# TIME-SERIES TESTS OF STOCHASTIC EARNINGS CONVERGENCE ACROSS US NONMETROPOLITAN COUNTIES, 1969-2004

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**Abstract**

This paper assesses whether per-capita income, measured as average wages and salaries per job, in U.S. nonmetropolitan counties is converging to the national or U.S. metropolitan average using data over the 1969 to 2004 period. Additional analysis explores whether per-capita income is converging to the national and metropolitan averages using several sub-sets of nonmetropolitan counties based on USDA typologies. The paper uses single equation and panel unit-root tests in the analysis and concludes that nonmetropolitan counties are converging to the national and metropolitan average in general with a few exceptions.

**Key Words:** Stochastic Convergence, Regional Analysis, the USA
***JEL* Classifications:** C13, C21, R11, R12

## 1. Introduction

The narrowing of the incomes and earnings gap between metro and nonmetro areas in the United States has been a policy priority for most local governments and the federal government. It has also been an important research topic. The findings by a number of researchers of non-convergence, weak convergence, or even divergence have been puzzling for policy makers and are at odds with the predictions of standard neoclassical growth theory of convergence. The theory of convergence states that poorer economies tend to grow faster than richer economies and therefore, all economies will eventually converge in terms of per capita income or earnings. This implies that a poorer economy's income/earnings will eventually "catch up" with a richer economy's income/earnings. This catch up is based on the assumption of decreasing returns to capital, which should cause more advanced economies to grow more slowly than less advanced ones. The income convergence hypothesis is more conceivable for regions within a country than among countries because of the more openness of regions for factor mobility. The regions within a country's borders may have easy access to capital to invest and hence to get out of the low-efficiency trap. With respect to nonmetropolitan areas of the US, the neoclassical theory suggests that the earnings and income gap between nonmetro and metro areas should reduce over time. Moreover, the emphasis in manufacturing promotion policies, retiree attraction, and government transfers and assistance programs (such as farm policy programs and federal economic development assistance programs) would suggest that earnings in nonmetropolitan counties should converge over time.

Regional incomes/earnings convergence in the United States has been extensively examined. The units of analysis for most of these studies are states, regions, or metropolitan areas. Early studies (Borts 1960; Borts and Stein 1964) on the convergence hypothesis for the United States find support for income convergence. While some of the more recent studies present evidence of convergence (Carlino and Mills 1993; Vohra

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1998; Tomljanovich and Vogelsang 2002; Ben-David et al. 2003; Rupasingha, et al. 2002, Miller and Genc 2005), others present divergence (Alvi and Rahman 2005; Drennan et al. 2004) or mix results (Carlino and Mills 1996a; Weber et al. 2005; Carvalho and Harvey 2005).

Only few studies have paid explicit attention to convergence in nonmetro areas (Henry 1993; Nissan and Carter 1999; Renkow 1996; Hammond 2004, 2006). But they too are limited to the within group convergence except Hammond (2006). Most of these studies find little evidence of convergence within metropolitan and nonmetropolitan regions. Hammond (2006) finds that non-metro incomes are diverging from below with respect to national income. He also finds that nonmetro counties with high initial farming and mining employment exhibiting divergence and counties with high manufacturing employment exhibiting mixed results.

Contrary to these findings, descriptive evidence on earnings gap between nonmetro and metro areas and nonmetro and national averages shows a tendency towards convergence over last 36 years.

We address the issue of stochastic convergence of earnings using time-series techniques for nonmetropolitan counties of the United States. To be specific, in this study, we employ a number of unit root tests to discover the existence of the so-called stochastic income convergence (or lack thereof) of US non-metropolitan relative earnings with respect to the metro as well as overall US average earnings over the relatively recent history. Technically speaking, Carlino and Mills (1996b) and Loewy and Papell (1996) consider a non-zero mean stationary process of a regional relative income to the national income as evidence for stochastic convergence whereas Bernard and Durlauf (1995, 1996) define the stochastic convergence as the existence of cointegration among the regional incomes of a country. We follow the former definition in this study. We make two significant contributions to the literature. First, we employ Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test and panel-based unit root tests (allowing for unobservable area-specific heterogeneity) to test for stochastic convergence of nonmetro earnings towards metro counties and the US national average. Existing literature usually applies Augmented Dickey-Fuller (ADF) test but findings based on this test are questionable as it is well-known that ADF type tests have low power in distinguishing between the null and alternative hypotheses, especially in the presence of time trends. Second, we address the issue that some types of nonmetropolitan counties may be outperforming their counterparts and advance towards convergence. We present a more disaggregated view of nonmetro convergence using county-level typology codes developed by the USDA ERS. Aggregation of data present several challenges in empirical work, both in terms of interpretation and the robustness of results in the face of disaggregation. We conjecture that some of the earlier results claiming non-convergence may be due to the nature of the data used in these studies, especially if the data are aggregated.

