UNLV University Libraries
University of Nevada, Las Vegas

Economics Faculty Publications Economics

6-21-2019

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

Furkan Emirmahmutoglu
Ankara Haci Bayram Veli University

Rangan Gupta
University of Pretoria

Stephen M. Millter
University of Nevada, Las Vegas, stephen.miller@unlv.edu

Tolga Omay
Atilim University

Follow this and additional works at: https://digitalscholarship.unlv.edu/econ_fac_articles

Part of the Econometrics Commons, and the Income Distribution Commons

Repository Citation

Emirmahmutoglu, F., Gupta, R., Millter, S. M., Omay, T. (2019). Is Real Per Capita State Personal Income Stationary? New Nonlinear, Asymmetric Panel-Data Evidence. *Bulletin of Economic Research* 1-13. Wiley.
http://dx.doi.org/10.1111/boer.12209

This Article is protected by copyright and/or related rights. It has been brought to you by Digital Scholarship@UNLV with permission from the rights-holder(s). You are free to use this Article in any way that is permitted by the copyright and related rights legislation that applies to your use. For other uses you need to obtain permission from the rights-holder(s) directly, unless additional rights are indicated by a Creative Commons license in the record and/or on the work itself.

This Article has been accepted for inclusion in Economics Faculty Publications by an authorized administrator of Digital Scholarship@UNLV. For more information, please contact digitalscholarship@unlv.edu.

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

Furkan Emirmahmutoglu[a], Rangan Gupta[b], Stephen M. Miller[c], and Tolga Omay[d]

ABSTRACT

This paper re-examines the stochastic properties of U.S. 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 two 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

JEL Classification*:* C12, C15, C23

a Ankara Haci Bayram Veli University, Department of Econometrics, 06500 Besevler/Ankara, Turkey (email: f.emirmahmutoglu@hbv.edu.tr)

b Department of Economics, University of Pretoria, Pretoria, 0002, South Africa (email: rangan.gupta@up.ac.za)

c Corresponding author, Department of Economics, University of Nevada, Las Vegas, 89154-6005, United States (email: stephen.miller@unlv.edu)

d Department of Economics, Atilim University, 06830 Kızılçaşar, Gölbaşı Ankara, Turkey (email: tolga.omay@edu.tr)

* We thank two anonymous referees for many helpful comments. Any remaining errors, however, are solely ours.

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 U.S. State real per capita personal income. Few researches investigate this variable at the 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 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- or 10-percent levels. 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 eight 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 eight 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 issues with respect to panel-data analysis and the identification of the data generation processes. 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 shortcomings, because it does not account for the panel properties of the sample. In addition, this approach provides no unique way to determine and separate the stationary and nonstationary series in the sample. In contrast, the SPSM method can identify such stationary and nonstationary series in the panel sample. Furthermore, his paper does not offer a test to determine whether the various series experience structural breaks or nonlinearities. Nonlinearity represents another issue in 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 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.

Our analysis generates the following outcomes. First, in the full sample, we discover stationarity with both the EO (2014) and UO (2009) tests. In the full sample, however, Romero-

[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.

Ávila (2012) finds nonstationarity using the CBL panel KPSS statistic. Therefore, from the beginning, we find full stationarity, whereas Romero-Ávila (2012) finds nonstationarity.

Second, Romero-Ávila (2012) searches for the states that cause the full-sample nonstationarity by employing individual KPSS test statistics with structural breaks. He finds that Alabama, Arkansas, Florida, Kentucky, Maryland, Oklahoma, Virginia, and Wyoming exhibit nonstationarity with the individual KPSS test with structural breaks. Then he restricts the full sample by excluding these states one at a time and employs the CBL test. In the end, he excludes Wyoming alone to achieve stationarity of the restricted full sample. This method, however, does not guarantee the stationarity of the other states. Rather, this method only shows the state that leads to the nonstationarity result of the remaining sample. In the best case, he identifies eight nonstationary states in the full sample, because this method does not show whether the remaining states are stationary in the full sample. Moreover, when he applies the bootstrap algorithm to remove cross-section dependency in the restricted full sample, the bootstrap algorithm adjusts the size of the test, thus, increasing the nonstationary states in the restricted full sample. In short, he can end up with more than eight nonstationary states. His method, however, cannot show how many states are nonstationary in the full sample. In our paper, we identify nonstationary states by using the SPSM methodology.

Third, as already noted, we discover stationarity in the full sample without making any further computations. Then we can divide the full sample into stationary and nonstationary state accurately. Thus, adjusting for the size distortion, we find 46 stationary and two nonstationary states. Romero-Ávila (2012), however, finds eight or more nonstationary states.

Finally, we claim that our state-dependent nonlinearity test provides a superior test for U.S. state income data. The precise estimates and test statistics appear in Table A3 in the Appendix. In Table A3, we estimate the ESTAR-LSTAR model to examine more carefully the data generating process of U.S. state income data. The findings in the Table support the use of state-dependent nonlinearity.

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 tests suggest that only five of the 48 states achieve a superior model with structural breaks. That is, the Romero-Ávila (2012) structural-break approach does not prove suitable for our sample. As an additional robustness check, 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.

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,

---

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

whereby the output dynamics follow a nonstationary process at some threshold, but a stationary process 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 United States shows that expansions exhibit longer durations than recessions (e.g., 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 tests in our study.[3] We also explicitly estimate the asymmetric state-dependent nonlinearity, -- the ESTAR-LSTAR model. These model estimations further show evidence of asymmetric state-dependent nonlinearity for the U.S. state level income data.

Depending on all of the aforementioned issues, we employ two different, but related, tests of a unit-root null hypothesis. First, we use a nonlinear symmetric heterogeneous panel-data approach developed by Ucar and Omay (2009) (UO), which builds on the work of Kapetanios et al. (2003). Second, we use 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

---

[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 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.

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) SPSM, that 43 states exhibit stationarity from the EO test because of nonlinearity and asymmetry -- 42 states exhibit stationary real personal income per capita because of nonlinearity from the UO test. In other words, we find only five states that exhibit nonstationarity after we accommodate nonlinearity and asymmetry. In sum, either the EO or the UO test, or both, identify 46 states that reject the null hypothesis of nonstationarity. Thus, we identify two nonstationary states -- Wyoming and California. This result further supports our findings that the state-level income data conform to a state-dependent nonlinearity instead of multiple structural breaks as in Romero-Ávila (2012).

Our 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

To determine our testing framework, we employ some preliminary identification tests – tests for linearity, tests for structural breaks, and 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]

$$y_t = \beta_{0,0} + \beta_0^{'} x_t + \beta_{1,0} tv_t + \beta_1^{'} x_t tv_t + e_t , \tag{1}$$

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 χ^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 Leybourne et al. (1998), which is given as follows:

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

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 τ determines the mid-point of transformation.

