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The Convergence of Poverty Rates among States across the U.S.

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Abstract Since income growth rate and poverty level are related, there is a possibility that the poverty rate may converge in the long run steady state as well. If the poverty rate converges, then for this study the state that begins with the high poverty rate would have a higher poverty reduction rate. To examine the convergence of poverty rate among the US states, this study uses two times series methodologies. First, in order to prevent the power loss from ignoring the structural break when testing for a unit root in a single time series, this study employs the newly developed panel LM unit root tests with level and trend shifts. The results of unit root tests of the log of poverty rate without allowing for structural breaks show that twenty six states reject the null hypothesis of unit root test for the ADF test, twenty five states for the LM test, and thirty five states for the RALS-LM test. The result of unit root tests that allow one structural break shows that the null hypothesis of a unit root test is rejected for twenty two states with the LM test, and thirty three states with the RALS-LM test. This supports poverty rates are converging among US states.

Key Words : Poverty Rates, Convergence, Unit Root Tests, LM Test, RALS-Lm Test

1. Introduction

For a decade, the percentage of the American population living below the poverty line has been continuously increasing. Based on a recent release by Census in September 2012, there is a record-high number of people that continue to live in poverty in the United States[1]. According to the newest data, one out of seven people in the United States are living in poverty, and almost one out of sixteen people in the United States are living in deep poverty[2]. Clearly, poverty is not only a big problem for developing countries. It is also a problem for one of the wealthiest countries on the planet. In 1997, the poverty rate was 12.5 percent. Three years later in 2010, the poverty rate increased to 15.1 percent. This is the highest poverty rate since 1993[3]. The US poverty rate in 2011 is 15.0 percent, still relatively high. As Besley and Burgess[4] argue, the answers provided by economists to the question of how to reduce poverty have changed over the last several decades. With this in mind, this paper examines the poverty percentage in the 50 states plus District of Columbia from 1988-2011. It tests if poverty rate converges overtime, with the goal of providing a better

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understanding of its property. Hopefully it can help to come up with a plan to reduce poverty overall. Income growth reflects the overall improvement of standard of living. The growth of income affects the poverty level one way or another. When the national income goes up, we would expect less poor in the nation. Danziger and Gottschalk found that income growth displayed a large effect on poverty in the period before 1970 and a moderate effect between 1973 and 1991. Also, Iceland found evidence that the income growth was strongly associated with the trend in absolute poverty over the period of 1949-1999. Based on the implication of Solow[5]'s model, we have numerous evidences that per capital incomes converge in the long run steady state. Thus, since income growth rate and poverty level are related, there is a possibility that the poverty rate may converge in the long run steady state as well. If the poverty rate converges, then for this study the state that begins with the high poverty rate would have a higher poverty reduction rate. To examine the convergence of poverty rate among the US states, this study uses two times series methodologies. First, in order to prevent the power loss from ignoring the structural break when testing for a unit root in a single time series, this study employs the newly developed panel LM unit root tests with level and trend shifts suggested by Meng and Lee[6]. Many existing studies gave little to no credits to multiple existing trend breaks in the data. This can lead to the existence of nuisance parameters in the model. Nuisance parameters can cause the spurious rejections of the null hypothesis. Perron [6] recognizes and gives warning about this issue. With the new developed method, my test results do not depend on the nuisance parameter indicating the trend shifts and allow for trend break under null hypothesis. In addition, to enhance the power of the test, this paper uses the new LM tests based on the RALS (residual augmented least square) regression suggested by H. J. Lee, M. Meng, and J. Lee [7]. With the new RALS-LM based test, there is a possibility that I can capture neglected nonlinearity through non-normal error. The nonlinear unit root test may suffer the loss of power due to the existence of non-normal errors or wrongly specified functional forms, stated by Lee et al[7] in his recent study. In general, for this paper I adopt the new panel LM unit root test together and the new RALS-LM test to test for poverty rate convergence. Since these two tests minimize the majority of discovered disadvantages of unit root test at the presence time, my confidence level for getting the right answer toward the poverty rate convergence issue increases. The rest of this study is arranged as follows: section 2 provides an overview of the literature; section 3 explains the methodologies employed; section 4 presents the data and empirical results; and section 5 provides concluding remarks.

