# Is Real Per Capita State Personal Income Stationary? New Nonlinear, Asymmetric Panel-Data Evidence

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## ABSTRACT

This paper re-examines the stochastic properties of US State real per capita personal income, using new panel unit-root procedures. The new developments incorporate non-linearity, asymmetry, and cross-sectional correlation within panel data estimation. Including nonlinearity and asymmetry finds that 43 states exhibit stationary real per capita personal income whereas including only nonlinearity produces the 42 states that exhibit stationarity. Stated differently, we find that 2 states exhibit nonstationary real per capita personal income when considering nonlinearity, asymmetry, and cross-sectional dependence.

**Key words**: Nonlinear, Panel Unit Root, Asymmetry, Cross-Sectional Dependence, Sieve Bootstrap

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## 1. Introduction

The pioneering empirical analysis of Nelson and Plosser (1982) revolutionized macroeconomic analysis, in general, and business cycle investigations, in particular. The debate between Keynesian and real business cycle proponents hinges in large part on whether real output follows a stationary or nonstationary process. Thus, much research focuses on strengthening the power of tests to distinguish between stationary and nonstationary macroeconomic time series.

One of the most frequently investigated variables is real GDP or real GDP per capita. This study investigates the stationarity properties of the US State real per capita personal income. Few researches investigate this variable at state level. In an exception, Romero-Ávila (2012) examines the nonstationarity of real per capita state personal income using the Carrion-i-Silvestre et al. (2005) (CBL) test for nonstationarity, which extends the Hadri (2000) test to a panel-data setting by allowing multiple breaks in the intercept and trend. That is, Romero-Ávila (2012) tests the null hypothesis of stationarity with a linear, symmetric panel-data test that permits multiple breaks in the mean and slope of the time trend and controlling for cross-sectional dependence. He examines the 48 contiguous states and the District of Columbia, using annual data from 1929 to 2004.

Romero-Ávila (2012) finds that the Hadri test rejects the null of stationarity at the 1- and 10-percent levels, where the 10-percent level rejection uses Monte Carlo simulation to generate the finite sample critical values. Additionally, he finds that the CBL test also rejects the null when the test accounts for multiple breaks in the intercept and trend at the 1-percent level, including the test based on the Monte Carlo simulated critical values. He then runs univariate tests of the Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) test on each state, finding that 41 states cannot reject the null of stationarity and 8 states -- Alabama, Arkansas, Florida, Kentucky, Maryland, Oklahoma, Virginia, and Wyoming -- do reject the null at the 5- or 10-

percent levels. He then reruns the pooled test for only the 41 states that report univariate stationarity, finding that the pooled test cannot reject the null hypothesis. Further, he reruns the pooled test for all contiguous states and the District of Columbia, dropping, in turn, each of the 8 states that rejected the null hypothesis in the univariate tests. He concludes that Wyoming alone causes the rejection of the null hypothesis of stationarity in the full panel test that allows for multiple structural breaks and controls for cross-sectional dependence.[1]

The approach adopted by Romero-Ávila (2012) possesses some shortcomings with respect to panel-data analysis and the identification of the data generation process. Taylor and Sarno (1998) note that panel unit-root tests may reject joint nonstationarity even if only one of the processes exhibits stationarity under the alternative hypothesis. If the test rejects the unit-root null, it still proves important to distinguish between nonstationary and stationary series within the panel. To resolve this problem, Choartareas and Kapetanios (2009), propose a sequential panel selection method (SPSM) that allows the identification of the stationary series. The Romero-Ávila (2012) method creates some deficiencies, because it does not account for the panel properties of the sample. Besides, with the Romero-Ávila (2012) approach, no unique way exists to determine and separate the stationary and non-stationary series in the sample. Therefore, the SPSM method can identify such stationary or nonstationary series in the panel sample. Furthermore, the Romero-Ávila (2012) paper does not offer a test to determine whether the various series experience structural breaks or nonlinearities. This issue of nonlinearity represents another shortcoming of the Romero-Ávila (2012) approach. For this purpose, we use the linearity test of Luukkonen et al. (1988) to identify the appropriate process for the real per capita state

[1] Why Wyoming exerts such influence over the pooled test remains an unanswered question. Further, finding non rejection of the null hypothesis of stationarity does not necessarily mean that all states in the pool exhibit stationary real per capita personal income. In fact, the univariate tests suggest that 8 states exhibit nonstationary behavior.

personal income. This linearity test identifies whether the series exhibits state-dependent or time-varying nonlinearity. We apply these additional preliminary tests to our sample.

These linearity tests determine that at the 31 of the 48 states exhibit state-dependent (regime-wise) nonlinearity and 16 states exhibit time-varying nonlinearity, where 11 states exhibit both significant state-dependent and time-varying nonlinearity. Hence, the linearity test suggests that only 5 of the 48 states achieve a superior model with a structural break. From these linearity tests, we can conclude that the Romero-Ávila (2012) structural-break approach does not prove suitable for our sample. As an additional robustness test of our linearity test results that sheds more light on the real data generation, we further estimate the nonlinear trend functions of the states by using the Leybourne et al (1998) (LNV) smooth structural-break methodology[2]. The nonlinear trend functions appear linear, since we include a long span data in our sample. Some structural shifts exist in the trends, but these shifts do not seem robust. This effect relates to the dimension of the sample. For example, if the same shift occurred in a small sample (time dimension), then nonlinear least squares identifies this shift as an important data generation characteristic and it receives a high weight in the nonlinear least squares procedure. At the same time, in a longer sample (time dimension), the nonlinear least squares estimation will weight this structural break less heavily than in the small sample (time dimension). The linearity results also support this view as only 16 out of 48 states exhibit time-varying nonlinearity. Thus, we conclude that we can well approximate these nonlinear trend functions by linear trend functions. That is, the nonlinearity tests and the LNV type nonlinear trend estimation allow us to conclude that the state-dependent nonlinearity best suits our sample data generation structure.

[2] We can also use the Kalman filter approach, or the Fourier transformation approach to detect smooth structural breaks.

Romero-Avila (2012) assumes that the long-run equilibrium occurs at a nonlinear trend attractor, which implies time-varying nonlinearity. Romero-Avila (2012) does not consider any prior identification tests to identify the data generating process. That is, the deterministic component of the stochastic process embodies the nonlinearity with the state variable time and the stationarity of the stochastic process investigates whether the process converges linearly to this nonlinear trend attractor. Thus, the mechanism implies that the convergence to this nonlinear long-run equilibrium occurs linearly and symmetrically. When we apply prior identification tests, we conclude that we can best represent our sample with nonlinear asymmetric convergence to a linear trend attractor.

Unlike Romero-Ávila (2012), who postulated the emergence of nonlinearity due to structural breaks, we investigate whether nonlinearities exist in the form of threshold effects, whereby the output dynamics follows a nonstationary process at some threshold, but a stationary outside of that threshold. In addition, we also incorporate asymmetric response depending on whether output falls above or below its trend. The testing for stationarity that incorporates nonlinearity and asymmetry makes sense in that the conventional view argues that the business cycle exhibits such behavior. For example, the observed business cycle in the US shows that expansions exhibit longer durations than recessions. The documentation of asymmetries in the business cycle appears in many papers, including Neftci (1984), Diebold and Rudebusch (1989), Hamilton (1989), and Sichel (1993). Our analysis focuses on real per capita state personal income. Much less work examines the business cycle at the state level (e.g., Carlino and Sill 2001 and Owyang, Piger, and Wall 2005). Thus, we use nonlinear symmetric and asymmetric panel unit root test in this study[3]

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[3] The low power of single-equation, unit-root tests leads to the development of panel unit-root tests by Levin, et al. (2002) (LLC) and Im, et al. (2003) (IPS), where the power of the test improved dramatically. Hadri developed the panel data equivalent to the

Depending on all the aforementioned issues, we employ two different, but related, tests of a unit-root null hypothesis, first with a nonlinear symmetric heterogeneous panel-data approach developed by Ucar and Omay (2009) (UO), which builds on the work of Kapetanios et al. (2003) and, second, with a nonlinear asymmetric heterogeneous panel-data approach developed by Emirmahmutoglu and Omay (2014) (EO), which builds on the work of Sollis (2009). In addition, we also test the real per capita Bureau of Economic Analysis (BEA) region personal income in a panel data framework as well as a univariate test for stationarity of national real per capita personal income, using the method of Sollis (2009), covering the annual period of 1929 to 2013.