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:

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

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

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

Cross-Sectionally Dependent Nonlinear Panel Unit-Root Tests

Since the UO test emerges as a special case of the EO test, we consider the EO test first. EO (2014) extends the test of Sollis (2009) to nonlinear asymmetric heterogeneous panels as follows:[5]

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

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

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

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- and outer-regime models, where γ_{1i} measures the 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.[6] [7] Because of the extreme assumption that $\gamma_{2i} \to \infty$, 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 γ_{2i}. At the other extreme for γ_{2i} (*i.e.*, $\gamma_{2i} \to 0$), no matter what values ρ_{1i} and ρ_{2i} take on, the composite function

---

[5] See also Kruse (2011), Holmes et. al. (2014), and Aslanidis and Fountas (2014) for a similar test.

[6] 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.

[7] We are thankful for the referee for his comment to estimate the state dependent nonlinear model. We have estimated this ESTAR-LSTAR function in Appendix Figure A3. This analysis further shed lights on the structure of the US state level income and supports the linearity test results. Moreover, we have shown that the US state level income is better characterized with state dependent nonlinearity instead of multiple structural breaks.

$G_{it}(\gamma_{1i}, y_{i,t-1})\{S_{it}(\gamma_{2i}, y_{i,t-1})\rho_{1i} + (1 - S_{it}(\gamma_{2i}, y_{i,t-1}))\rho_{2i}\}$ 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:

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

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 (i.e., γ_{2i}, ρ_{1i} and ρ_{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

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

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 $\phi_{2i} = a(\rho_{2i}^{*} - \rho_{1i}^{*})\gamma_{1i}\gamma_{2i}$,[8] 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 asymmetric ESTAR processes. Thus,

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

Since individual $F_{i,AE}$ exhibit 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*. If the disturbances are dependent, then the proposed limit distributions of the test statistics 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 the $\bar{F}_{AE}$ and $\bar{t}_{AE}^{as}$ test statistics.

3. Real per Capita Personal Income

Our paper improves over the traditional panel-data testing procedures that assume linearity, symmetry, and cross-sectional independence. Therefore, our testing procedure incorporates nonlinearity and asymmetry within a heterogeneous panel context via the sieve bootstrap method.

---

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

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 appears 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 Eq. (3) (see Tables A1 and A2). 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. We also employ the linearity test in Eq. (1) (see Table A3). These results suggest that the best model for the data generation process is state-dependent nonlinearity. In addition, we estimate the nonlinear trend using Eq. (2), supporting the results in Table A3. We also graph the estimation results in Figure A1.

We show 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 U.S. economy to obtain the real counterpart of the variable, given that state-level CPIs are 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 SPSM in Chortareas and Kapetanios (2009) (CK) to identify the stationary series in the panel of observations.

The SPSM procedure of CK (2009) proceeds as follows:[9] 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 $\bar{t}_{i,AE}^{as}$ tests, while Table 3 reports the SPSM findings for the $\bar{t}_{i,NL}$ tests. In Table 2, we reject linear nonstationarity against

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

the alternative of stationary ESTAR nonlinearity with the $F_{i,AE}$ for 43 states. Further, we reject with the $\bar{t}_{i,AE}^{as}$ 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.[10]

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 $\bar{t}_{i,AE}^{as}$ tests identify 43 states that reject nonstationarity. The $\bar{t}_{i,NL}$ symmetric, nonlinear panel test identifies 42 states that reject the null hypothesis. The $F_{i,AE}$ and $\bar{t}_{i,AE}^{as}$ 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 $\bar{t}_{i,AE}^{as}$ tests do not.[11]

In sum, either the EO or the UO test, or both identify 46 states that reject the null hypothesis of nonstationarity. Nevertheless, two 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.

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

[11] 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.

Considering an alternative level of aggregation, we redid the four tests -- $\bar{F}_{AE}$, $\bar{t}_{AE}^{as}$, $\bar{t}_{NL}$, and $\bar{t}_{IPS_B}$ -- using the eight BEA regions as the unit of analysis.[12] 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 globally stationary nonlinear symmetric or asymmetric process. Tables 5 reports the results of the SPSM findings for the $F_{i,AE}$ and $\bar{t}_{i,AE}^{as}$ tests, while Table 6 reports the SPSM findings for the $\bar{t}_{i,NL}$ 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, the $\bar{t}_{i,AE}^{as}$ test rejects the null hypothesis of symmetric ESTAR nonlinearity against the alternative of stationary asymmetric ESTAR nonlinearity for one BEA region, 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 (2009) univariate test for nonlinear asymmetric nonstationarity, using the aggregate real per capita personal income data from the

[12] 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.

BEA. The $\bar{F}_{AE}$ (=10.079) and $\bar{t}_{AE}^{as}$ (=1.808) both reject the null hypothesis of nonlinear, asymmetric nonstationarity at the 1- and 10-percent levels, respectively.

4. Conclusion

Our paper uses recently developed panel unit-root tests by EO (2014) and UO (2009), which allow 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 United States. The procedures test 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 include sieve bootstrapping developed recently by EO (2014) and UO (2009). Our findings prove superior to those of Romero-Ávila (2012), where he finds nonstationarity for his full sample. By restricting the full sample, he still discovers eight or more non stationary state-level income. Fortunately, we discover stationarity in the full sample for both testing strategies -- UO and EO, finding state-dependent nonlinearity for the state-level income. After employing the SPSM method, the UO and EO methods identify only two nonstationarity states.

Our analysis implies that we must model state-level income by state-dependent nonlinearity instead of multiple structural breaks. Moreover, we also show that the state-dependent nonlinear estimation of the 48 states further supports the nonlinear panel unit-root test results and shows that the state-level income variables exhibit at least five regime shifts, which does not support the estimation with structural breaks. Finally, the nonstationary behavior for California carries over to the Far West region.

References

Aslanidis, N., and S. Fountas, 2014. Is real GDP stationary? Evidence from a panel unit root test with cross-sectional dependence and historical data. *Empirical Economics* 46(1), 101-108.

Ball, L., and Mankiw, N. G., 1994. Asymmetric price adjustment and economic fluctuations. *The Economic Journal* 104, 247–261.

Breusch, T. S., and Pagan, A. R., 1980. The Lagrange Multiplier test and its applications to model specification in econometrics. *Review of Economic Studies* 47, 239-253.

Carlino, G., and Sill, K., 2001, Regional income fluctuations: Common trends and common cycles, *Review of Economics and Statistics* 83, 446-456.

Carrion-i-Silvestre, J. L, Barrio-Castro, T., and López-Bazo, E., 2005. Breaking the panels: An application to the GDP per capita. *Econometrics Journal* 8, 159–75.

Chang, Y., 2004. Bootstrap unit root tests in panels with cross-sectional dependency. *Journal of Econometrics* 120, 263–293.

Chang, T., Chu, H-P., and Ranjbar, O., 2014. Are GDP fluctuations transitory or permanent in African countries? Sequential Panel Selection Method. *International Review of Economics and Finance* 29, 380-399.

Chortareas, G., Kapetanios, G., 2009. Getting PPP right: Identifying mean-reverting real exchange rates in panels, *Journal of Banking and Finance* 33, 390–404.

Diebold, F. X., and Rudebusch, G. D., 1994. Measuring business cycles: A modern perspective. *Review of Economics and Statistics* 78, 67-77.