2. Overview of Literature

Poverty frequently refers to economic deprivation. In the United States, the official poverty rate is determined based on a yearly poverty threshold issued by the Census Bureau. The poverty thresholds are the minimum dollar amounts required to support families of various sizes that the Census Bureau uses to determine poverty status. The methodology used to calculate the poverty threshold has stayed the same since it first use in the mid-1960s with the annual changes of inflation taken into account. If a family's pretax income is below its poverty threshold, then that family is counted as poor. The US poverty rates have been receiving increasing attention in recent years especially after the 2007 financial and economic crisis. (see, e.g., Udaya[9]; Sandoval, Rank, and Hirschl[10]; Gittell and Tebaldi[11]). In addition, there are quite a number of literatures dedicated to find the relationship between poverty rates and other economic factors. Iceland finds evidence that income growth, economic inequality and changes in family structures have an effect on the US poverty level. Waitzman and Smith [12] point out that the higher the poverty rate, the greater the risk of mortality. Kainz, Willoughby, Vernon-feagans, and Burchinal [13] have evidence to prove that poverty status is associated with the lower cognitive skills for 36 month old kids. However, no previous study has tested if the US poverty rates among the 50 states are converging.

For the rest of the globe, there are a small number of studies focusing on poverty convergence issue using the data from foreign countries. Among those few studies, there is a disagreement. Ravallion[14] finds no evidence for poverty convergence among the 100 developing countries due to the high initial poverty rate and the poverty disadvantage package such as human underdevelopment, policy distortion, and so on. On the other hand, by using panel unit root tests that are robust to cross-sectional dependence, Samarjit, Gouranga and Tushar[15] point out that the poverty rates converge among India's states. Since the economic condition is different between all the developing countries and the United States, there is a probability that the result of this study can be different.

3. Methodology

With the null hypothesis Ho: β=1 implies the series has a unit root and non-stationary. This study applies the LM unit root tests with level of trends and shifts suggested by Meng and Lee[16] and Lee et al[6]. This paper imitates their procedure using the US poverty rates data from 1988-2011. Rejecting the null hypothesis means there is evidence that the data is stationary, or in the other words, there is sign of convergence. Here is the methodology for this study.

Utilizing the unobserved components representation in time series, I consider the following model:

$$y_t = \delta' Z_t + e_t e_t = \beta e_{t-1} + \epsilon_t, \tag{1}$$

where Z_t contains exogenous variables. In order to include multiple breaks in this test, I denote T_{Bi} for the time period of each break and consider multiple dummy variables as:

$$Z_t = [1, t, D_{1t}, \dots, D_{Rt}, DT^*_{1t}, \dots, DT^*_{Rt}]', \tag{2}$$

where $\begin{cases} D^*_{it} = 1 \text{ for } t > T_{Bi}, \; i = 1, \dots\dots, R \\ D^*_{it} = 0, \text{otherwise} \end{cases}$

and $\begin{cases} DT^*_{it} = t - T_{Bi} \text{ for } t \geq T_{Bi} + 1 \\ DT^*_{it} = 0, \text{otherwise} \end{cases}$

For the first step of testing the time series data, I impose the null hypothesis H_0: â=1, and consider the following regression in difference:

$$\Delta y_t = \delta' \Delta Z_t + u_t \tag{3}$$

where ä=[$ä_1$,$ä_2$,$ä'_{3i}$,$ä'_{4i}$] and i= 1, ..,R. Then, I let $\tilde{\tau}^*$ be the t-statistics for ϕ=0 and obtain the unit root test statistics from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + e_t \quad (4)$$

where $\tilde{S}_t$ is the de-trended series that is calculated :

$$\tilde{S}_t = y_t - \tilde{\Psi} - Z_t \tilde{\delta} \quad (5)$$

where $\tilde{\Psi}$ is the restricted maximum likelihood estimation (MLE) of Ψ and formulated as $\tilde{\Psi} = y_1 - Z_1 \tilde{\delta}$ and $\tilde{\delta}$ is the coefficient in the regression of Δy_t on ΔZ_t in (3).

