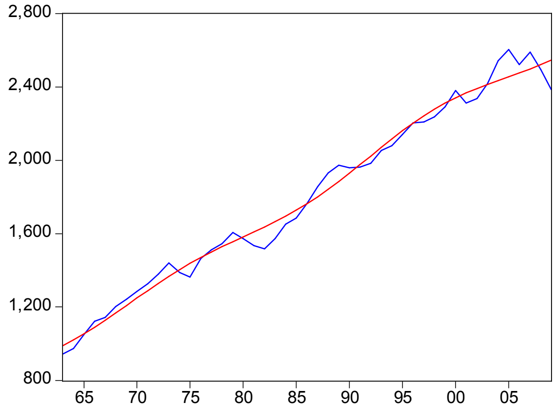
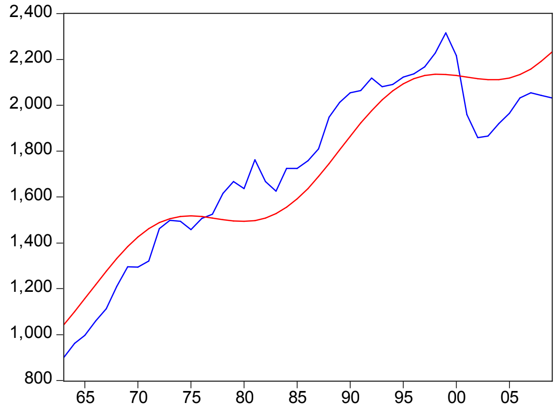


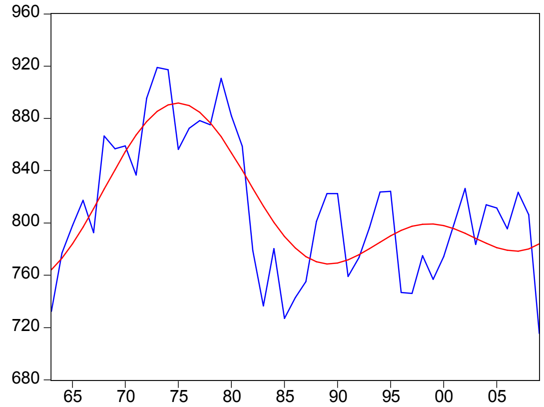
Fig. 5 Plots of Energy Consumption and Fitted Nonlinearities (37 to 45 States)



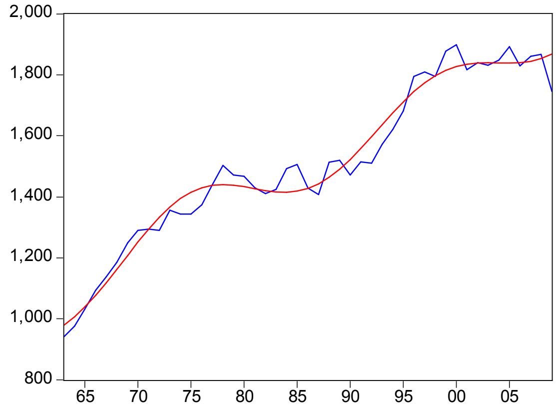
Plots of Energy Consumption and Fitted Nonlinearities - Virginia



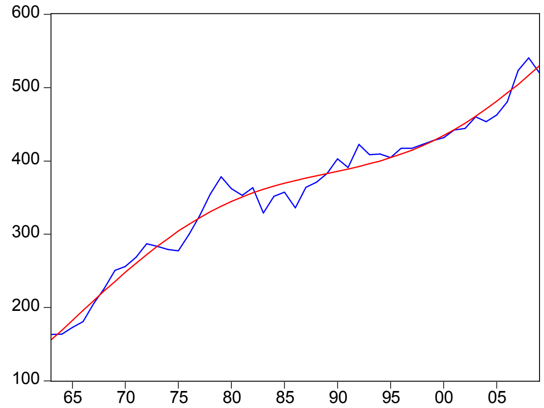
Plots of Energy Consumption and Fitted Nonlinearities - Washington



Plots of Energy Consumption and Fitted Nonlinearities - West Virginia



Plots of Energy Consumption and Fitted Nonlinearities - Wisconsin



Plots of Energy Consumption and Fitted Nonlinearities - Wyoming

Fig. 6 Plots of Energy Consumption and Fitted Nonlinearities (46 to 5o States)

C. Economic and Policy Implications

The findings of this research have several important policy implications. First, if the data were erroneously treated as non-stationary and the causality tests for energy consumption and other macroeconomic variables (such as GDP) were applied to the first difference, then spurious causality would result. Second, overwhelming evidence in favor of the I(0) stationary hypothesis is found, implying that the shocks in energy consumption are only temporary. This result also implies that after a major structural change in energy markets, energy consumption will return to its original equilibrium over a period of time. When energy consumption deviates from the trend because of a shock in the energy market, then governments should not adopt unnecessary targets. Third, the stationarity properties of energy consumption have important implications on modeling the relationship between energy consumption and macroeconomic variables. Fourth, the stationary behavior of the energy consumption also has important implications on forecasting energy consumption. Forecasts of energy consumption are crucial for the formulation of energy policies. Considering the importance of having a safe energy supply for economic growth, reliable forecasts of energy demand should be obtained to formulate future energy policies. If energy consumption is a stationary process, then future energy demand can be forecasted based on past observations. However, if energy consumption is characterized by a stochastic trend, then past observations would be useless in forecasting future trends in energy demand. The fact that energy consumption shows I(0) stationarity indicates that the series should be able to forecast future trends in energy demand based on past behavior.

V. Conclusions

This study applied SPSM proposed by Chortareas and Kapetanios (2009) to investigate the time-series properties of energy consumption in 50 US states from 1963 to 2009. SPSM classifies the entire panel into a group of stationary series and a group of non-stationary series to identify how many and which series in the panel are stationary processes. Empirical results from SPSM combined with panel KSS unit root test (Ucar and Omay, 2009) and a Fourier function indicate that energy consumption in all the 50 US states are stationary. Our results have important policy implications for the 50 US states.

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