Emirmahmutoglu, F., and Omay, T., 2014. Reexamining the PPP hypothesis: A nonlinear asymmetric heterogeneous panel unit root test. *Economic Modelling* 40, 184-190.

Hadri, K. 2000. Testing for stationarity in heterogeneous panel data. *Econometrics Journal* 3, 148–161.

Hamilton, J. D., 1989. A new approach to the economic analysis of non-stationary time series and the business cycle. Econometrica 57, 357-384

Holmes, M., Otero, J. and Panagiotidis, T., 2014. A note on the extent of U.S. regional income convergence. *Macroeconomic Dynamics* 18(7), 1635-1655.

Im, K. S., Pesaran, H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115, 53–74.

Kapetanios, G., Shin, Y., Snell, A., 2003. Testing for a unit root in the nonlinear star framework. *Journal of Econometrics* 12, 359–379.

Kruse, R., 2011. A new unit root test against ESTAR based on a class of modified statistics," Statistical Papers. *Statistical Papers* 52(1), 71-85.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics* 54, 159-178.

Leybourne, S., Newbold, P., and Vougas D., 1998. Unit roots and smooth transitions. *Journal of Time Series Analysis* 19, 83–97.

Levin, A., Lin, C., and Chu, C. J., 2002. Unit root tests in panel data: asymptotic and finite sample properties. *Journal of Econometrics* 108, 1–24.

Luukkonen, R., Saikkonen, P., and Terasvirta, T., 1988. Testing linearity against smooth transition autoregressive models. *Biometrika 75*, 491-499.

Narayan, P.K., and Popp, S., 2009. Investigating business cycle asymmetry for the G7 countries: Evidence from over a century of data. *International Review of Economics and Finance* 18, 583-591.

Neftci, S. N., 1984. Are economic time series asymmetric over the business cycle? *Journal of Political Economy* 92, 307-328.

Owyang, M. T., Piger, J., and Wall, H.J., 2005. Business Cycle Phases in U.S. States. *Review of Economics and Statistics* 87, 604-616.

Pesaran, M. H., 2004. General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics No.0435, Faculty of Economics, University of Cambridge.

Romero-Ávila, D., 2012. Multiple trend shifts and unit roots in US state income levels: Implications for long-run growth. *Annals of Regional Science* 48, 641-661.

Sichel, D. E., 1993. Business Cycle Asymmetry: A Deeper Look. *Economic Inquiry* 31, 224-236.

Sollis, R., 2009. A simple unit root test against asymmetric star nonlinearity with an application to real exchange rates in NORDIC countries. *Economic Modelling* 26, 118–125.

Stine, R.A., 1987. Estimating properties of autoregressive forecasts. *Journal of the American Statistical Association* 82, 1072–1078.

Taylor, M.P., Sarno, L., 1998. The behavior of real exchange rates during the post-Bretton Woods period. *Journal of International Economics* 46, 281-312.

Tobin, J., 1972. Inflation and unemployment. *American Economic Review* 62, 1–18.

Ucar, N., Omay, T., 2009. Testing for unit roots in nonlinear heterogeneous panels. *Economics Letters* 104, 5–8.

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)

Note1: * and ** denote significance at the 5% and 10% levels, respectively, based on the sieve bootstrap p-values. The tests are carried by using the intercept and trend versions. The sieve bootstrap approach, which we use to obtain p-values, account for cross-section dependency.

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 : The sequential panel selection method (SPSM) procedure is explained explicitly in Page 13 of this paper. * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values. The tests use intercept and trend versions. The sieve bootstrap approach, which we use to obtain p-values, account for cross-section dependency.

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. The tests use intercept and trend versions. The sieve bootstrap approach, which we use to obtain p-values, account for cross-section dependency.

Table 4. Panel Unit Root Test Results

EO		UO
$\bar{F}_{AE}$	$\bar{t}_{AE}^{as}$	$\bar{t}_{NL}$
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. The tests use intercept and trend versions. The sieve bootstrap approach, which we use to obtain p-values, account for cross-section dependency.

Table 5. SPSM results based on EO Test

Sequence	$\bar{F}_{AE}$	$\bar{t}_{AE}^{as}$	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: The SPSM procedure is explained explicitly in Page 13 of this paper. * and ** denote significance at the 5% and 10% levels, respectively, based on the bootstrap *p*-values. The tests use intercept and trend versions. The sieve bootstrap approach, which we are to obtain p-values, account for cross-section dependency.

Table 6. SPSM results based on UO Test

Sequence	$\bar{t}_{NL}$	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. The tests use intercept and trend versions. The sieve bootstrap approach, which we use to obtain p-values, account for cross-section dependency.

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

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 and the number of regimes pass

States	**State Dependent** $s_t = y_{t-1}$		**Time Varying** $s_t = t$		**Results**	**Transition Function**
	F-Test	**Significance**	**F-Test**	**Significance**		**# regime p.**
Alabama	7.437	0.008	3.482	0.066	SD*/TV‡	14
Arizona	2.962	0.089	3.338	0.071	SD‡/TV‡	14
Arkansas	3.574	0.062	2.411	0.124	SD**	15
California	1.117	0.294	1.744	0.190	-	16
Colorado	4.073	0.047	3.020	0.086	SD**/TV‡	15
Connecticut	0.220	0.640	1.776	0.186	-	7
Delaware	0.027	0.870	2.917	0.092	TV‡	18
Florida	6.380	0.013	3.996	0.049	SD**/TV**	13
Georgia	7.681	0.007	4.646	0.034	SD*/TV**	10
Idaho	22.311	0.000	1.943	0.167	SD*	12
Illinois	2.139	0.147	2.067	0.154	-	14
Indiana	3.626	0.060	2.440	0.122	SD**	16
Iowa	10.328	0.002	1.351	0.249	SD*	19
Kansas	2.981	0.088	1.951	0.166	SD‡	18
Kentucky	2.927	0.091	2.985	0.088	SD‡/TV‡	12
Louisiana	4.063	0.047	1.847	0.178	SD**	7
Maine	1.122	0.293	2.226	0.140	-	7
Maryland	0.717	0.400	3.363	0.070	TV‡	7
Massachusetts	1.431	0.235	2.350	0.129	-	5
Michigan	6.017	0.016	2.439	0.122	SD**	14
Minnesota	6.511	0.013	2.488	0.119	SD**	14
Mississippi	4.040	0.048	2.412	0.124	SD**	12
Missouri	4.154	0.045	3.436	0.067	SD**/TV‡	12
Montana	3.260	0.075	1.760	0.188	SD‡	13
Nebraska	14.654	0.000	1.392	0.241	SD*	11
Nevada	3.543	0.063	4.497	0.037	SD‡/TV**	16
New Hampshire	1.554	0.216	3.477	0.066	TV‡	5
New Jersey	1.048	0.309	3.103	0.082	TV‡	7
New Mexico	4.846	0.031	2.447	0.122	SD**	13
New York	1.784	0.185	1.834	0.179	-	11

Table A3. Linearity Tests and the number of regimes pass (continued)