That means the de-trending procedure from (5) was found using first difference data from equation (3). With this method, I am able to remove the dependency on nuisance parameters with one level shift, but I am not able to remove the dependency on nuisance parameters in the model with the existence of trend breaks. So if there are trend shifts existing in my data, the power of my test would be reduced. Due to that reason, this study uses the new transformation formula below suggested by Lee et al.[6] to remove the dependency on the nuisance parameter in the model with trend shifts:

$$\tilde{S}_t^* = \begin{cases} \frac{T}{T_{B_1}} \tilde{S}_t & \text{for } t \le T_{B_1} \\ \frac{T}{T_{B_2} - T_{B_1}} \tilde{S}_t & \text{for } T_{B_1} \le t \le T_{B_2} \\ \vdots & \\ \frac{T}{T - T_{B_R}} \tilde{S}_t & \text{for } T_{B_R} \le t \le T \end{cases} \quad (6)$$

Replacing $\tilde{S}_{t-1}$ in the testing regression (4) with $\tilde{S}^*_{t-1}$, I get the followed regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}^*_{t-1} + \sum_{j=1}^{k} d_j \Delta \tilde{S}_{t-j} + e_t \quad (7)$$

Letting $\tilde{\tau}^*_{LM}$ be the t-statistics for $\phi=0$ from (7), following the transformation, the asymptotic distribution of $\tilde{\tau}^*_{LM}$ depends only on the number of trend breaks, and no longer depends on the nuisance parameters $ë_i^*$. That happens because the distribution at this time is given as the sum of R+1 independent stochastic term. For R breaks, the distribution of $ë_i^*$ is the same as the untransformed test $\tilde{\tau}^*_{LM}$ in regression (4) using $ë_i=i/(R+1)$, i=1, .n , R. So there is no need to stimulate the new critical value for all the possible break point combinations. The critical values of $\tilde{\tau}^*_{LM}$ are available in Lee et al[6].

After that, in order to identify the location of the structural breaks, I apply the max F test. With this test, I can test the significance of each break at the 10% level and determine the optimal lags given the number and location of breaks. For this study, I first set the maximum number of structural breaks equal to 1 (R=1), then applying the test. If the null hypothesis for no trend break is not rejected, I repeat the procedure with R-1 structural breaks. This procedure is repeated until the number of breaks equals to zero or the test result for all data breaks is significant. If there is no break is found, I use the no break unit root test. Otherwise, I can use Lee and Strazicich [8]'s R-breaks test with the number, the location of breaks and the determined corresponding optimal lags. In the process of doing the max F test, I am able to get the LM test statistic $\tilde{\tau}^*_{LM}$.

Although the LM test used for this study is generally more powerful than the usual DF type test, I can still improve the power of the LM statistic $\tilde{\tau}^*_{LM}$ by adopting the residual augmented least squares (RALS) method suggested by Meng et al[17]. This method utilizes the information on non-normal error. The RALS procedure extends the testing regression (7) with the following term $\widehat{w_t}$ showed as below:

$$\hat{w}_t = h(\hat{e}_t) - \hat{K} - \hat{e}_t \hat{D}_2 \quad (8)$$

where $h(\hat{e}_t) = [\hat{e}_t^2, \hat{e}_t^3]'$, $\hat{K} = \frac{1}{T}\sum_{t=1}^{T} h(\hat{e}_t)$ and $\widehat{D_2} = \frac{1}{T}\sum_{t=1}^{T} h'(\hat{e}_t)$.

The reason why $h(\hat{e}_t) = [\hat{e}_t^2, \hat{e}_t^3]$ which involves the second and the third moments of $\hat{e}_t$ is to capture the information of non-normal errors. After that, letting $\widehat{m_j} = T^{-1}\sum_{t=1}^{T}(\hat{e}_t^j)$, the augmented term can be given as:

$$\widehat{w_t} = [\hat{e}_t^2 - \widehat{m}_2, \hat{e}_t^3 - \widehat{m}_3 - 3\widehat{m}_2\hat{e}_t]' \quad (9)$$

where $\hat{e}_t^2$ is the condition of no heteroskedasticity $E[(\hat{e}_t^2 + \sigma_e^2)y_t] = 0$. With this condition, the estimator of ϕ can become more efficient when the error term is not symmetric. Besides that, the second term of equation (9) $\widehat{m}_2, \hat{e}_t^3$ also helps to improve efficiency unless $m_4 = 3\sigma^4$. In general, the terms that contain the knowledge of higher moment m_{j+1} obtained are uninformative if the redundancy condition $m_{j+1} = j\sigma^2 m_{j-1}$ is not fulfilled. The only distribution that satisfies the redundancy condition is the normal distribution. So if the distribution of the error term is not normal, the condition is not satisfied. If that is the case, one way to increase efficiency is extending the testing regression (7) with an additional term $\widehat{w}^t$. At that time, the transformed RALS-LM test statistics is obtained from the regression given as follows:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1}^* + \sum_{j=1}^{p} d_j \Delta \tilde{S}_{t-j} + \hat{w}_t' \gamma + u_t \quad (10)$$

