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Are USA regional incomes converging? A nonlinear perspective

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This article deviates from the current practice of regional convergence by allowing output convergence to follow a non-linear process. In this scenario all standard linear unit root tests have low power, thus frequently leading to misguided conclusions. In light of this we adopt a unit root test based on a non-linear model which tests the null hypothesis of a unit root against a non-linear alternative. Our findings overwhelmingly support the tendency of US regions to converge over time.

Key words: Convergence; non-linearities; E-STAR models**.**

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1. Introduction.

In a recent paper Choi (2004) states that, although a number of studies have provided empirical evidence that the states of the U.S.A. tend to converge to a common stochastic trend (Barro, 1991; Barro and Sala-i-Martin, 1992; Carlino and Mills, 1993), more recent studies (Johnson and Takeyama, 2001; Rey and Montouri, 1999; Tsionas, 2001) have questioned this view, leaving the issue of convergence open. Within this framework Choi (2004) re-examines the convergence hypothesis in the light of the premise that U.S. states are converging *stochastically*. In this approach, output convergence occurs when per capita cross-state output differentials are stationary. His findings provide little evidence in favor of the convergence hypothesis.

Given this uncertainty concerning regional convergence in the U.S.A. we adopt a different methodology in the present paper. *Firstly*, we assert that the proper way to test for output convergence is to use time series methods. According to Evans (1998), cross-sectional studies generate inconsistent estimates of convergence rates, which lead in turn to incorrect inference about the neoclassical prediction. *Secondly*, all unit root tests, whether univariate or multivariate, for examining the notion of stochastic convergence empirically, work upon the hypothesis that the data have a linear structure. However, non-linearities seem to play an important in the convergence hypothesis. If this is true then the presence of non-linearities in the data generating process affect the stationarity properties of the data seriously (Enders and Granger, 1998).

The possibility that non-linearities could play an important role in the convergence hypothesis has not received so far any attention in the convergence literature. Barro and Sala-i-Martin (1995), incorporating poverty traps into the economic development process, demonstrate theoretically that if an economy attempts to escape from them then it comes back to the initial level of output per capita. In particular they argue that "*one way for a poverty trap to arise is for the economy to have an interval of diminishing average product of capital that is followed by a range of rising average product*" (Barro and Sala-i-Martin, 1995, p. 49). In this line of research Galor and Weil (1996) relate the poverty traps with multiple equlibria where income levels are inversely linked to fertility rates while De La Croix (2001), using an overlapping generation model, shows that low educational spending leads the economy into a poverty trap. In this line of thought Urban et al (2001) prove that regions with low human capital stock have a lower steady-state level of income. Finally, Hassler and Rodriguez (2000) claim that a high growth economy supplies many entrepreneurs thus reinforcing high growth whereas a low growth economy provides few entrepreneurs which support low growth. All these issues reveal that the relationship between output growth and output per capita might be nonmonotonic. This means growth rates are increasing over some range of income levels but decreasing over a different range. In this direction Fiaschi and Lavezzi (2003) developed a non-linear graphical growth model and tested its empirical validity using Markov transition matrices. Their findings lend support to the contention that non-linearity is an important feature of the growth process, thus affecting the speed of convergence. They concluded that the detection of non-linearities is of paramount importance for the design of economic policies.

From the above discussion, the important role of non-linearities in the growth process is clear. This calls for the application of unit root tests that account for a non-linear structure in the data generating process if we are to obtain sensible results. More specifically, in this paper we use recent non-linear statistical techniques to estimate the convergence hypothesis in the states of the U.S.A. over the period 1929-2001.

The remainder of the article is structured as follows: Section 2 defines the notion of convergence in a time series context while in Section 3 we introduce the non linear model considered. In Section 4 we describe a non-linear test and Section 5 contains the empirical results. The final Section 6 concludes the paper.

2 Defining output convergence in a time series context

A time series based approach examines long run output movements. According to Bernard and Durlauf (1995, 1996) two regions i and j converge if the long run forecasts of their real output per capita (z) are equal:

$$\lim_{t\to\infty} E(z_{it} - z_{jt}) = 0 \tag{1}$$

Equation (1) equates the notion of convergence with the tendency of output per capita differentials to disappear as the forecast horizon increases. From an empirical point of view the time series notion of convergence requires that per capita output differentials between regions i and j be stationary. If the output per capita series is trend stationary, definition (1) implies that the time series trends for each region must be identical. Pairwise convergence must hold for all pairs of regions.