We find, using the Chortareas and Kapetanios (2009) sequential panel selection method (SPSM), that 43 states exhibit stationarity from the EO test -- 42 states exhibit stationary real personal income per capita because of nonlinearity whereas the same 43 states exhibit stationarity because of nonlinearity and asymmetry. In other words, we find only 5 states that exhibit nonstationarity after we accommodate nonlinearity and asymmetry.

This paper proceeds as follows. Section 2 briefly describes the methods of the nonlinear and nonlinear asymmetric heterogeneous panel estimation introduced by UO (2009) and EO (2014), respectively. Section 3 describes the data and presents the econometric results. Section 4 concludes.

## 2. The Model and Testing Framework

*Preliminary Identification Tests*

In order to determine our testing framework, we employ some preliminary identification tests – tests for linearity, estimates of structural breaks using the Luukkonen et al (1988) method, and

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KPSS single-equation test, where stationarity is the null hypothesis. Carrion-i-Silvestre et al. (2005) (CBL) extend the Hadri (2000) test to a panel-data setting with multiple breaks in the intercept and trend. Ucar and Omay (2009) (UO) introduce nonlinear response by extending the KSS time-series unit-root test to a panel setting. Finally, Emirmahmutoglu and Omay (2014) (EO) extend the Sollis (2009) nonlinear panel-data unit-root test to include asymmetric adjustment.

tests for cross-sectional dependence. We start with the appropriate linear model. The linearity tests are complicated by the presence of unidentified nuisance parameter under the null hypothesis. To overcome this problem, we can replace the transition function with the appropriate Taylor approximation following the suggestion of Luukkonen et al (1988). The linearity test obtained from the first-order Taylor approximation results in the following auxiliary regression[4]

$$y_t = \beta_{0,0} + \beta_0^{'} x_t + \beta_{1,0} tv_t + \beta_1^{'} x_t tv_t + e_t . \quad (1)$$

where $tv_t$ denotes the transition variable. The null hypothesis of linearity implies that the parameters $\beta_{1,0}$ and $\beta_1^{'}$ of the auxiliary equation equal zero. We test this null hypothesis by a standard variable addition test. The test statistic, denoted as LM1, conforms to an asymptotic $\chi^2$ distribution with degrees of freedom $p+1$, where $p$ is the dimension of the vector $x_t$. Here, in our testing process, the vector $x_t$ contains the independent variables obtained from the Taylor approximation, whereas the state (transition) variable $tv_t$ is defined as $y_{t-1}$ for the nonlinear unit-root tests. The transition function is the composite function used in Solis (2009).

To estimate the nonlinear deterministic trend, we use model C of the Leybourne et al. (1998), which is given as follows:

$$y_t = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + \beta_2 t S_t(\gamma, \tau) + \varepsilon_t , \quad (2)$$

where $S_t(\gamma,\tau) = [1 + \exp\{-\gamma(t - \tau T)\}]^{-1}$ is the logistic smooth transition function based on a sample of size $T$, $\gamma > 0$, and $\tau$ determines the mid-point of transformation.

[4] For further details, see Luukkonen et al (1988).

For panel unit-root testing, the issue of cross-sectional dependence proves important in the testing procedure. We employ the cross-sectional dependence (CD) test of Pesaran (2004), which is given as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \quad (3)$$

where $\hat{\rho}_{ij}$ is the estimated correlation coefficient between error terms for the individuals $i$ and $j$.

*Cross-Sectionally Dependent Nonlinear Unit-Root Tests*

Since the UO test emerges as a special case of the EO test, we consider the EO test in this section. EO (2014) extends the test of Sollis (2009) to nonlinear asymmetric heterogeneous panels as follows:

$$\Delta y_{it} = G_{it}(\gamma_{1i}, y_{i,t-1})\{S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i}\}y_{i,t-1} + \varepsilon_{it}, \quad (4)$$

$$G_{it}(\gamma_{1i}, y_{i,t-1}) = 1 - \exp(-\gamma_{1i}\, y_{i,t-1}^{2}) \quad \gamma_{1i} \geq 0 \ \text{ for all } i \quad (5)$$

$$S_{it}(\gamma_{2i}, y_{i,t-1}) = [1 + \exp(-\gamma_{2i}\, y_{i,t-1})]^{-1} \quad \gamma_{2i} \geq 0 \ \text{ for all } i \quad (6)$$

where $\varepsilon_{it} \sim iid(0, \sigma_i^2)$. If $\gamma_{1i} > 0$ and $\gamma_{2i} \to \infty$, a large deviation of the state variable ($y_{i,t-1}$) exists and an ESTAR transition occurs between the central regime and outer regime model, where $\gamma_{1i}$ measures transition speed. For negative deviations of the state variable, the outer regime is $\Delta y_{it} = \rho_{2i} y_{i,t-1} + \varepsilon_{it}$ and for positive deviations, the outer regime is $\Delta y_{it} = \rho_{1i} y_{i,t-1} + \varepsilon_{it}$, where the transition functions take the extreme values 0 and 1, respectively, for these two cases. If $\rho_{1i} \neq \rho_{2i}$ for all $i$, the model generates asymmetric autoregressive adjustment.[5] Because of the

[5] Eq. (1) nests the panel symmetric ESTAR specification of the UO (2009) test when $\rho_{1i} = \rho_{2i} = \rho_i$ for all *i*. That is, the UO test imposes the restriction that no asymmetry exists exogenously.

extreme assumption $\gamma_{2i} \to \infty$, the logistic function reduces to a simple step function and behaves like the TAR model. Asymmetry can also occur for small and moderate values of $\gamma_{2i}$. At the other extreme for $\gamma_{2i}$ (*i.e.*, $\gamma_{2i} \to 0$), no matter the values of $\rho_{1i}$ and $\rho_{2i}$, the composite function $G_{it}(\gamma_{1i}, y_{i,t-1})\{S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i}\}$ becomes symmetric since $S_{it}(\gamma_{2i}, y_{i,t-1}) \to 0.5$ for $\forall t$ and $\forall i$. Therefore, this feature can test whether the series exhibits symmetric or asymmetric dynamics.

For serially correlated errors in Eq. (4), EO (2014) extend Eq. (4) to allow for higher order dynamics as follows:

$$\Delta y_{it} = G_{it}\left(\gamma_{1i}, y_{i,t-1}\right)\left\{S_{it}\left(\gamma_{2i}, y_{i,t-1}\right)\rho_{1i} + \left(1 - S_{it}\left(\gamma_{2i}, y_{i,t-1}\right)\right)\rho_{2i}\right\} y_{i,t-1} + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \qquad (7)$$

We can test the unit-root hypothesis against the alternative hypothesis of globally stationary symmetric or asymmetric ESTAR nonlinearity with a unit-root central regime by testing $H_0 : \gamma_{1i} = 0$ in Eq. (4). Unidentified parameters exist, however, under this null, that is, $\gamma_{2i}$, $\rho_{1i}$ and $\rho_{2i}$. Following the KSS test, EO (2014) address this problem by deriving an auxiliary model using a Taylor approximation. To solve the unidentified parameters problem, the composite function must contain two different transition functions and, therefore, Taylor approximations around both $\gamma_{1i} = 0$ and $\gamma_{2i} = 0$ are derived. Thus, EO (2014) follow Sollis (2009) and obtain the auxiliary equation in two steps within the panel context. Replacing $G_{it}(\gamma_{1i}, y_{i,t-1})$ in Eq.(4) with a first-order Taylor expansion around $\gamma_{1i} = 0$ gives

$$\Delta y_{it} = \rho_{1i}\gamma_{1i} y_{i,t-1}^3 S_{it}\left(\gamma_{2i}, y_{i,t-1}\right) + \rho_{2i}\gamma_{1i} y_{i,t-1}^3 \left(1 - S_{it}\left(\gamma_{2i}, y_{i,t-1}\right)\right) + \varepsilon_{it} \qquad (8)$$