The RALS-LM estimator is obtained through the usual least square estimation applied to regression (10). At this point, letting $\tau_{RALS-LM}^*$ be the corresponding t-statistic for ϕ =0, the asymptotic distribution of $\tau_{RALS-LM}^*$ is no longer dependent on the break location parameter λ_i^*. So there is no need to simulate new critical value for all possible break location combinations anymore. The asymptotic distribution of $\tau_{RALS-LM}^*$ is given as follow:

$$\tau_{RALS-LM}^* \rightarrow \rho \tilde{\tau}_{LM}^* + \sqrt{1-\rho^2}\, Z \quad (11)$$

To check for the critical value of the RALS-LM test, I use the table provided in Meng et al.[17]. Meng et al[17]'s RALS-LM test helps to improve the power of LM test when the non-normal error exits in the data, but display asymmetry or the patterns of fat-tailed distributions.

4. Data and Results

I utilize the United States Census Bureau Data provided on poverty rate over the period 1988-2011 to examine the convergence issue in 50 US states plus the District of Columbia. The fifty states considered in the analysis are: Alabama, Alaska, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming.

For each state *i*, I examine the natural logarithm of the poverty rate (PR) relative to the average of all states in the sample as the follows:

$$y = \ln\left(\frac{PR}{average\, PR_t}\right) \quad (12)$$

In order to test the log of relative poverty rate in (12), I use the two steps LM and the three steps RALS-LM unit root test developed by Lee et al[6] and Meng et al[16] with the maximum of four lags.

The two step LM test can be briefly described as follows. First, I set a maximum structural break number R (R=1), then apply the test to identify the break locations. After that, I test for the significance of each break and simultaneously determine the optimal lags with the corresponding number and location of break. If the null of no trend break is not rejected or the null of no trend break is rejected but one of break dummy variables is not significant based on the standard t-statistics, then I move to the beginning of the first step with the structure break number equal to. This process is continued until the break number becomes zero or all identified break dummy variables are significant. If this procedure indicates the break number equal to zero, then I use the usual no break LM unit root test of Schmidt and Phillips[18]. In contrast, if one or more breaks are found, then I use the one break (or R breaks) LM unit root test of Amsler and Lee[19] and Lee and Strazicich[8] with the break number, location and the corresponding lags determined by previous actions. At this point, I obtain the LM statistics, denoted as.

The first two steps of the three steps RALS-LM are similar to the two steps LM test. The RAL-LM uses the higher moment information obtained from the second step and augments it to the regression of the two step LM test as the third step denoted as. In order to get enough observations to perform a valid test, I use the grid search within 0.10~0.90 intervals of the whole sample period when examining the optimal number of breaks. I use a general to specific method with maximum lag equal to four to choose the corresponding number of lags.

The results from employing the one break LM and one break RALS-LM unit root tests for the sample period 1988-2011 are shown in Table 1. The null hypothesis of unit root test in relative poverty rate is rejected at the 10% significance level in twenty two states using the LM test and thirty three states with the RALS-LM test. Further examination reveals that the one structural break in the trend (are significant (t-value significant at 10% level) in forty states.

For Arizona, Delaware, Illinois, Iowa, Maine, Maryland, North Carolina, Ohio, Utah, Vermont and Wisconsin, one break identified for each state is not significant at the 10% level; therefore a no break root test appears more appropriate. To examine the effect of including one break instead of none, I perform the ADF, LM and RALS-LM tests with no break. The results for the no break tests are shown in Table 2. Twenty six states reject the unit root null hypothesis with the ADF tests, and the rejection number for no break LM and RALS-LM tests are twenty five and thirty five, respectively. Among the eleven states that are not significant with the one break test, eight states reject the null hypothesis with no break LM test and nine states reject the null hypothesis with no break RALS-LM