This definition of convergence has a testable counterpart in the unit root literature. In particular we investigate whether the ratio of real output per capita (z_{it}) in region i at time t to the mean of regions $\bar{z}_t = N^{-1}\sum_{i=1}^{N} z_{it}$ has a unit root. Acceptance of the null hypothesis of a unit root provides evidence against the convergence hypothesis *i.e.*

$$H_0 : x_{it} = I(1) \qquad \text{i=1,2,…..N.} \qquad \text{t=1,2,…..T} \qquad (2)$$

where $x_{it} = \frac{z_{it}}{\bar{z}_t}$, while $I(1)$ indicates a unit root non-stationary process.

In this case all shocks have a permanent impact on the output per capita of region i, leading this region away from its equilibrium level. Other things being equal, the presence of a unit root in output per capita suggests that the series does not revert to its average value.

Since the testing procedure might contain a constant, or a constant and a time trend, there are two alternative definitions of output convergence. If a constant is included in the unit root regression, then output convergence is called *deterministic convergence* (Li and Papell, 1999). If a constant and a time trend are included in the fitted regression, output convergence is called *stochastic convergence* (Carlino and Mills, 1993).

3. Unit root tests based on non-linear models

To test for the existence of a non-linear data generating process we consider a smooth transition model (STR) with two regimes (Teräsvirta,1998)

$$x_{it} = \rho x_{it-1} + \rho^* x_{it-1}\Phi(s_t) + \varepsilon_t \qquad (3)$$

where x_{it} is stationary and ergodic, $\varepsilon_t \sim iid(0,\sigma^2)$ and $\Phi(s_t)$ is the transition function defining the regime.

The transition function is bounded by zero and unity with s_t being the transition variable that determines the regime. At the extremes of $\Phi(s_t)=0$ and $\Phi(s_t)=1$ the STR model (3) is linear with coefficient vectors ρ and $\rho+\rho^*$, respectively. The corresponding AR(1) models are given by:

$$x_{it} = \rho x_{it-1} + \varepsilon_t \tag{4}$$

$$x_{it} = (\rho+\rho^*)x_{it-1} + \varepsilon_t \tag{5}$$

It is obvious that the AR(1) models in equations (4) and (5) differ as long as $\rho^* \neq 0$, implying different speeds of mean reversion.

Following Kilic and de Jong (2005), we consider the exponential form for the transition function $\Phi(s_t)$.

$$\Phi(s_t) = [1-\exp(-\theta z_{t-d}^2)] \tag{6}$$

where $z_{t-d} = \Delta x_{it-d}$ is the transition variable[i], $d \geq 1$ is an integer denoting the delay parameter and θ $(\theta > 0)$ determines the speed of mean reversion.

Next, we set $\rho = 1$ and $d = 1$ in equation (3) obtaining the following exponential STR form,

$$\Delta x_{it} = \rho^* x_{it-1}\{1-\exp(\theta z_{t-1}^2)\} + \varepsilon_t \tag{9}$$

A test procedure for the null hypothesis of a unit root

$$H_0 : \rho^* = 0 \tag{10}$$

against the alternative

$$H_0 : \rho^* < 0\,, \tag{11}$$

could be based on $\tilde{t}_{\rho^*=0}(\theta)$. However, since θ is not identified under the null (Davies, 1987) the null hypothesis (10) cannot be tested in this way.

To test (10) directly Kilic and de Jong (2005) developed the following t-statistic

$$\text{Sup-}t = \sup_{(\theta)\in\Theta}\left\{\frac{\tilde{\rho}^*(\theta)}{s.e.(\tilde{\rho}^*(\theta))}\right\}_{\rho^*=0} \tag{12}$$

where $\Theta = [\underline{\theta}, \overline{\theta}]$ and $0 < \underline{\theta} < \theta < \overline{\theta}$. This corresponds to the values of θ yielding the smallest sum of squared residuals. The initial value of θ is estimated using a grid search method over [0.1,0.2,……100].

Kilic and de Jong (2005) concluded from Monte Carlo simulations that this test has superior power to the ADF test under the alternative of an exponential STR model. It was also found that it performs better and is more powerful than the non-linear ADF test of Kapetanios et al. (2003). Asymptotic critical values of $\sup-t$ are tabulated in Kilic and de Jong (2005).