Replacing $S_{it}(\gamma_{2i}, y_{i,t-1})$ in Eq.(7) with a first-order Taylor expansion around $\gamma_{2i} = 0$ gives

$$\Delta y_{it} = a(\rho_{2i}^{*} - \rho_{1i}^{*})\gamma_{1i}\gamma_{2i} y_{i,t-1}^{4} + \rho_{2i}^{*}\gamma_{1i} y_{i,t-1}^{3} + \varepsilon_{it} \tag{9}$$

where $a = 1/4$. Rearranging the coefficients as $\phi_{1i} = \rho_{2i}^{*}\gamma_{1i}$ and $\phi_{2i} = a(\rho_{2i}^{*} - \rho_{1i}^{*})\gamma_{1i}\gamma_{2i}$,[6] the following auxiliary equation emerges:

$$\Delta y_{it} = \phi_{1i} y_{i,t-1}^{3} + \phi_{2i} y_{i,t-1}^{4} + \varepsilon_{it} \tag{10}$$

EO (2014) extend Eq. (10) and its augmented version as follows:

$$\Delta y_{it} = \phi_{1i} y_{i,t-1}^{3} + \phi_{2i} y_{i,t-1}^{4} + \sum_{j=1}^{p_i} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{11}$$

The null hypothesis $H_0 : \gamma_{1i} = 0$ for all $i$ in Eq.(1) becomes $H_0 : \phi_{1i} = \phi_{2i} = 0$ for all $i$ in the auxiliary model. EO (2014) compute the proposed test statistic by taking the average of the individual $F_{i,AE}$ statistics for the AESTAR processes. Thus,

$$\bar{F}_{AE} = N^{-1} \sum_{i=1}^{N} F_{i,AE}. \tag{12}$$

Since individual $F_{i,AE}$ exhibits a non-standard $F-$distribution, the panel $\bar{F}_{AE}$ test statistic also exhibits a non-standard distribution. EO (2014) compute exact critical values of $\bar{F}_{AE}$ via stochastic simulation for different values of *N* and *T*. On the other hand, if we reject the unit-root hypothesis that $\phi_{1i} = \phi_{2i} = 0$ for all $i$, then we can test the null hypothesis of symmetric ESTAR nonlinearity against the alternative of asymmetric ESTAR nonlinearity. That is, we test $H_0 : \phi_{2i} = 0$ for all $i$ against $H_1 : \phi_{2i} \neq 0$ in Eq. (11). Under the symmetric null hypothesis, Since Sollis (2009) proposes using the individual $t-$statistics ($t_{i,AE}^{as}$) with standard $t-$distribution, EO (2014) compute $\bar{t}_{AE}^{as}$, in the panel framework, taking the average of the individual statistics, which have a standard distribution.

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[6] Our notation follows that in Emirmahmutoglu and Omay (2014).

If the disturbances are not independent, then the limit distributions of the test statistics proposed no longer remain valid, given cross correlations among the cross section units. Therefore, EO (2014) use the Sieve bootstrap methodology proposed by Chang (2004) to obtain the empirical distributions of $\overline{F}_{AE}$ and $\overline{t}_{AE}^{as}$ test statistics.

## 3. Real per Capita Personal Income

This paper improves over the traditional panel-data testing procedures that assume linearity, symmetry, and cross-sectional independence. Therefore, our testing procedure incorporates nonlinearity, asymmetry within a heterogeneous panel context via the sieve bootstrap method. Our proposed panel unit-root test appears in Eq. (4). Section 2 derives that precise estimating form as shown in Eq. (11).

The supporting identification test for our testing procedure are employed and given in the Appendix. As indicated in Tables A1 and A2 in the Appendix, we reject the null of no cross-sectional dependence at conventional levels of significance both for the case of the 48 contiguous states as well as the aggregated census regions by using the test in equation (3). Clearly, these results provide support for our decision to use a panel-data framework rather than a pure time-series structure to test for the unit-root properties of the real personal per capita income. On the other hand we also employ the linearity test in equation (1) and report the linearity test results in Table A3 in the Appendix. These results suggest that the best model for the data generation process is state-dependent nonlinearity. In addition, we estimate the nonlinear trend using equation (2), support the results reported in Table A3 in the Appendix. We also graph the estimation results in Figure A1 in the Appendix.

We prove that real per capita state personal income potentially follows an asymmetric, nonlinear, and cross-sectional dependent stationary process. We compare and contrast three different unit-root tests that all use sieve bootstrap technique – the IPS (2003, $\bar{t}_{IPS_B}$) linear, symmetric test, the UO (2009, $\bar{t}_{NL}$) nonlinear, symmetric test, and the EO (2014, $\bar{F}_{AE}$ and $\bar{t}_{AE}^{as}$) nonlinear, asymmetric test. We apply the various tests to the natural logarithms of annual real per capita state personal income of the 48 contiguous states over the 1929 to 2013 sample period. Note that we deflate the nominal personal per capita state personal income by the consumer price index (CPI) of the overall US economy to obtain the real counterpart of the variable, given that state-level CPI is not available for the period under consideration. As with the nominal personal per capita income of the states, the CPI data also comes from the BEA.

Table 1 reports the results of the tests applied using the sieve bootstrap method outlined in EO (2014). We use the empirical distributions of the tests generated by 5000 replications to obtain their *p*-values. For all tests, we choose the lag length using the Swartz-Bayesian information criterion (SBIC).

We see that two of the three tests -- $\bar{F}_{AE}$, $\bar{t}_{IPS_B}$, and $\bar{t}_{NL}$ -- can reject the null hypothesis of nonstationarity against the alternative of globally stationary nonlinear symmetric or asymmetric process. These results establish that the real data generating process of real per capita state personal income follows either a nonlinear or a nonlinear and asymmetric process. Thus, panel unit-root tests that do not incorporate nonlinearity, asymmetry, and cross-sectional dependence may generate misleading findings.

Taylor and Sarno (1998) argue that panel unit-root tests may reject joint nonstationarity even if only one of the processes exhibits stationary under the alternative hypothesis. If we reject the unit-root null, we need to distinguish between nonstationary and stationary series. We adopt the sequential panel selection method (SPSM) in Chortareas and Kapetanios (2009) (CK) to identify the stationary series in the panel of observations[7].

The SPSM procedure of CK (2009) proceeds as follows:[8] First, we estimate using all series in the panel and apply the unit-root test to the full sample. If we cannot reject the unit-root null, then we stop and accept nonstationarity of the panel. If we reject the null, then we continue to other steps. Second, we drop the series with the maximum significant $F_{i,AE}$ statistic, which indicates the state with the strongest evidence for stationarity, repeat the analysis for the remaining panel data set. We end when the individual $F_{i,AE}$ proves insignificant.

Tables 2 reports the results of the SPSM findings for the $F_{i,AE}$ and $\overline{t}_{i,AE}^{as}$ tests while Table 3 reports the SPSM findings for the $\overline{t}_{i,NL}$ tests. In Table 2, we reject linear nonstationarity against the alternative of stationary ESTAR nonlinearity with the $F_{i,AE}$ for 43 states. Further, we reject with the $\overline{t}_{i,AE}^{as}$ test the null hypothesis of symmetric ESTAR nonlinearity against the alternative of stationary asymmetric ESTAR nonlinearity for 43 states. Finally, in Table 3, we reject linear nonstationarity against the alternative of stationary nonlinearity for 42 states.[9]

Comparing the EO (2014) and UO (2009) tests of the panel unit-root null hypothesis, we see that the EO and UO tests nearly encompass each other. More specifically, the $F_{i,AE}$ and $\overline{t}_{i,AE}^{as}$ tests identify 43 states that reject nonstationarity. The $\overline{t}_{i,NL}$ symmetric, nonlinear panel test

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[7] The steps of the SPSM procedure are as follows. First, estimate the model for all the series in the panel. If the unit root null is not rejected, then accept the nonstationary hypothesis and stop. In this case, all the series in the panel are found to be non-stationary. On the contrary, if the null is rejected, go to Step 2. Second, drop the series with the maximum $F_{i,AE}$ statistic, which shows the strongest evidence in favor of stationarity and go to Step 3. Third, return to Step 1 for the remaining series, or stop if all series are removed from the panel.