States	State Dependent $s_t = y_{t-1}$		Time Varying $s_t = t$		Results	Transition Function
	F-Test	Significance	F-Test	Significance		# regime p.
North Carolina	8.932	0.004	4.379	0.040	SD	10
North Dakota	1.856	0.177	1.366	0.246	-	13
Ohio	2.406	0.125	2.238	0.139	-	18
Oklahoma	3.035	0.085	1.023	0.315	SD	11
Oregon	3.851	0.053	2.566	0.113	SD	10
Pennsylvania	1.651	0.203	2.404	0.125	-	13
Rhode Island	1.197	0.277	1.463	0.230	-	5
South Carolina	7.179	0.009	4.645	0.034	SD*/TV**	12
South Dakota	5.678	0.020	1.375	0.244	SD**	13
Tennessee	7.307	0.008	3.225	0.076	SD*/TV‡	12
Texas	2.970	0.089	2.016	0.159	SD‡	13
Utah	3.710	0.058	2.166	0.145	SD‡	12
Vermont	0.904	0.345	1.248	0.267	-	7
Virginia	4.299	0.041	4.646	0.034	SD**/TV**	7
Washington	2.127	0.149	2.766	0.097	TV‡	13
West Virginia	4.447	0.038	1.876	0.175	SD**	7
Wisconsin	3.012	0.086	2.321	0.132	SD‡	13
Wyoming	0.759	0.386	0.042	0.839	-	9

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 ‡ denote significance at the 1%, 5%, and 10% levels, respectively

Table A3 reports the linearity test findings and the number of regimes, using the Sollis (2009) unit-root test. Using the 10-percent significance level, 31 of the 48 states exhibit state-dependent (regime-wise) nonlinearity and 17 states exhibit time-varying nonlinearity, where 12 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 note 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. Therefore, nonlinear panel unit-root tests or panel unit-root tests with structural breaks can successfully model long time spans of data without loss of any relevant information.

For robustness, we also estimate the ESTAR-LSTAR model, which is the alternative hypothesis of our testing procedure of EO (2014) test. Table A3 shows that the nonlinear and asymmetric test (EO 2014) provides a better test than a structural-break panel unit-root test. Moreover, the transition function with respect to time and the time of regime changes shown in Figure A2 implies that "the non-linearity simply results in a transition that is smoother but not really different from a structural break." Romero-Ávila (2012) finds at most 3 structural breaks. We discover a minimum of five regime shifts for Rhode Island and the number of regime changes rises to a maximum of 19 for Iowa. Thus, our approaches better describe the dynamics of the state income variable.

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

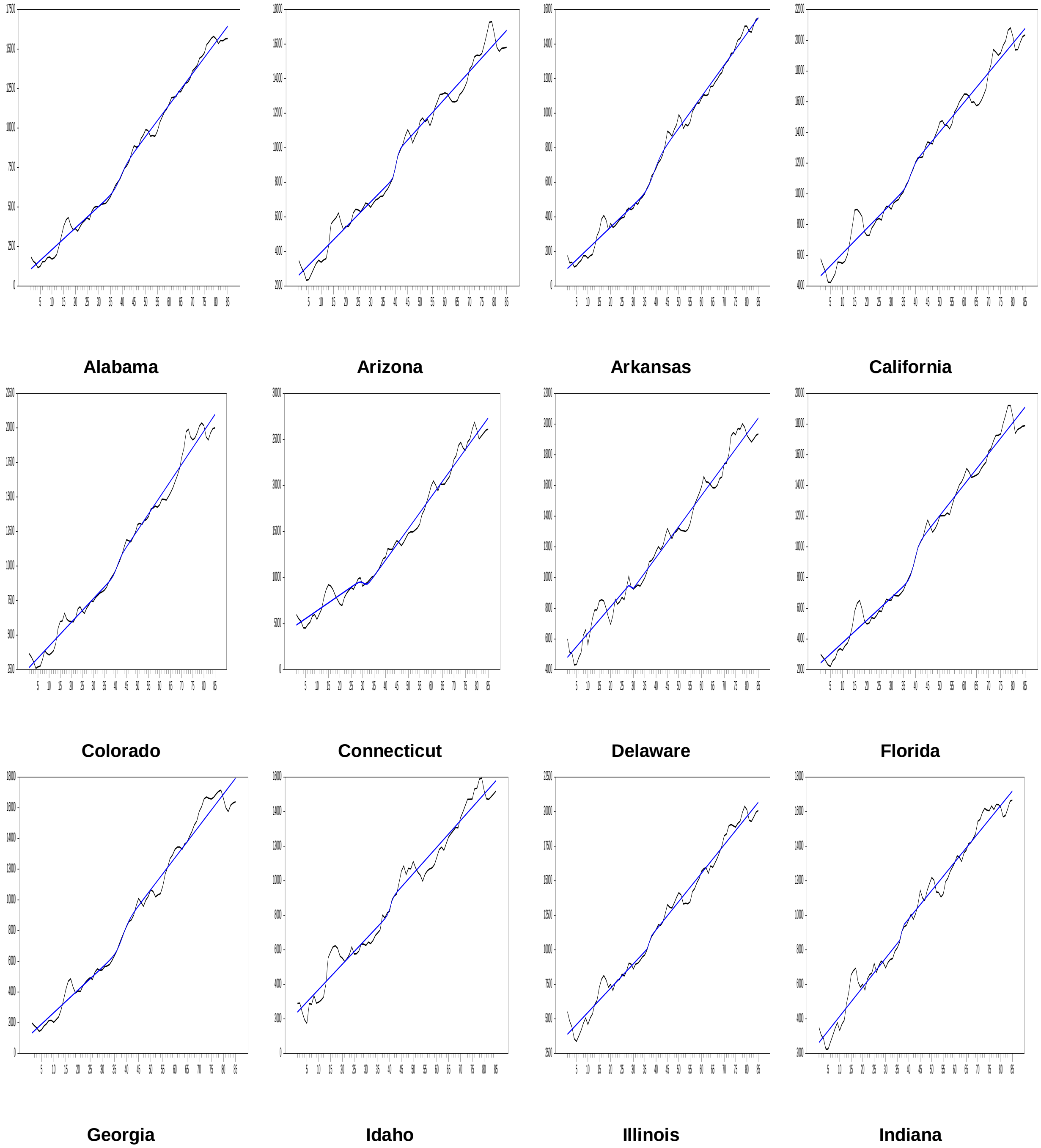


Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)