The USDA ERS has developed county-level typology codes that capture a county's economic and social characteristics, assuming that these characteristics have significant effects on county development and have policy-relevant information about diverse county conditions to policymakers, public officials, and researchers. As shown in Table 1, counties are classified as farming, manufacturing, mining, services, or government dependent, depending on the share of earned income from these categories.[1] Counties that do not meet the criteria for these categories are considered non-specialized. Under different economic conditions one might expect counties with a different specialization to either underperform or overperform national or metro average earnings. Such a disaggregated view will also shed some light on the issue that various policies aimed at promoting rural development such as manufacturing recruitment, farm subsidies, government spending (that are intended to benefit constituents), and retiree attraction are helping those particular areas to narrow their earnings gap between them and metro areas and nation.

Agriculture has dominated the economic well-being of most of the rural population for a long time and agricultural policy has played a major role in shaping farming communities. But the significance of agriculture in rural earnings has decreased over time and rural households depend more on off-farm earnings as a source of economic growth. Manufacturing as a source of off-farm earnings has undoubtedly played a significant role in rural economies. In the 1960s and 1970s manufacturing dependent counties experienced rapid increases in per capita income and early 1990s a significant number of retirement destination counties have had increased per capita income (Kusmin, Redman and Sears 1996). Attracting retirees has been a popular rural development policy since 1980s and retiree-destination nonmetro counties have enjoyed significantly more rapid population and employment growth and economic diversification than other types of nonmetro counties (Reeder 1998). Some recent descriptive evidence suggests that retail trade and services sector are replacing agriculture and manufacturing as the economic drivers of rural America (Beaulieu 2002). A general observation about mining-dependent counties is that most of these counties are distressed counties with high poverty and unemployment rates. On the other hand, because of high poverty and unemployment rates, these counties may be receiving higher percentage of federal assistance. In view of these changes and reasons, it is important to know whether the earnings in these and other county types in nonmetro areas are catching up with earnings in metro areas and with the US average in general.

The rest of the paper is organized as follows. The following section presents the data and develops the econometric model along with the econometric tools used for testing convergence. The empirical results are presented in the next section. Discussion of results is presented next. Concluding comments are presented in the final section of the paper.

## 2. Data, Econometric Model and Methodology

We address the issue of convergence of nonmetro earnings using time-series techniques for nonmetropolitan areas of the United States and use county level data on average wages and salaries per job (average earnings hereafter) from the Bureau of

[1] A second classification scheme is oriented around the influence of government policy and individual behavior. Categories are: retirement destination, commuting, federal lands, persistent poverty and transfer payment dependent. These categories are neither mutually exclusive nor exhaustive but serve to identify the importance of a specific characteristic that may have an important impact upon growth. Out of these, we include the category of retirement destination counties in our analysis because of its policy significance.

Economic Analysis' (BEA) Regional Economic Information Systems (REIS) over the past 36 years (1969-2004) as a measure of convergence. The convergence can either be unconditional or conditional and the most commonly used measure of convergence is beta convergence.[2] Beta convergence takes place when economies with initially low levels of per capita income or output grow faster than economies with initially high levels of per capita income or output, leading to an eventual convergence of income or output between poor and rich economies.

The idea of convergence originates from the seminal work of Solow (1956) and Swan (1956), which is widely known as the Solow model of growth[3]. In the Solow model, the countries with similar rates of savings (*s*), population (*n*), and depreciation (*d*), as well as similar level of total factor productivity (*z*) are only distinguished from each other with the various levels of per capita capital. Thus, in the long run steady state equilibrium, the per capita capital (k*) for all economies can be obtained by solving

(1) $$szf(k^*) - (n+d)k^* = 0$$

For $k^*$, where *f*() is the per capita production function. The authors show that irrespective of the initial value of the per capita capital, all economies converge to the same level of per capita capital. Since the per capita production (income) is $y = f(k^*)$ at this level, per capita income levels in all countries will be the same eventually. If, however, the countries have different levels of *z*, *d*, *s*, and/or *n*, steady state levels of $k^*$ may differ leading to divergence of per capita income in different countries.