[8] Since we cannot reject the unit-root null for the $IPS_B$ tests, we cannot use the SPSM procedure for these tests.

[9] The EO test implicitly sets $\rho_1 = \rho_2$ exogenously.

identifies 42 states that reject the null hypothesis. The $F_{i,AE}$ and $\bar{t}^{as}_{i,AE}$ tests identify Arizona, Connecticut, Delaware, and Georgia as rejecting the null, whereas the $\bar{t}_{i,NL}$ test does not. Further, the $\bar{t}_{i,NL}$ symmetric, nonlinear panel test identifies that Kentucky, North Carolina, and South Carolina reject the null hypothesis of nonstationarity, but the $F_{i,AE}$ and $\bar{t}^{as}_{i,AE}$ tests do not.[10]

In sum, either the EO or the UO test, or both identify 46 states that reject the null hypothesis of nonstationarity. Nevertheless, 2 states still do not reject either null of nonstationarity – California and Wyoming. The inability to reject nonstationarity for Wyoming proves consistent with Romero-Ávila (2012), who finds that Wyoming alone causes the rejection of the null hypothesis of stationarity in the full panel test that allows for multiple structural breaks and controls for cross-sectional dependence. Our finding for California differs from Romero-Ávila (2012). The linearity test and the nonlinear trend estimations in the Appendix also confirm these results.

Considering an alternative level of aggregation, we redid the four tests -- $\bar{F}_{AE}$, $\bar{t}^{as}_{AE}$, $\bar{t}_{NL}$, and $\bar{t}_{IPS_B}$ -- using the eight BEA regions as the unit of analysis.[11] Table 4 reports the findings for the full panel estimates for the eight BEA regions. Once again, we find that two of the three tests -- $\bar{F}_{AE}$, and $\bar{t}_{NL}$ -- can reject the null hypothesis of nonstationarity against the alternative of

[10] In the symmetry cases, the UO test possesses more power than the EO test, since we estimate more parameters with the EO test. That is, although the EO test nests the UO test, the power of the UO test exceeds that of the EO because of symmetry. Thus, we identify these three states as stationary.

[11] The BEA regions are defined as follows: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont); the Mideast (Delaware, District of Columbia, Maryland, New Jersey, New York, and Pennsylvania); the Great Lakes (Illinois, Indiana, Michigan, Ohio, and Wisconsin); the Plains (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota); the Southeast (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia); the Southwest (Arizona, New Mexico. Oklahoma, and Texas); the Rocky Mountain (Colorado, Idaho. Montana, Utah, and Wyoming); and the Far West (Alaska, California, Hawaii, Nevada, Oregon, and Washington).When we use the data for BEA regions, Alaska and Hawaii enter the data for the Far West region and the District of Columbia enters the Mideast region. We do not consider these three "states" in our prior analysis.

globally stationary nonlinear symmetric or asymmetric process. Tables 5 reports the results of the SPSM findings for the $F_{i,AE}$ and $\overline{t}_{i,AE}^{as}$ tests while Table 6 reports the SPSM findings for the $\overline{t}_{i,NL}$ tests. In Table 5, we reject linear nonstationarity against the alternative of stationary ESTAR nonlinearity with the $F_{i,AE}$ for seven BEA regions. Only the Far West region cannot reject the null hypothesis. Further, we reject with the $\overline{t}_{i,AE}^{as}$ test the null hypothesis of symmetric ESTAR nonlinearity against the alternative of stationary asymmetric ESTAR nonlinearity for one BEA regions, the Far West again. Finally, in Table 6, we reject linear nonstationarity against the alternative of stationary nonlinearity for seven BEA regions. And again, only the Far West region cannot reject the null hypothesis. This proves consistent with our state by state findings, since we could not reject nonstationarity for California. California is the major component of the Far West region.

Finally for completeness, we examine the Sollis (2000) univariate test for nonlinear asymmetric nonstationarity using the aggregate real per capita personal income data from the BEA. The $\overline{F}_{AE}$ (=10.079) and $\overline{t}_{AE}^{as}$ (=1.808) both reject the null hypothesis of nonlinear, asymmetric nonstationarity at the one- and ten-percent levels, respectively.

## 4. Conclusion

This paper uses recently developed panel unit-root tests by EO (2014) and UO (2009) that allows for the simultaneous existence of nonlinear and asymmetric mean reversion within a panel context to test for the stationarity of real per capita state personal income for the 48 contiguous states in the US. The procedure tests whether a series exhibits a unit root against the alternative of globally stationary symmetric or asymmetric ESTAR nonlinearity. In addition, the tests accommodate cross-sectional dependence, using the sieve bootstrap algorithm. We compare the findings from these tests to the standard IPS (2003) panel test, where we also employ the sieve bootstrap algorithm.

Romero-Ávila (2012) finds that real per capita state personal income exhibits stationary behavior in the panel stationarity test of CBL (2005), which incorporates multiple breaks in the intercept and trend of the panel test. We consider nonlinear, asymmetric mean reversion in panel data tests that includes sieve bootstrapping developed recently by EO (2014) and UO (2009). Our findings generally support those of Romero-Ávila (2012), except that we find consistent evidence of nonstationary behavior for California and Wyoming. Moreover, the nonstationary behavior for California carries over to the Far West region. In light of this, an interesting extension of our work would use a hybrid testing process that accommodates nonlinearities both due to structural breaks and threshold effects. By using this newly proposed test, may resolve the stationarity problem of Wyoming and California.

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**Table 1. Panel Unit-Root Test Results for US State Real Personal per Capita Income**

| EO | | UO | IPS |
|---|---|---|---|
| $\bar{F}_{AE}$ | $\bar{t}_{AE}^{as}$ | $\bar{t}_{NL}$ | $\bar{t}_{IPS_B}$ |
| 6.493* | 1.668* | -2.733* | -1.461 |
| (0.000) | (0.033) | (0.000) | (0.511) |

Note: * and ** denote significance at the 5% and 10% levels, respectively, based on the sieve bootstrap p-values..