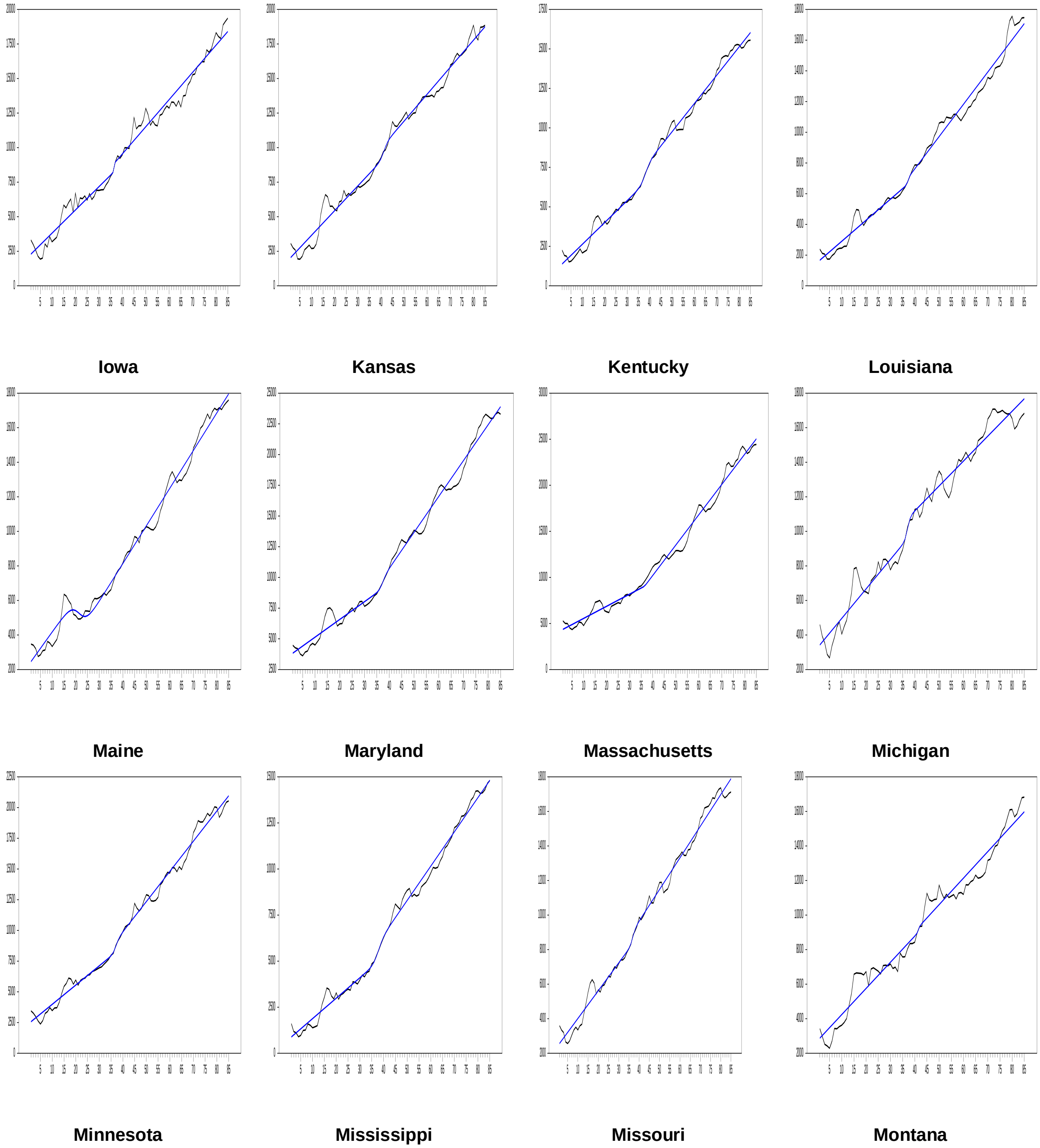


Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)

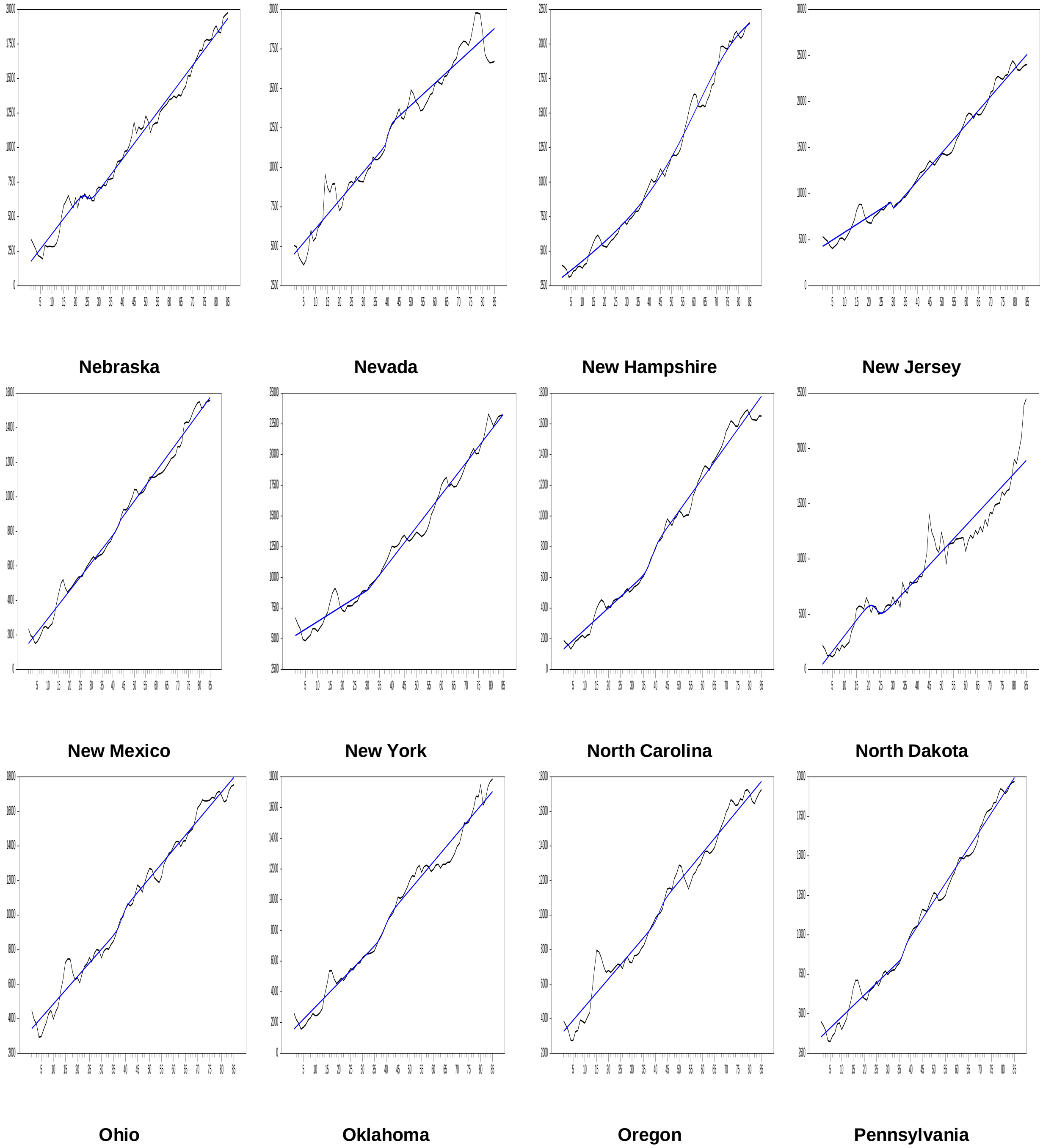


Figure A1. Nonlinear Trend Function with structural break in intercept and trend (LNV) (continued)