4. Testing for linearity and the form of non-linearity

Before attempting to test for the existence of a non-linear unit root process it is important to test the hypothesis of non-linearity. Since the arbitrary choice of a non-linear function entails the risk of spurious fit. Teräsvirta (1994) proposes a method of testing for smooth transition thresholds non-linearities against the null of linearity by approximating the transition function $\Phi(s_t)$ by a Taylor expansion about $\theta = 0$. To carry out the test we estimate the following auxiliary regression.

$$x_{it} = \mu_0 + \sum_{j=1}^{p} (\mu_{0j} x_{it-j} + \mu_{1j} x_{it-j} z_{t-1} + \mu_{2j} z_{t-j} z_{t-1}^2) + e_t \qquad (13)$$

where e_t is an error term.

The null hypothesis of linearity is represented by $H_0 = \mu_{1j} = \mu_{2j} = 0$ for $j = 1,2,.....p$ against the alternative $H_1 = \mu_{1j} = \mu_{2j} \neq 0$.

Teräsvirta (1994) derived a test following an $F-$distribution with $2k$ and $T-3k$ degrees of freedom(where k is the number of regressors in the linear model).

5. Empirical results

Following Choi (2004) we use the logarithms of regional aggregated regional real personal income per capita data over the period 1929-2001. All the data were provided by Choi (2004).

As stated in Section 2, a necessary condition for regional convergence is that x_{it} variable is stationary. To this direction, we calculate simple standard linear ADF statistics along with the KPSS test in which the null hypothesis is stationarity (Kwiatkowski *et al*. 1992). A drawback of the ADF unit root test is that it has low power in finite samples against the relevant alternative such as stable autoregressive model unit roots near unity. This weakness suggests the use of tests where the null hypothesis is stationarity; see Dejong et al. (1992). Within this context Maddala and Kim (1998) claim that to ensure the validity of the ADF we have to perform tests where the null hypothesis is that of stationarity against the alternative of a unit root process. The results are reported in the following Table 1.

[Insert Table 1]

According to the ADF statistic the null hypothesis of a unit root when only a constant is included in the fitted regression can be rejected in four out of eight regions under examination, that is, New England, Mideast, Southwest and Rocky Mountain. Using the KPSS stationarity test the results are much less favourable for the convergence hypothesis. According to this statistic only two regions (New England and Rocky Mountain) move to the steady state. This means that in the majority of the regions *deterministic convergence* is not a characteristic of the data generating process. The results remain qualitatively similar when we test for stochastic convergence (to test for stochastic convergence a constant and a time trend we included in the fitted regression). In particular, only two regions (Great Lakes and Rocky Mountain) using the ADF statistic and one region (Far West) with the KPSS stationarity tests present evidence in favour of stochastic convergence.

Given that ADF and KPSS statistics both have low power in the presence of misspecified dynamics we investigate the presence of non-linearities using equation (13). Table 2 reports values of the linearity test statistic F. From Table 2 it can been that linearity is rejected at the 1% level of significance for all regions under examination except New England and Southwest. This means that there is significant evidence of non-linearity which is reasonably approximated by an exponential STR model.

[Insert Table 2]

Next we apply the unit root statistic Sup-t described in (12) proposed by Kilic and de Jong (2005) when a constant (*deterministic convergence*) or a constant and time trend (*stochastic convergence*) are included in the non-linear ADF regression (9). It should be noted that we apply the non-linear ADF regression model (9) only to the regions where the linearity hypothesis was rejected. For the remaining regions, where the linearity hypothesis could not be rejected, the ADF and KPSS statistics provide robust results. Before applying the Sup-t test we regressed the x_{it} series on a constant and also on a constant and a time trend and saved the residuals each time, thus generating a new variable which is either de-meaned or de-meaned and de-trended. In the following Tables 3 and 4 we show the results for both these cases.

[Insert Table 3]

[Insert Table 4]

Examination reveals that the Sup-t statistic without a trend (*deterministic convergence*) rejects the non-convergence hypothesis for two regions (Mideast and Rocky Mountain) while with a trend it rejects the non-convergence hypothesis for four regions, that is, Mideast, Greta Lakes, Southeast and Far West. Comparing our findings with Table 1 we see that: (a) the Sup-t statistic provides additional evidence for the deterministic convergence hypothesis for one region, Mideast, where both the

ADF and KPSS statistics failed to establish convergence; (b) the Sup-t statistic can detect stochastic convergence against the results of the ADF and KPSS statistics in two regions, Mideast and Southeast, while in the Far West it finds stronger evidence in favour of the convergence hypothesis; and (c) the joint use of ADF and Sup-t statistics produces evidence in favour of the convergence hypothesis for 7 out of 8 regions. The exception is Plains. These findings stand at variance with the findings of Johnson and Takeyama (2000), Rey and Montouri (1999), Tsionas (2001) and Choi (2004), who concluded that regional convergence, could not be established from these data.