**Table 2. SPSM results based on EO Test for Real Personal per Capita Income**

| Sequence | $\bar{F}_{AE}$ | $\bar{t}_{AE}^{as}$ | Max individual F Stat. | I(0) Series | Sequence | $\bar{F}_{AE}$ | $\bar{t}_{AE}^{as}$ | Max individual F Stat. | I(0) Series |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 10.144* | 1.723* | 26.600 | Utah | 23 | 6.833* | 1.427* | 9.610 | Washington |
| 2 | 9.794* | 1.733* | 23.062 | Rhode Island | 24 | 6.722* | 1.464* | 8.444 | Oklahoma |
| 3 | 9.506* | 1.647* | 18.285 | Nevada | 25 | 6.650* | 1.439* | 8.352 | Ohio |
| 4 | 9.311* | 1.580* | 17.849 | New Mexico | 26 | 6.576* | 1.422* | 8.348 | Arizona |
| 5 | 9.117* | 1.583* | 16.248 | Delaware | 27 | 6.495* | 1.384* | 8.278 | Kansas |
| 6 | 8.951* | 1.577* | 16.130 | Massachusetts | 28 | 6.410* | 1.435* | 8.210 | Illinois |
| 7 | 8.780* | 1.521* | 15.788 | South Dakota | 29 | 6.320* | 1.414* | 8.156 | New Hampshire |
| 8 | 8.609* | 1.532* | 15.059 | Iowa | 30 | 6.224* | 1.481* | 8.119 | Vermont |
| 9 | 8.448* | 1.550* | 13.982 | New York | 31 | 6.119* | 1.520* | 7.959 | Florida |
| 10 | 8.306* | 1.510* | 13.598 | Tennessee | 32 | 6.010* | 1.478* | 7.920 | Georgia |
| 11 | 8.167* | 1.501* | 13.509 | Texas | 33 | 5.891* | 1.360* | 7.844 | Louisiana |
| 12 | 8.022* | 1.498* | 13.371 | Nebraska | 34 | 5.761* | 1.268* | 7.355 | Wisconsin |
| 13 | 7.874* | 1.478* | 12.550 | Pennsylvania | 35 | 5.647* | 1.266* | 7.200 | Indiana |
| 14 | 7.740* | 1.474* | 11.317 | Idaho | 36 | 5.528* | 1.292* | 6.835 | Virginia |
| 15 | 7.635* | 1.506* | 10.773 | New Jersey | 37 | 5.419* | 1.290* | 6.778 | Maine |
| 16 | 7.540* | 1.542* | 10.759 | Connecticut | 38 | 5.295* | 1.275* | 6.568 | Mississippi |
| 17 | 7.439* | 1.457* | 10.240 | Oregon | 39 | 5.168* | 1.340* | 6.261 | West Virginia |
| 18 | 7.349* | 1.484* | 10.204 | Michigan | 40 | 5.046* | 1.344* | 6.165 | Missouri |
| 19 | 7.254* | 1.481* | 10.102 | Montana | 41 | 4.907* | 1.296* | 5.980 | Maryland |
| 20 | 7.155* | 1.500* | 10.023 | Arkansas | 42 | 4.753** | 1.396* | 5.524 | Minnesota |
| 21 | 7.053* | 1.489* | 10.020 | Alabama | 43 | 4.625** | 1.292** | 5.250 | North Dakota |
| 22 | 6.943* | 1.493* | 9.814 | Colorado | | | | | |

Note: * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values.

**Table 3. SPSM results based on UO Test for Real Personal per Capita Income**

| Sequence | $\bar{t}_{NL}$ | Min individual t stat. | I(0) Series | Sequence | $\bar{t}_{NL}$ | Min individual t stat. | I(0) Series |
|---|---|---|---|---|---|---|---|
| 1 | -4.027* | -7.145 | Utah | 22 | -3.342* | -4.082 | Kansas |
| 2 | -3.960* | -5.751 | New Mexico | 23 | -3.314* | -4.062 | New Hampshire |
| 3 | -3.921* | -5.506 | South Dakota | 24 | -3.284* | -4.040 | Arkansas |
| 4 | -3.886* | -5.436 | Iowa | 25 | -3.252* | -3.964 | Vermont |
| 5 | -3.851* | -5.224 | Nebraska | 26 | -3.221* | -3.963 | Ohio |
| 6 | -3.819* | -5.203 | South Carolina | 27 | -3.188* | -3.876 | New York |
| 7 | -3.786* | -5.128 | North Carolina | 28 | -3.155* | -3.780 | Massachusetts |
| 8 | -3.753* | -4.968 | North Dakota | 29 | -3.124* | -3.683 | Indiana |
| 9 | -3.723* | -4.876 | Texas | 30 | -3.094* | -3.655 | Maine |
| 10 | -3.693* | -4.835 | Minnesota | 31 | -3.063* | -3.641 | Rhode Island |
| 11 | -3.663* | -4.793 | Tennessee | 32 | -3.029* | -3.587 | Mississippi |
| 12 | -3.633* | -4.772 | Idaho | 33 | -2.994* | -3.488 | Oklahoma |
| 13 | -3.601* | -4.692 | Pennsylvania | 34 | -2.961* | -3.436 | Virginia |
| 14 | -3.570* | -4.657 | New Jersey | 35 | -2.928* | -3.421 | Maryland |
| 15 | -3.538* | -4.504 | Oregon | 36 | -2.890* | -3.352 | Nevada |
| 16 | -3.509* | -4.399 | Montana | 37 | -2.851* | -3.322 | West Virginia |
| 17 | -3.481* | -4.378 | Washington | 38 | -2.808* | -3.311 | Wisconsin |
| 18 | -3.452* | -4.230 | Alabama | 39 | -2.758* | -3.219 | Florida |
| 19 | -3.426* | -4.227 | Louisiana | 40 | -2.707** | -3.158 | Kentucky |
| 20 | -3.398* | -4.197 | Michigan | 41 | -2.650** | -3.033 | Colorado |
| 21 | -3.370* | -4.115 | Illinois | 42 | -2.596** | -3.018 | Missouri |

Note: * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values.

**Table 4. Panel Unit Root Test Results**

| EO | | UO |
|---|---|---|
| $\bar{F}_{AE}$ | $\bar{t}^{as}_{AE}$ | $\bar{t}_{NL}$ |
| 9.251* | 1.654** | -3.764* |
| (0.000) | (0.000) | (0.000) |

Note: * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values.

**Table 5. SPSM results based on EO Test**

| Sequence | $\bar{F}_{AE}$ | $\bar{t}^{as}_{AE}$ | Max individual F Stat. | I(0) Series |
|---|---|---|---|---|
| 1 | 9.251* | 1.654* | 12.933 | Southwest |
| 2 | 8.789* | 1.615* | 11.498 | Mideast |
| 3 | 8.214* | 1.450* | 11.315 | Rocky Mountain |
| 4 | 7.639* | 1.454* | 9.102 | Plains |
| 5 | 6.861* | 1.505* | 8.278 | New England |
| 6 | 6.038* | 1.126 | 7.344 | Great Lakes |
| 7 | 5.167** | 1.380 | 6.364 | Southeast |

Note: * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values.

**Table 6. SPSM results based on UO Test**

| Sequence | $\overline{t}_{NL}$ | Min individual t stat. | I(0) Series |
|---|---|---|---|
| 1 | -3.764$^{*}$ | -4.539 | Southwest |
| 2 | -3.655$^{*}$ | -4.427 | Rocky Mountain |
| 3 | -3.523$^{*}$ | -4.035 | Plains |
| 4 | -3.338$^{*}$ | -3.879 | Great Lakes |
| 5 | -3.194$^{*}$ | -2.967 | Mideast |
| 6 | -2.954$^{*}$ | -2.614 | New England |
| 7 | -2.785$^{**}$ | -2.516 | Southeast |

Note: $^{*}$ and $^{**}$ denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values.

**Appendix:**

**Table A1. Cross-sectional dependence tests for aggregated by local area**

| | EO | UO | IPS |
|---|---|---|---|
| BP | 2922.8* | 2777.4* | 2642.4* |
| CD | 161.1* | 156.0* | 150.1* |

Note: * and ** denote significance at the 5% and 10% levels, respectively, for all CD tests, we use the residuals from related model. For example, to implement the CD-LM test for the EO model, we estimate the EO model and recover the residuals from that model. BP stands for the Breusch and Pagan (1980) test and CD stands for the Pesaran (2004) test.