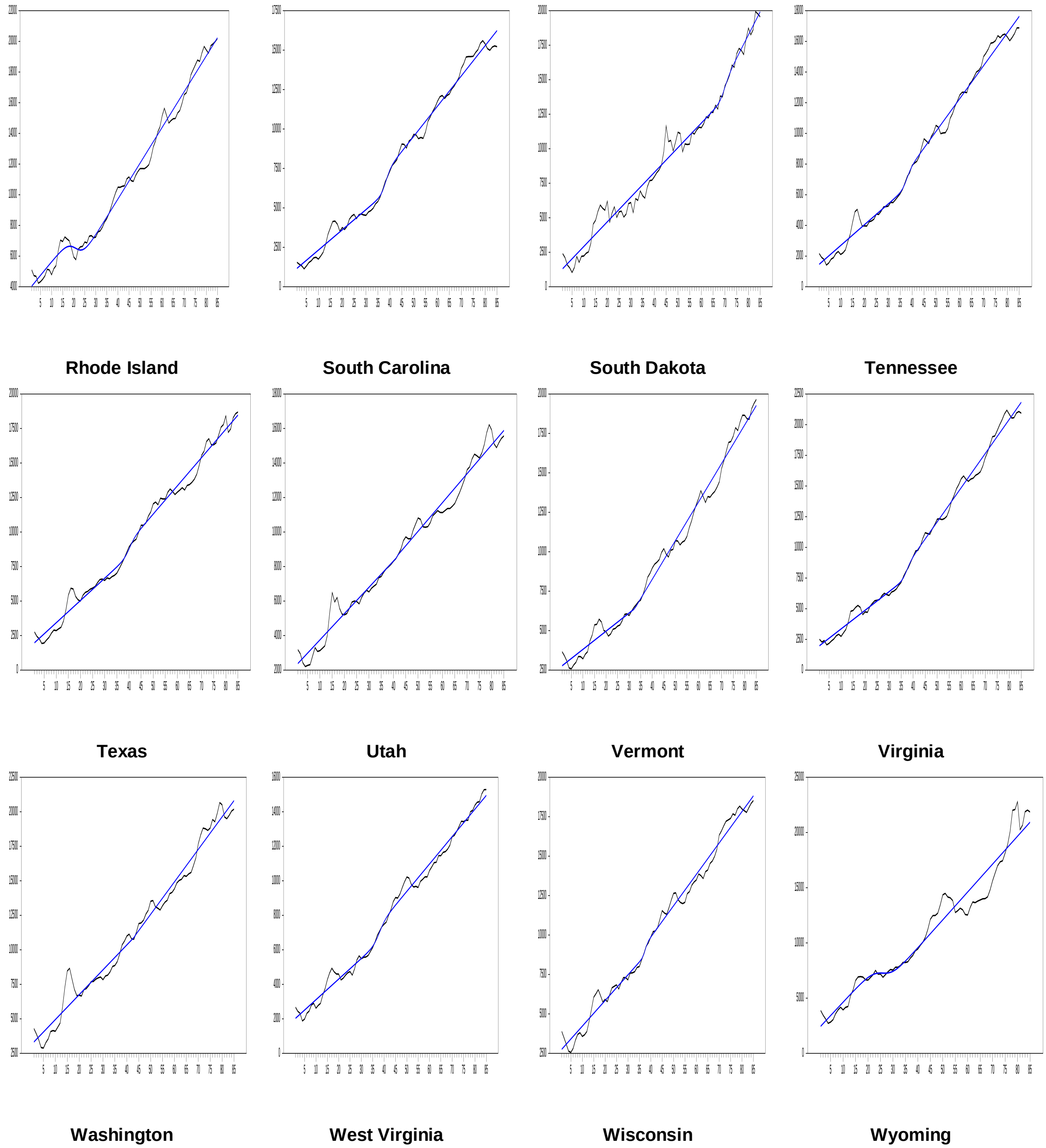
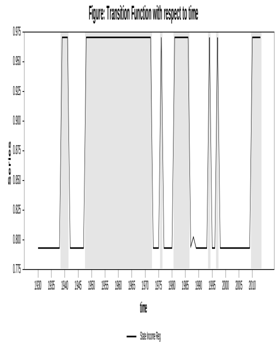
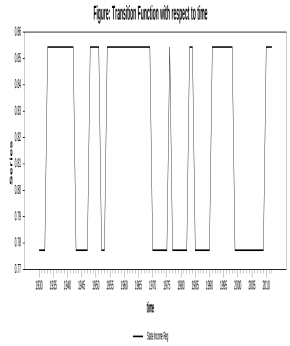


Figure A1 shows that we can well approximate the nonlinear trend functions obtained by Leybourne, Newbold, and Vogus (1998) method (Model C) with a linear trend function.

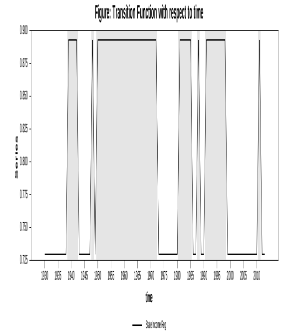
Figure A2. Transition functions with respect to time