Table 1 Results from One-Break TR-LM and TR-RALS-LM Unit Root Tests

Commodity	LM τ^*_{LM}	RALS-LM $\tau^*_{RALS-LM}$	RALS-LM $\hat{\rho}^2$	$\hat{T}_B$	$\hat{K}$
Alabama	-2.691	-4.893 ***	0.32198	2000	4
Alaska	-4.714 **	-5.900 ***	0.5265	1996	4
Arizona	-2.752	-3.085	0.73969	2008 n	0
Arkansas	-3.159	-4.331 ***	0.34357	2001	4
California	-3.550	-2.933	1.16379	2004	3
Colorado	-4.073 **	-10.277 ***	0.13317	1994	3
Connecticut	-2.119	-3.566 **	0.38598	1994	4
Delaware	-3.088	-1.027	0.76086	1995 n	3
DC	-2.385	-4.424 ***	0.30742	1996	4
Florida	-3.757 *	-3.723 **	0.78813	1999	3
Georgia	-1.944	-0.908	0.67972	2005	4
Hawaii	-2.688	-2.941	0.91633	1995	3
Idaho	-3.926 *	-5.722 ***	0.36529	1998	3
Illinois	-2.820	-2.208	1.08011	2006 n	4
Indiana	-3.157	-3.584 **	0.50003	2000	4
Iowa	-3.186	-3.589 **	0.53319	1996 n	3
Kansas	-3.192	-3.933 **	0.76612	1995	4
Kentucky	-3.606 *	-3.553 **	0.35682	1995	4
Louisiana	-2.632	-2.557	0.92278	2008	3
Maine	-2.538	-5.728 ***	0.22398	2003 n	3
Maryland	-2.415	-2.609	1.04195	2007 n	4
Massachusetts	-2.463	-2.009	1.10316	1994	4
Michigan	-2.581	-1.560	0.88266	2005	4
Minnesota	-2.655	-3.347 *	0.66519	1999	4
Mississippi	-7.000 ***	-8.996 ***	0.61215	1999	0
Missouri	-3.978 **	-3.858 *	1.00089	1994	3
Montana	-4.158 **	-4.223 **	0.91916	1999	4
Nebraska	-4.557 **	-4.542 ***	0.53626	2001	4
Nevada	-1.218	-0.908	1.12014	2008	4
New_Hampshire	-5.928 ***	-4.671 **	1.03726	1999	1
New_Jersey	-2.840	-2.115	0.69924	1997	4
New_Mexico	-0.335	-0.733	0.84647	1993	3
New_York	-4.818 ***	-5.190 ***	0.6666	2002	4
North_Carolina	-3.233	-4.895 ***	0.52821	1997 n	0
North_Dakota	-4.438 **	-6.700 ***	0.3175	2000	4
Ohio	-1.251	-2.234	0.25555	2006 n	4
Oklahoma	-1.258	-0.926	1.00116	2006	4
Oregon	-3.474	-7.341 ***	0.16579	1997	3
Pennsylvania	-5.140 ***	-7.833 ***	0.3463	2001	4
Rhode_Island	-0.869	-1.927	0.3431	1997	4
South_Carolina	-4.725 **	-10.076 ***	0.27634	1994	4
South_Dakota	-3.315	-3.109	1.16221	1998	4
Tennessee	-6.120 ***	-15.064 ***	0.19808	1999	0
Texas	-4.993 ***	-15.503 ***	0.09059	1998	4
Utah	-5.845 ***	-4.719 **	1.10477	1999 n	0
Vermont	-5.166 ***	-5.396 ***	0.86292	2001 n	1
Virginia	-4.202 **	-7.408 ***	0.43547	2003	3
Washington	-4.122 **	-9.209 ***	0.16911	2001	4
West_Virginia	-1.473	-2.614	0.61145	1993	4
Wisconsin	-4.690 **	-4.324 **	1.09253	2003 n	0
Wyoming	-5.202 ***	-4.120 **	1.20481	1999	4
	22	33			

Notes: $\hat{T}_B$ denotes the estimated break point. The n next to some of these break points means that break point is not significant at the 10% level. $\hat{K}$ denotes the optimal number of lagged first-differenced terms τ^*_{LM}. and $\tau^*_{RALS-LM}$ denote the test statistics for the one-break LM test and RALS-LM test, respectively. Finally *, **, and *** denote that the test statistic is significant at the 10%, 5%, and 1% levels, respectively.