**Table A2. Cross-sectional dependence (CD) tests for states depending on full sample**

| | EO | UO | IPS |
|---|---|---|---|
| BP | 962.6* | 925.5* | 863.8* |
| CD | 30.1* | 29.3* | 28.1* |

Note: * and ** denote significance at the 5% and 10% levels, respectively,

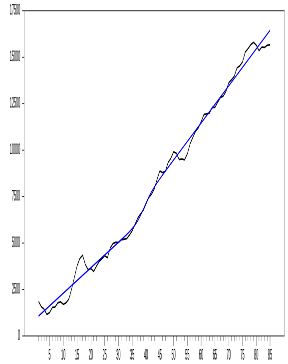
## Table A3. Linearity Tests

| States | State Dependent $s_t = y_{t-1}$ | | Time Varying $s_t = t$ | | Results |
|---|---|---|---|---|---|
| | F-Test | Significance | F-Test | Significance | |
| **Alabama** | 7.437 | 0.008 | 3.482 | 0.066 | SD*/TVǂ |
| **Arizona** | 2.962 | 0.089 | 3.338 | 0.071 | SDǂ/TVǂ |
| **Arkansas** | 3.574 | 0.062 | 2.411 | 0.124 | SD** |
| **California** | 1.117 | 0.294 | 1.744 | 0.190 | - |
| **Colorado** | 4.073 | 0.047 | 3.020 | 0.086 | SD**/TVǂ |
| **Connecticut** | 0.220 | 0.640 | 1.776 | 0.186 | - |
| **Delaware** | 0.027 | 0.870 | 2.917 | 0.092 | TVǂ |
| **Florida** | 6.380 | 0.013 | 3.996 | 0.049 | SD**/TV** |
| **Georgia** | 7.681 | 0.007 | 4.646 | 0.034 | SD*/TV** |
| **Idaho** | 22.311 | 0.000 | 1.943 | 0.167 | SD* |
| **Illinois** | 2.139 | 0.147 | 2.067 | 0.154 | - |
| **Indiana** | 3.626 | 0.060 | 2.440 | 0.122 | SD** |
| **Iowa** | 10.328 | 0.002 | 1.351 | 0.249 | SD* |
| **Kansas** | 2.981 | 0.088 | 1.951 | 0.166 | SDǂ |
| **Kentucky** | 2.927 | 0.091 | 2.985 | 0.088 | SDǂ/TVǂ |
| **Louisiana** | 4.063 | 0.047 | 1.847 | 0.178 | SD** |
| **Maine** | 1.122 | 0.293 | 2.226 | 0.140 | - |
| **Maryland** | 0.717 | 0.400 | 3.363 | 0.070 | TVǂ |
| **Massachusetts** | 1.431 | 0.235 | 2.350 | 0.129 | - |
| **Michigan** | 6.017 | 0.016 | 2.439 | 0.122 | SD** |
| **Minnesota** | 6.511 | 0.013 | 2.488 | 0.119 | SD** |
| **Mississippi** | 4.040 | 0.048 | 2.412 | 0.124 | SD** |
| **Missouri** | 4.154 | 0.045 | 3.436 | 0.067 | SD**/TVǂ |
| **Montana** | 3.260 | 0.075 | 1.760 | 0.188 | SDǂ |
| **Nebraska** | 14.654 | 0.000 | 1.392 | 0.241 | SD* |
| **Nevada** | 3.543 | 0.063 | 4.497 | 0.037 | SDǂ/TV** |
| **New Hampshire** | 1.554 | 0.216 | 3.477 | 0.066 | TVǂ |
| **New Jersey** | 1.048 | 0.309 | 3.103 | 0.082 | TVǂ |
| **New Mexico** | 4.846 | 0.031 | 2.447 | 0.122 | SD** |
| **New York** | 1.784 | 0.185 | 1.834 | 0.179 | - |
| **North Carolina** | 8.932 | 0.004 | 4.379 | 0.040 | SD |
| **North Dakota** | 1.856 | 0.177 | 1.366 | 0.246 | - |
| **Ohio** | 2.406 | 0.125 | 2.238 | 0.139 | - |
| **Oklahoma** | 3.035 | 0.085 | 1.023 | 0.315 | SD |
| **Oregon** | 3.851 | 0.053 | 2.566 | 0.113 | SD |
| **Pennsylvania** | 1.651 | 0.203 | 2.404 | 0.125 | - |
| **Rhode Island** | 1.197 | 0.277 | 1.463 | 0.230 | - |
| **South Carolina** | 7.179 | 0.009 | 4.645 | 0.034 | SD*/TV** |
| **South Dakota** | 5.678 | 0.020 | 1.375 | 0.244 | SD** |
| **Tennessee** | 7.307 | 0.008 | 3.225 | 0.076 | SD*/TVǂ |
| **Texas** | 2.970 | 0.089 | 2.016 | 0.159 | SDǂ |
| **Utah** | 3.710 | 0.058 | 2.166 | 0.145 | SDǂ |
| **Vermont** | 0.904 | 0.345 | 1.248 | 0.267 | - |
| **Virginia** | 4.299 | 0.041 | 4.646 | 0.034 | SD**/TV** |
| **Washington** | 2.127 | 0.149 | 2.766 | 0.097 | TVǂ |
| **West Virginia** | 4.447 | 0.038 | 1.876 | 0.175 | SD** |
| **Wisconsin** | 3.012 | 0.086 | 2.321 | 0.132 | SDǂ |
| **Wyoming** | 0.759 | 0.386 | 0.042 | 0.839 | - |
| **West Virginia** | 4.447 | 0.038 | 1.876 | 0.175 | SD** |

**Note:** The linearity tests obtained by using the Solis (2009) unit root test for time series. SD denotes the state dependent nonlinearity; TV denotes time varying nonlinearity and – means no nonlinearity captured at conventional significance levels. *, **, and **ǂ** denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3 reports the linearity test findings, using the Sollis (2009) unit-root test. Using the significance level, 31 of the 48 states exhibit state-dependent (regime-wise) nonlinearity and 16 states exhibit time-varying nonlinearity, where 11 states exhibit both significant state-dependent and time-varying nonlinearity. Finally, 12 states exhibit linearity at conventional significance levels. Except for three states, Rhode Island, Vermont, and Wyoming – the other nine states exhibit nonlinearity when we use the 20-percent significance level. We noted in the introduction that "approximating time-varying nonlinearity by using state-dependent (regime-wise) nonlinearity proves the better approach" based on our empirical findings. The test results find 36 of the 48 states exhibit nonlinear behavior with significance levels close to each other as we claimed in the introduction. Therefore, nonlinear panel unit-root tests or panel unit-root tests with structural break can successfully model long time spans of data without loss of any relevant information. On the other hand, Table A3 shows and we argue that the nonlinear and asymmetric test (EO 2014) provides a better test than a structural break type panel unit-root test.

**Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV)**



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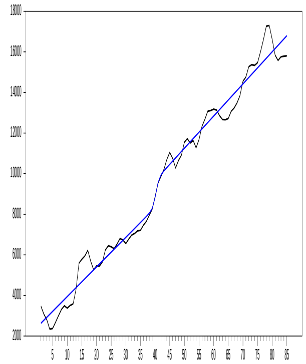

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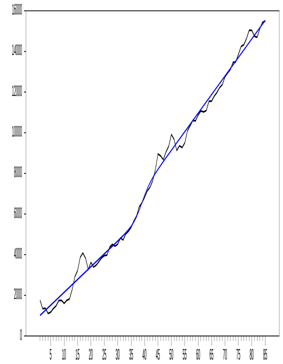

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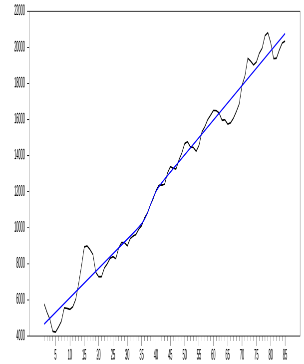

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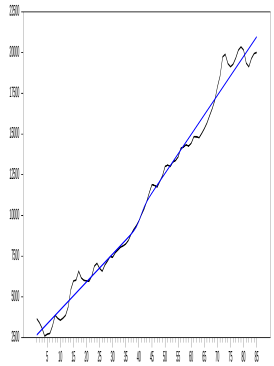

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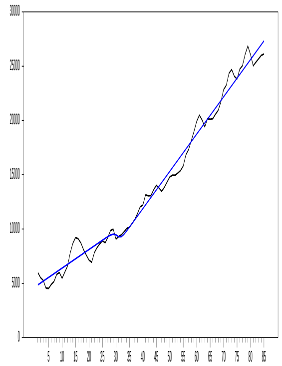

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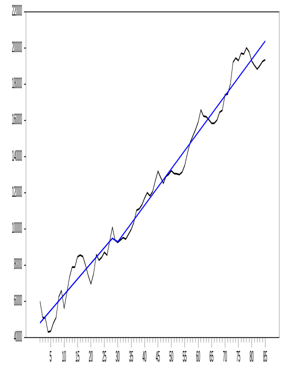