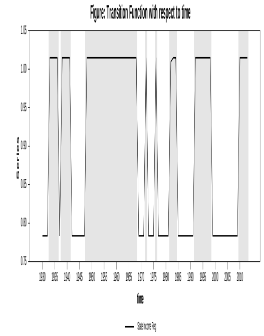
Alabama



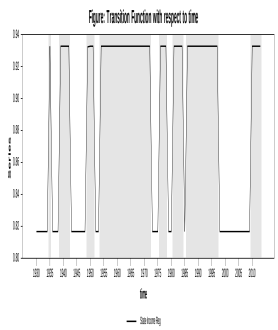
Arizona



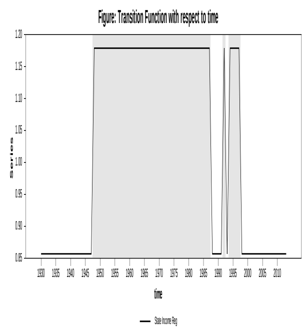
Arkansas



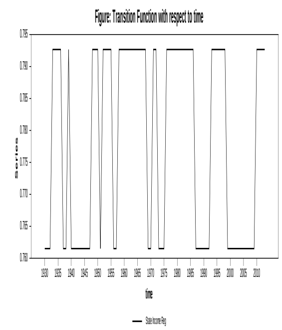
California



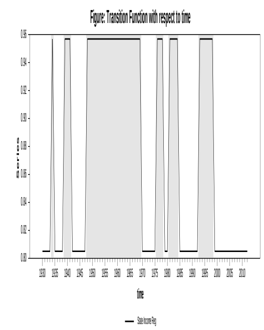
Colorado



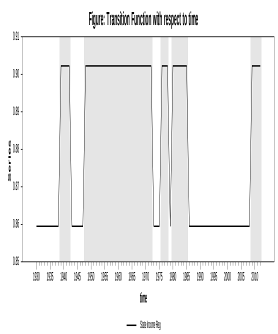
Connecticut



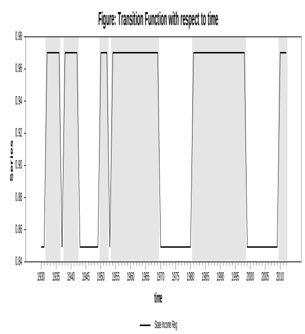
Delaware



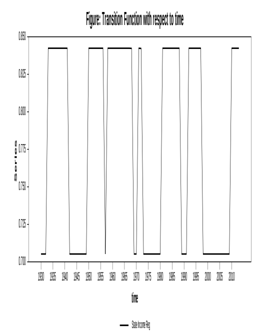
Florida



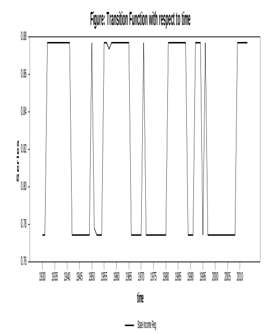
Georgia



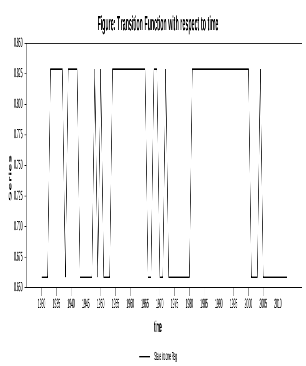
Idaho



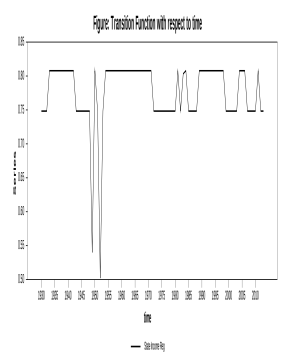
Illinois



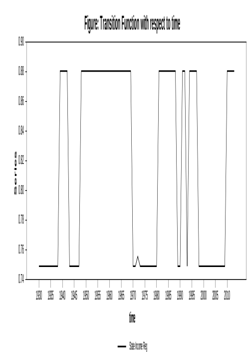
Indiana



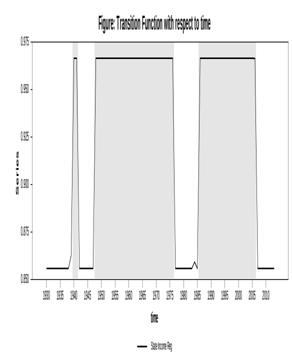
Iowa



Kansas

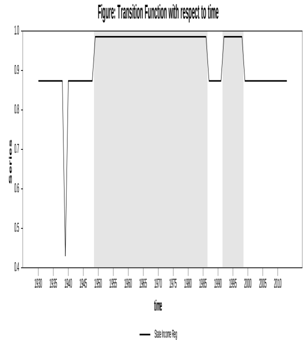


Kentucky

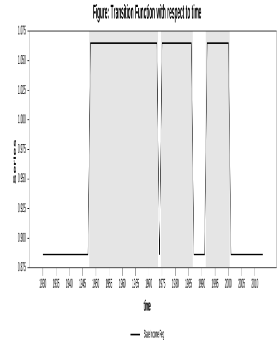


Louisiana

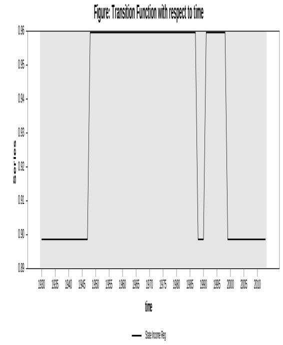
Figure A2. Transition functions with respect to time (continued)