Table 2 Results from ADF Test and No-Break LM and TR-RALS-LM Unit Root Tests

Commodity	ADF τ_{ADF}	ADF $\widehat{K}$	LM τ^*_{LM}	RALS-LM $\tau^*_{RALS-LM}$	RALS-LM $\widehat{T}_B$	$\widehat{K}$
Alabama	-4.552 ***	0	-1.635	-1.349	1.09953	1
Alaska	-3.079	0	-2.843 *	-3.346 **	0.75879	0
Arizona	-3.153	0	-3.239 **	-4.247 ***	0.62465	0
Arkansas	-4.085 **	0	-3.160 **	-3.283 **	0.78593	0
California	-2.357	3	-2.216	-2.313	1.08377	3
Colorado	-2.364	1	-1.504	-5.076 ***	0.26037	1
Connecticut	-2.732	0	-2.029	-1.843	0.95267	0
Delaware	-5.195 ***	0	-5.332 ***	-4.797 ***	0.73137	0
DC	-3.971 **	0	-0.562	0.726	0.76122	2
Florida	-2.835	2	-1.615	-1.659	0.78360	1
Georgia	-1.585	1	-1.921	-1.948	0.55587	1
Hawaii	-2.979	0	-2.986 *	-3.341 **	0.57345	0
Idaho	-2.933	3	-3.142 *	-3.464 **	0.56622	0
Illinois	-2.004	1	-2.099	-2.191	0.83685	1
Indiana	-2.343	0	-2.148	-0.640	0.86006	4
Iowa	-2.598	3	-2.807	-2.492 *	0.39608	3
Kansas	-6.222 ***	0	-0.564	-0.597	0.64355	4
Kentucky	-2.579	4	-2.263	-4.022 ***	0.40137	4
Louisiana	-4.933 ***	2	-4.331 ***	-4.371 ***	0.85509	2
Maine	-5.105 ***	0	-4.713 ***	-4.906 ***	0.85935	0
Maryland	-4.120 **	0	-4.119 ***	-4.715 ***	0.57778	0
Massachusetts	-5.019 ***	0	-4.853 ***	-7.982 ***	0.36538	0
Michigan	-2.453	0	-2.515	-3.613 ***	0.51308	0
Minnesota	-1.854	0	-2.228	-2.301 *	0.30049	4
Mississippi	-4.251 **	0	-1.249	-0.598	1.04481	1
Missouri	-3.050	0	-3.145 *	-5.643 ***	0.18688	0
Montana	-3.020	0	-3.069 *	-4.586 ***	0.30711	0
Nebraska	-2.683	0	-2.659	-3.337 **	0.76254	0
Nevada	-4.191 **	0	-2.160	-4.120 ***	0.41768	4
New_Hampshire	-4.662 ***	1	-4.766 ***	-7.870 ***	0.24013	1
New_Jersey	-2.848	4	-1.625	-1.954	0.86694	0
New_Mexico	-2.206	4	-2.130	-2.144	0.61274	4
New_York	-2.201	3	-1.667	-3.348 ***	0.30766	3
North_Carolina	-2.892	0	-2.748	-1.767	0.83049	0
North_Dakota	-2.489	0	-2.681	-3.014 **	0.73988	0
Ohio	-4.991 ***	0	-4.544 ***	-4.777 ***	0.92908	0
Oklahoma	-6.077 ***	3	-1.348	-2.103	0.33512	4
Oregon	-4.079 **	0	-4.153 ***	-4.213 ***	0.81412	0
Pennsylvania	-4.197 **	4	-3.345 **	-2.860 *	1.01024	4
Rhode_Island	-3.404 *	0	-3.028 *	-3.710 ***	0.73845	0
South_Carolina	-4.943 ***	0	-1.857	-2.785 **	0.45872	2
South_Dakota	-2.564	3	-2.575	-2.033	0.94993	3
Tennessee	-5.283 ***	0	-1.886	-2.702	0.82306	1
Texas	-5.191 ***	0	-3.555 **	-3.260 **	1.03670	0
Utah	-5.629 ***	0	-5.192 ***	-5.023 ***	1.05693	0
Vermont	-4.492 ***	0	-3.958 ***	-3.865 ***	0.92047	0
Virginia	-4.325 **	3	-4.021 ***	-4.229 ***	0.84470	3
Washington	-2.887	0	-2.904 *	-2.924 *	1.05625	0
West_Virginia	-5.374 ***	0	-5.495 ***	-6.721 ***	0.77025	0
Wisconsin	-4.269 **	0	-3.553 **	-3.343 **	1.01670	0
Wyoming	-3.451 *	0	-3.068 *	-6.304 ***	0.34572	0
# rejections	26		25	35		