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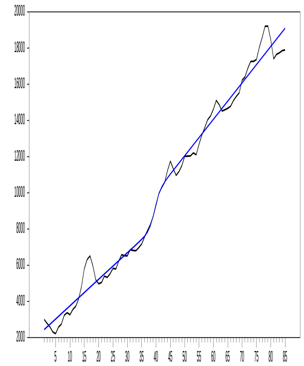

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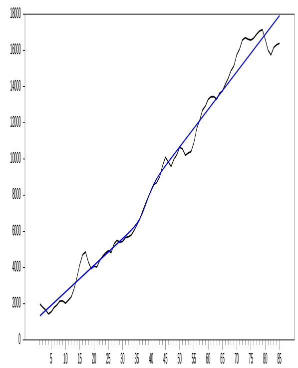

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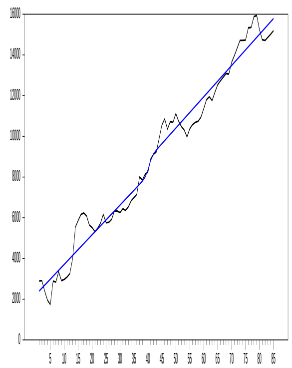

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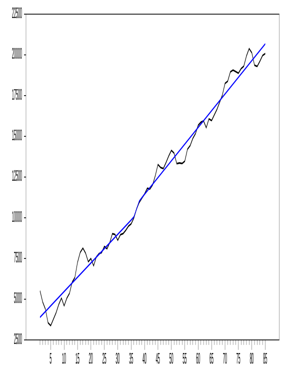

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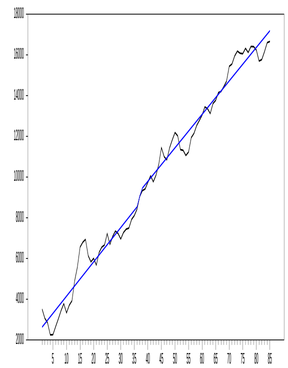
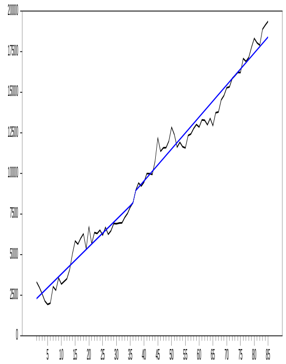
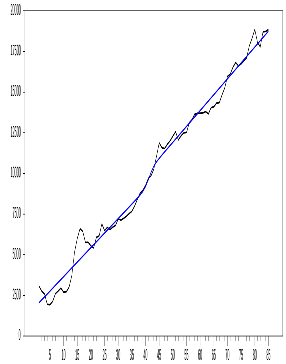


Indiana

**Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)**



Iowa



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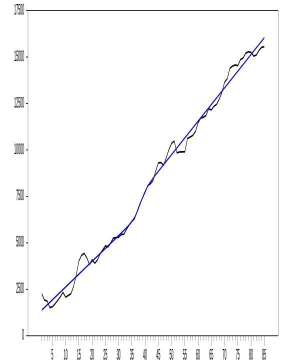

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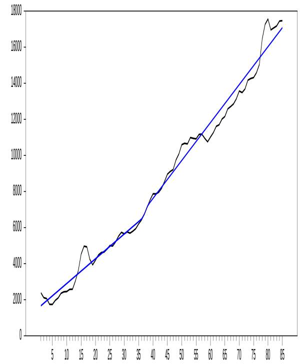

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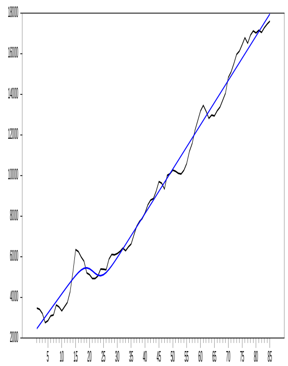

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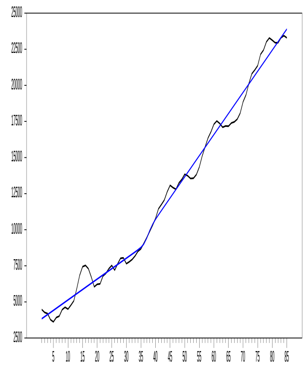

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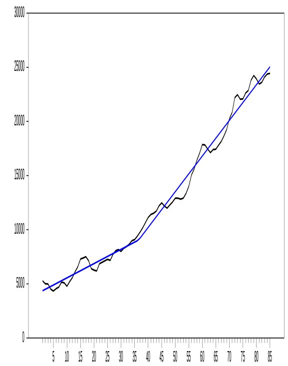

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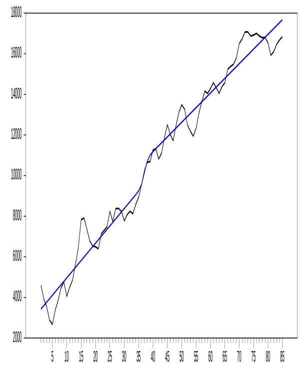
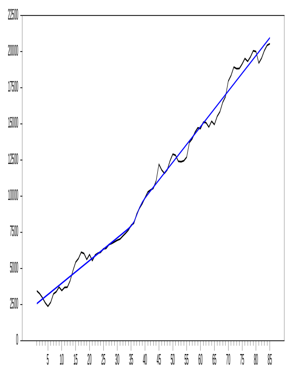
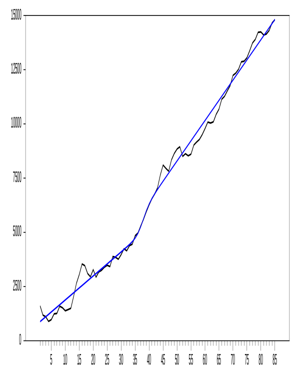


Michigan



Minnesota



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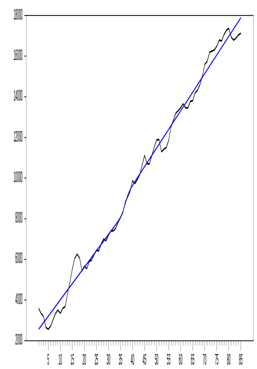

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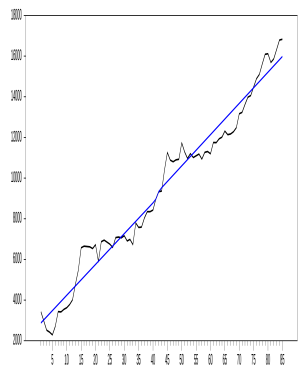
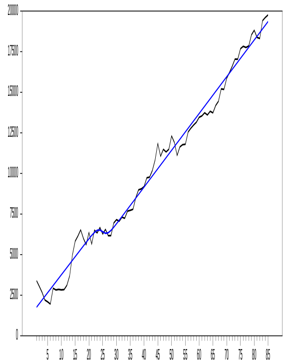
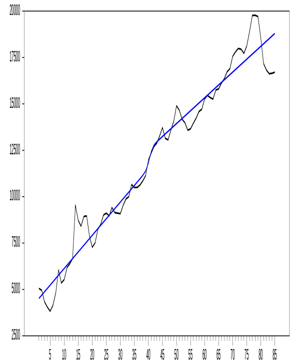


Montana

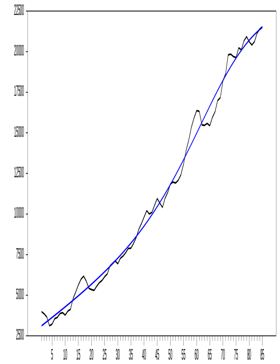
**Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)**