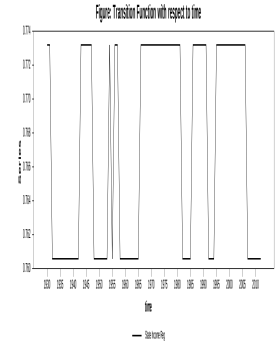
Maine



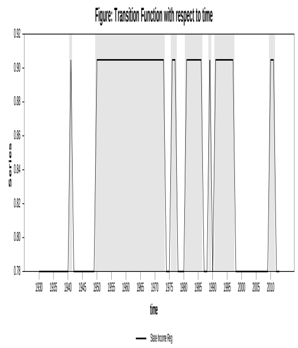
Maryland



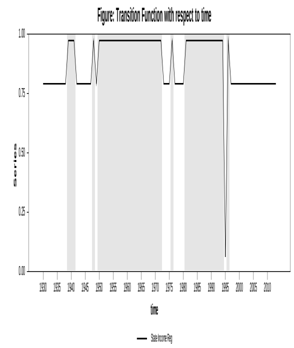
Massachusetts



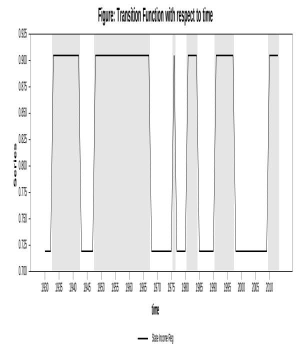
Michigan



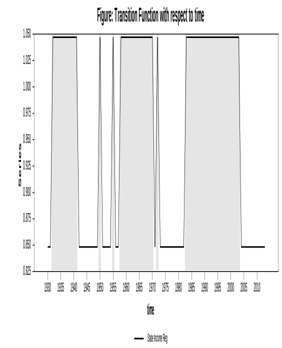
Minnesota



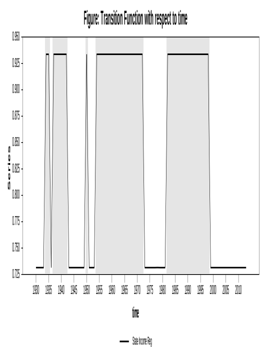
Mississippi



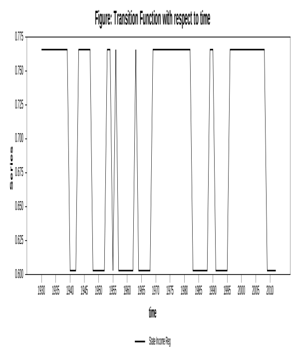
Missouri



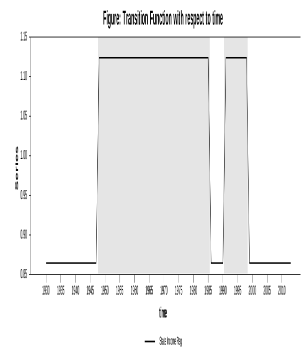
Montana



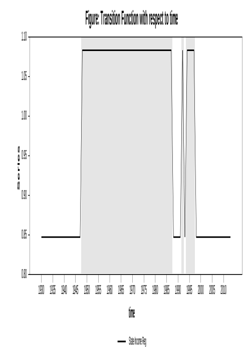
Nebraska



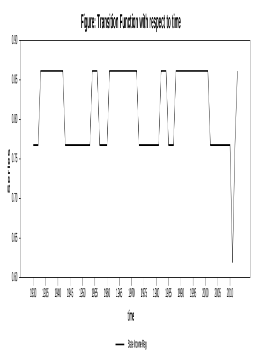
Nevada



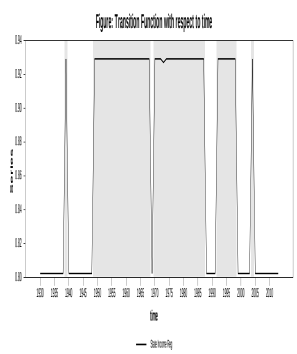
New Hampshire



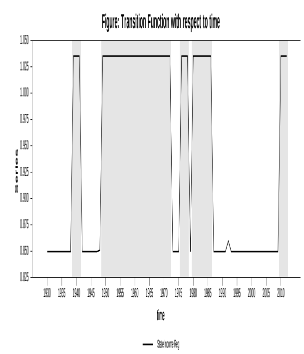
New Jersey



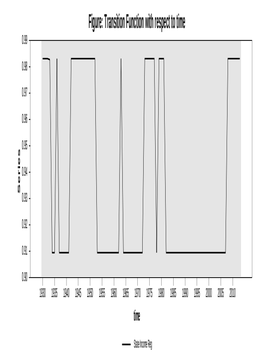
New Mexico



New York

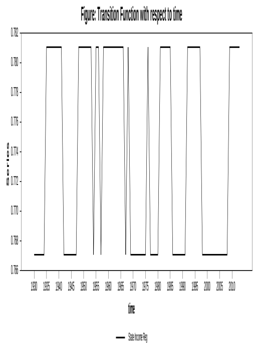


North Carolina

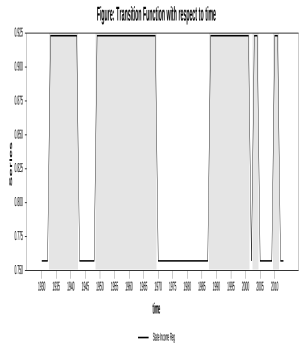


North Dakota

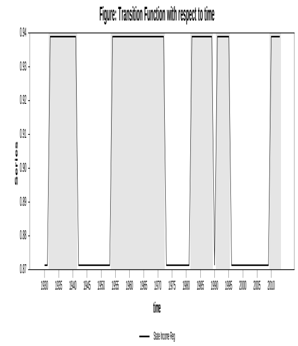
Figure A2. Transition functions with respect to time (continued)



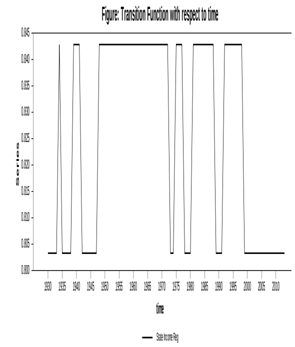
Ohio



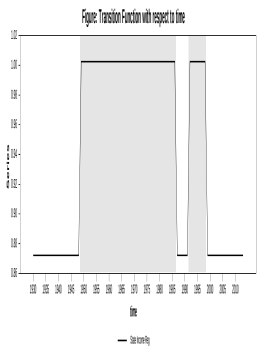
Oklahoma



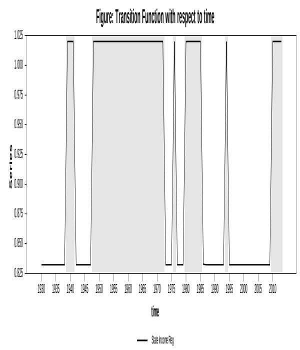
Oregon



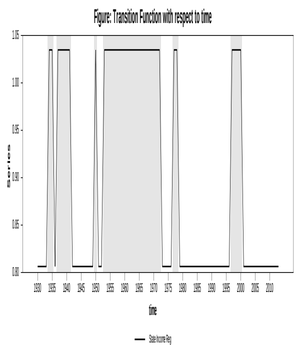
Pennsylvania



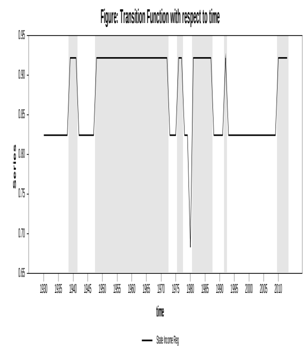
Rhode Island



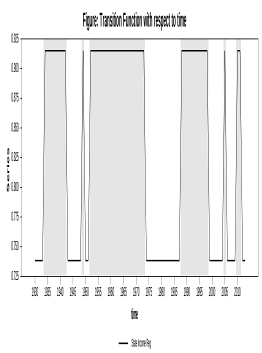
South Carolina



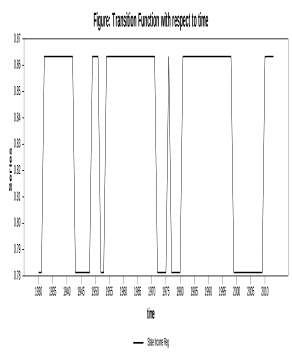
South Dakota



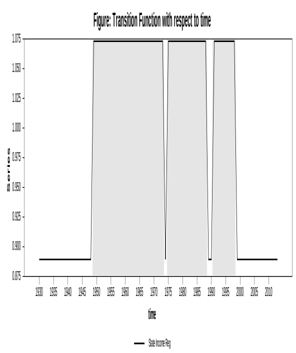
Tennessee



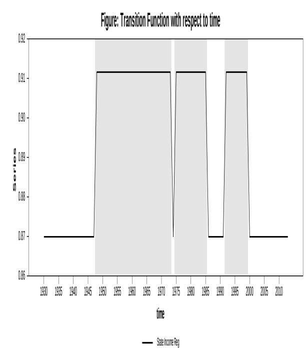
Texas



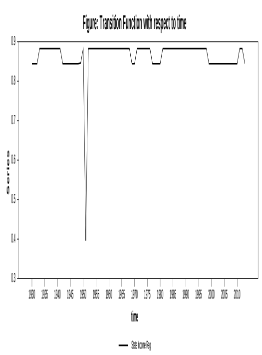
Utah



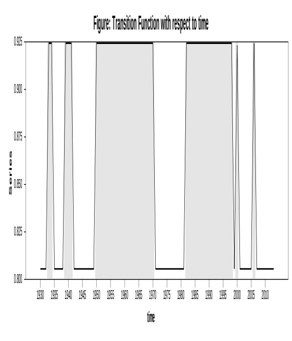
Vermont



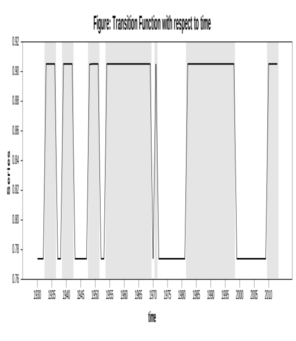
Virginia



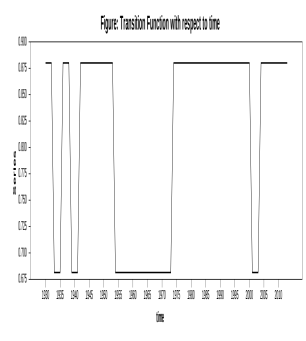
Washington



West Virginia



Wisconsin



Wyoming