6. Concluding remarks

In this paper we have examined the long run behavior of output per capita movements in a U.S. aggregate regions over the period 1929-2001. Results for or against output convergence are obtained based on whether an output differential series is stationary or has a unit root. Unit root tests could be used to test the convergence hypothesis empirically. However, standard unit root tests along the lines of ADF have lower power to reject the unit root null hypothesis when the data generating process is non-linear stationary. This issue has not so far received any attention in the empirical literature. Our findings are based on the well-known ADF statistic as well as on recently proposed non-linear unit root tests. We find considerable evidence in favor of the convergence hypothesis when we combine the linear ADF unit root test with non-linear alternative ones.

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Table 1. Unit root tests.

Region	Constant		Constant and a time trend	
	ADF	*KPSS*	*ADF*	*KPSS*
New England	-2.93** [0.07] $k = 4$	0.43**	-2.30 [0.45] $k = 4$	0.27
Mideast	-4.48*** [0.01] $k = 4$	0.57	-2.85 [0.17] $k = 4$	0.29
Great Lakes	-1.32 [0.69] $k = 2$	1.20	-3.47** [0.04] $k = 2$	0.22
Plains	-2.30 [0.17] $k = 3$	0.86	-2.06 [0.60] $k = 3$	0.27
Southeast	-2.44 [0.13] $k = 4$	1.39	-0.68 [0.97] $k = 4$	0.32
Southwest	-3.00** [0.04] $k = 2$	1.03	-2.33 [0.45] $k = 2$	0.28
Rocky Mountain	-3.60*** [0.01] $k = 2$	0.23*	-3.45** [0.05] $k = 2$	0.22
Far West	-0.75 [0.89] $k = 3$	1.39	-2.89 [0.17] $k = 3$	0.08*

Notes: ADF is the augmented Dickey-Fuller unit root test. The optimal lag (k) structure for the ADF regression was selected via the Pantula et al. (1994) principle. KPSS is the Kwiatkowski et al. (1992) stationarity test. Schwert's (1989) formula was used to determine the optimal lag order for the KPSS statistic. Figures in brackets represent asymptotic p-values associated with the ADF tests. The 5% and 10% critical values are 0.463 and 0.347, respectively, in the constant model and 0.146 and 0.216 in the constant and trend model. Underlying values denote sampling evidence in favour of unit roots. (***), (**) and (*) signify stationarity at the 1%, 5% and 10% levels of significance, respectively.

Table 2. F – values for the linearity test.

Region	F -Statistic	Critical Values at 1% level
New England	2.22	2.50
Mideast	<u>4.30</u>	2.47
Great Lakes	<u>4.70</u>	2.50
Plains	<u>5.15</u>	2.50
Southeast	<u>3.16</u>	2.47
Southwest	0.86	2.25
Rocky Mountain	<u>2.43</u>	1.89
Far West	<u>2.89</u>	2.25

Notes. Underlying values signify rejection of linearity null hypothesis at the 1% level.

Table 3. Unit root tests based on non-linear model (9) for de-meaned data.

Region	Sup-t
Mideast	-3.64**
Great Lakes	-0.72
Plains	-1.66
Southeast	-0.19
Rocky Mountain	-2.25*
Far West	-0.30

Notes. (**) and (*) signify rejection of the unit root hypothesis at the 1% and 10% level, respectively. The critical values at 1% and 10% are –2.40 and –2.06 respectively. Underlying values denote sampling evidence in favour of unit roots.

Table 4. Unit root tests based on non-linear model (9) for de-meaned and de-trended data.

Region	Sup-*t*
Mideast	-2.37*
Great Lakes	-3.97**
Plains	-2.00
Southeast	-3.26**
Rocky Mountain	-2.15
Far West	-2.29*

***Notes**. (**) and (*) signify rejection of the unit root hypothesis at the 1% and 10% level, respectively. The critical values at 1% and 10% are –2.60 and –2.26 respectively. Underlying values denote sampling evidence in favour of unit roots.*

Endnotes:

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[i] According to Kilic and de Jong (2005) the choice of Δx_{it-d} as a transition variable ensures that the Δx_{it-d} variable is not a highly persistent process, such as a local to unity process, even in the neighbourhood of null hypothesis of unit root.