Notes: $\widehat{K}$ denotes the optimal number of lagged first-differenced terms. τ_{ADF} denotes the test statistic for the ADF test.. τ^*_{LM}. and $\tau^*_{RALS-LM}$ denote the test statistics for the one-break LM test and RALS-LM test, respectively. Finally *, **, and *** denote that the test statistic is significant at the 10%, 5%, and 1% levels, respectively

Table 3 Optimal Model

Commodity	ADF		LM	RALS-LM		$\widehat{T_B}$	$\widehat{K}$
	τ_{ADF}	$\widehat{K}$	τ^*_{LM}	$\tau^*_{RALS-LM}$	$\widehat{\rho^2}$		
Alabama	-4.552 ***	0	-2.691	-4.893 ***	0.32198	2000	4
Alaska	-3.079	0	-4.714 **	-5.900 ***	0.52650	1996	4
Arizona	-3.153	0	-3.239 **	-4.247 ***	0.62465		0
Arkansas	-4.085 **	0	-3.159	-4.331 ***	0.34357	2001	4
California	-2.357	3	-3.550	-2.933	1.16379	2004	3
Colorado	-2.364	1	-4.073 **	-10.277 ***	0.13317	1994	3
Connecticut	-2.732	0	-2.119	-3.566 **	0.38598	1994	4
Delaware	-5.195 ***	0	-5.332 ***	-4.797 ***	0.73137		0
DC	-3.971 **	0	-2.385	-4.424 ***	0.30742	1996	4
Florida	-2.835	2	-3.757 *	-3.723 **	0.78813	1999	3
Georgia	-1.585	1	-1.944	-0.908	0.67972	2005	4
Hawaii	-2.979	0	-2.688	-2.941	0.91633	1995	3
Idaho	-2.933	3	-3.926 *	-5.722 ***	0.36529	1998	3
Illinois	-2.004	1	-2.099	-2.191	0.83685		1
Indiana	-2.343	0	-3.157	-3.584 **	0.50003	2000	4
Iowa	-2.598	3	-2.807	-2.492 *	0.39608		3
Kansas	-6.222 ***	0	-3.192	-3.933 **	0.76612	1995	4
Kentucky	-2.579	4	-3.606 *	-3.553 **	0.35682	1995	4
Louisiana	-4.933 ***	2	-2.632	-2.557	0.92278	2008	3
Maine	-5.105 ***	0	-4.713 ***	-4.906 ***	0.85935		0
Maryland	-4.120 **	0	-4.119 ***	-4.715 ***	0.57778		0
Massachusetts	-5.019 ***	0	-2.463	-2.009	1.10316	1994	4
Michigan	-2.453	0	-2.581	-1.560	0.88266	2005	4
Minnesota	-1.854	0	-2.655	-3.347 *	0.66519	1999	4
Mississippi	-4.251 **	0	-7.000 ***	-8.996 ***	0.61215	1999	0
Missouri	-3.050	0	-3.978 **	-3.858 *	1.00089	1994	3
Montana	-3.020	0	-4.158 **	-4.223 **	0.91916	1999	4
Nebraska	-2.683	0	-4.557 **	-4.542 ***	0.53626	2001	4
Nevada	-4.191 **	0	-1.218	-0.908	1.12014	2008	4
New_Hampshire	-4.662 ***	1	-5.928 ***	-4.671 **	1.03726	1999	1
New_Jersey	-2.848	4	-2.840	-2.115	0.69924	1997	4
New_Mexico	-2.206	4	-0.335	-0.733	0.84647	1993	3
New_York	-2.201	3	-4.818 ***	-5.190 ***	0.66660	2002	4
North_Carolina	-2.892	0	-2.748	-1.767	0.83049		0
North_Dakota	-2.489	0	-4.438 **	-6.700 ***	0.31705	2000	4
Ohio	-4.991 ***	0	-4.544 ***	-4.777 ***	0.92908		0
Oklahoma	-6.077 ***	3	-1.258	-0.926	1.00116	2006	4
Oregon	-4.079 **	0	-3.474	-7.341 ***	0.16579	1997	3
Pennsylvania	-4.197 **	4	-5.140 ***	-7.833 ***	0.34630	2001	4
Rhode_Island	-3.404 *	0	-0.869	-1.927	0.34310	1997	4
South_Carolina	-4.943 ***	0	-4.725 **	-10.076 ***	0.27634	1994	4
South_Dakota	-2.564	3	-3.315	-3.109	1.16221	1998	4
Tennessee	-5.283 ***	0	-6.120 ***	-15.064 ***	0.19808	1999	0
Texas	-5.191 ***	0	-4.993 ***	-15.503 ***	0.09059	1998	4
Utah	-5.629 ***	0	-5.192 ***	-5.023 ***	1.05693		0
Vermont	-4.492 ***	0	-3.958 ***	-3.865 ***	0.92047		0
Virginia	-4.325 **	3	-4.202 **	-7.408 ***	0.43547	2003	3
Washington	-2.887	0	-4.122 **	-9.209 ***	0.16911	2001	4
West_Virginia	-5.374 ***	0	-1.473	-2.614	0.61145	1993	4
Wisconsin	-4.269 **	0	-3.553 **	-3.343 **	1.01670		0
Wyoming	-3.451 *	0	-5.202 ***	-4.120 **	1.20481	1999	4
	26		27	36			