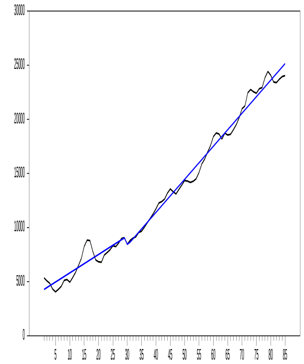
Nebraska



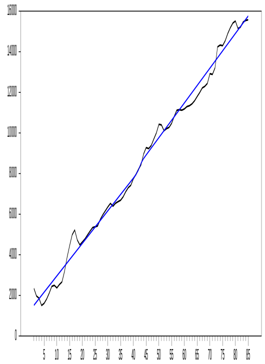
Nevada



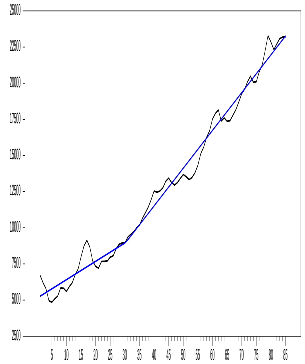
New Hampshire



New Jersey



New Mexico



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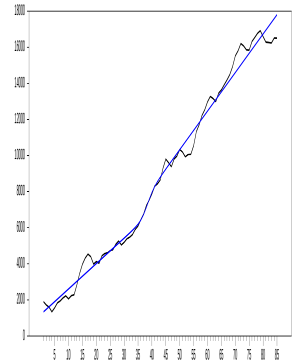
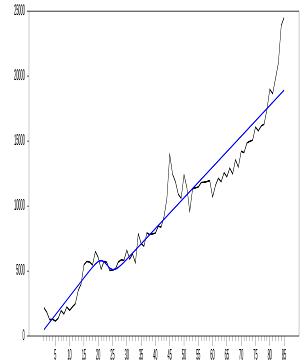
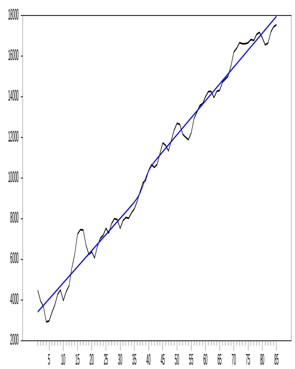


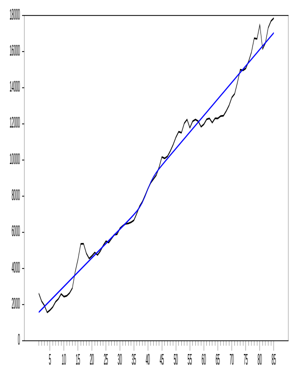
North Carolina



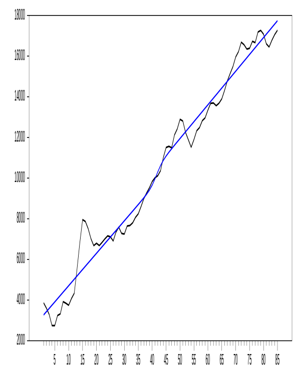
North Dakota



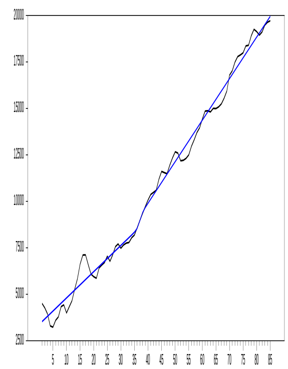
Ohio



Oklahoma

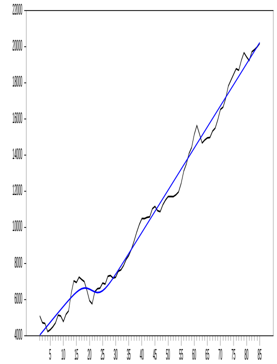


Oregon

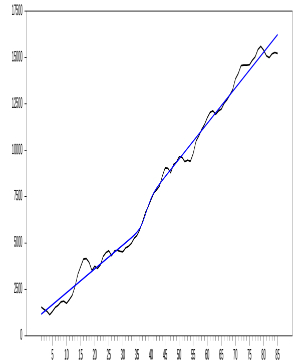


Pennsylvania

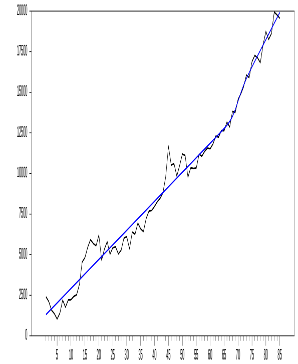
**Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)**



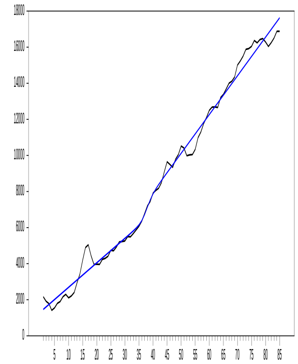
Rhode Island



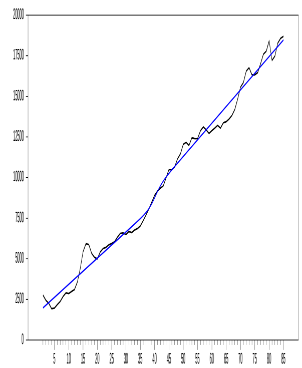
South Carolina



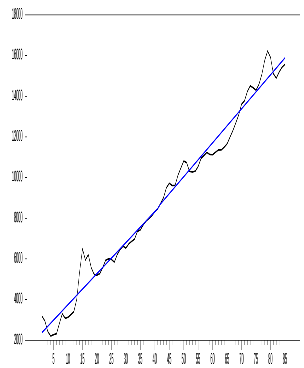
South Dakota



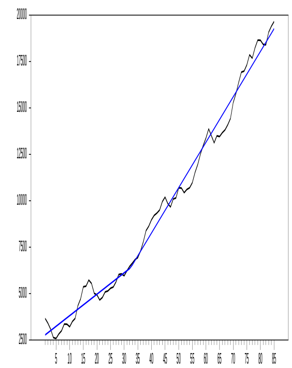
Tennessee



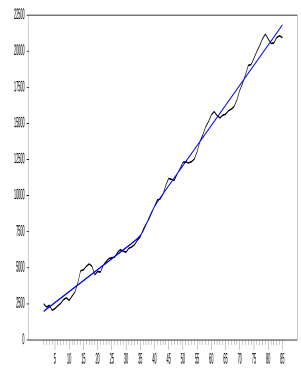
Texas



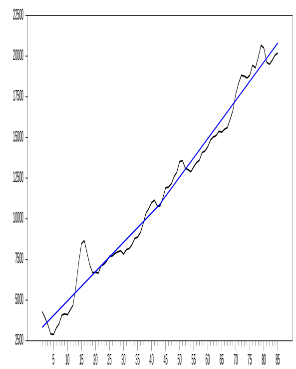
Utah



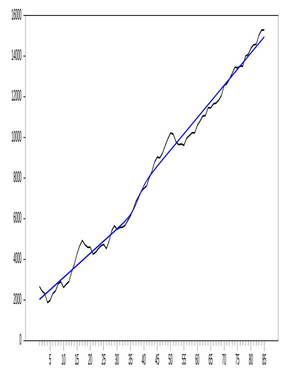
Vermont



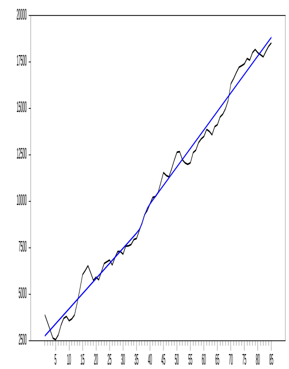
Virginia



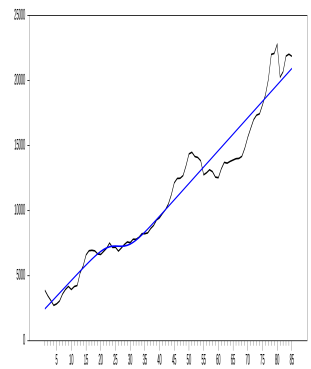
Washington



West Virginia



Wisconsin



Wyoming

Figure A1 shows that we can well approximate the nonlinear trend functions obtained by Leybourne, Newbold, and Vogus (1998) method (Model C) with a linear trend function.