Notes: $\widehat{K}$ denotes the optimal number of lagged first-differenced terms. τ_{ADF} denotes the test statistic for the ADF test.. τ^*_{LM}. and $\tau^*_{RALS-LM}$ denote the test statistics for the one-break LM test and RALS-LM test, respectively. $\widehat{T_B}$ denotes the estimated break point. Finally *, **, and *** denote that the test statistic is significant at the 10%, 5%, and 1% levels, respectively.

test. One point worth noticing with the results is that the poverty rate of Arizona, Delaware, and Maryland cannot reject the unit root test with the one break LM and RALS-LM tests, but can reject the unit root with no break. This indicates that increasing the number of structural breaks may not lead to more rejection of the unit root.

In general, this study provides significant support for poverty rate convergence among the fifty US states plus the District of Columbia. With the appropriate number of structural breaks, poverty rate in twenty seven and thirty six states for the LM and RALS-LM tests respectively are found to be stationary. This result can be found in Table 3. If the trend break coefficient is significant with one break test, this study selects one break test; otherwise, the no break test is chosen.

To have a clear vision of my result, I overlay the level and trend break identified by the one break test in Table 1 and plot the poverty rate for each state. Linear trends are then estimated using OLS to connect the break points. The results are displayed in Figure 1. Based on the graph, I can see that for the majority of the states, poverty rate appears to be stationary after allowing for structural breaks. Further examination of the break points in Table 1 reveals some interesting observations. There are fifteen states (Alaska, Colorado, Connecticut, D.C, Hawaii, Kansas, Kentucky, Massachusetts, Missouri, New Jersey, New Mexico, Oregon, Rhode Island, South Carolina, and West Virginia) that have the break happen five years after the end of saving and loan crisis in 1992. These breaks vary in the period from 1993 to 1997. Besides that, there are eighteen states (Alabama, Arkansas, Florida, Idaho, Indiana, Minnesota, Mississippi, Montana, Nebraska, New Hampshire, New York, North Dakota, Pennsylvania, South Dakota, Tennessee, Texas, Washington, and Wyoming) that have the break occurred in the five year period from 1998 to 2002 during the dot-com bubble.

5. Concluding Remarks

This study focuses on the stochastic conditional convergence of poverty rate in fifty US states plus the District of Columbia using newly developed LM unit root tests with trend breaks suggested by Meng et al (2012) and Lee et al (2012). The results of unit root tests of the log of poverty rate without allowing for structural breaks show that twenty six states reject the null hypothesis of unit root test for the ADF test, twenty five states for the LM test, and thirty five states for the RALS-LM test. The result of unit root tests that allow one structural break shows that the null hypothesis of a unit root test is rejected for twenty two states with the LM test, and thirty three states with the RALS-LM test, this study provides significant support for poverty rate convergence among the fifty US states plus the District of Columbia.

From the above observations, it is easy to recognize that most of structural breaks in poverty rate (82.5%) of the fifty US states plus the District of Columbia occur during the business recovery and prosperity phases of the business cycle. After the tests of poverty rate convergence overtime with the goal of providing a better understanding of its property, this study can help to come up with a policy to reduce poverty overall.

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