The hypothesis of the Solow model is that rich countries will grow slower and poorer countries will grow faster to attain the convergence as capital will flow from the rich to poor countries where the marginal productivity of capital is higher (thus higher return for capital in poor countries with low levels of capital). A testable version of the model can be formulated as follows (Romer 1996):

(2) $$\ln \frac{y_{it}}{y_{i0}} = \alpha + \beta \ln y_{i0} + \varepsilon_t$$

Where ln is the natural logarithm, $y_t$ is the per capita income (or earnings in the present study) at time *t*, *T* is the end of the period, and 0 is the beginning of the period and $\varepsilon$ is the white noise error term. The left hand side is the approximate growth rate of per capita income of country *i* during the study period. The explanatory variable here is the natural log of the initial per capita income level of country *i*. If $\beta<0$, then the convergence is said to be achieved. This is known as the absolute beta convergence (Miller and Genc 2005). Econometrically speaking, this is a cross sectional estimation. It is possible to interpret *y* as the ratio of the income of one county to another. In this sense *y* becomes the

[2] Another measure of convergence is sigma convergence, which means the tendency of the variation of income among places to diminish over time (Quah 1993). Sigma convergence is usually measured by the standard deviation of per capita income or output for places over time.
[3] See De La Fuente (1995 and 1998) for a more detailed discussion on growth modeling.

relative income of one county to that of another. Carlino and Mills (1993, 1996a and b) show that a time series version of this model can be written as

3. $$\ln y_t = \theta_1 + \theta_2 TT_t + \varepsilon_t$$

Where *TT* is the time trend, and $\varepsilon$ is a white noise process. If $\varepsilon$ is not white noise, then it has to be whitened out through an appropriate ARMA process. By subtracting the lagged value of the dependent variable from both sides, we obtain

4. $$\Delta \ln y_t = \theta_1 + \theta_2 TT_t + \theta_3 \ln y_{t-1} + \varepsilon_t .$$

Where $\Delta$ is the difference operator. If $\varepsilon$ is not white noise, we have various lags of the dependent variable as well as the error term on the right hand side. This equation is the basis for what is known as the stochastic convergence tests.

The empirical studies in the growth literature present a range of results regarding convergence. The major difficulty in the empirical studies is to find a set of economic regions with a similar set of parameters for *s*, *n*, *d* and *z*. One of the issues in sustaining different levels of these parameters may be attributed to lack of free flow of inputs of production between countries, precluding the equalization of marginal product of capital across countries. However, it is probably more sensible to carry out a convergence test among regions of the same country as the capital would have more freedom to move to more productive areas of the country.

In this study we analyze earnings convergence in nonmetro (rural) areas in the US with respect to metro areas and the US average and then between various sub-classifications of the US non-metro areas with respect to metro areas and US average. As for the sub-classifications, we compare the average earnings of such county typological areas as farming, mining, manufacturing, federal/state government dependent, service sector dependent, counties with no specialization, and retirement destination counties. First six typologies are classified as mutually exclusive categories of economic dependence, and the retirement destination typology is one of seven overlapping categories of policy-relevant themes (Table 1). We use 2004 county typology codes in the present analysis.

Average earnings for each region are generated as the ratio between total earnings of the region and the total full and part-time employment in that region. Total earnings comprise of wages and salaries, other labor income, and the net income of proprietors or self-employed. Thus the variables generated are

5. $$r_{tkj} = \frac{\sum_{k=1}^{Kj} y_{tkj}}{\sum_{k=1}^{K} p_{tkj}}$$

Where $r_{tkj}$ stands for average earning of the region in question at period *t*. The $y_{tkj}$ represents the total earnings of this region at the same period, and $p_{tkj}$ is the number of full and part-time employment of region *j* at time *t*. The coverage period, *t*, runs from 1969 to 2004, and $j$ = {US, Metro areas, nonmetro areas, farming areas, mining areas, manufacturing areas, government dependent areas, service areas, retirement areas and no-specialty areas}. As the summation sign in the formula makes it clear, we sum the data for each year for each region, *j*, depending on the number of counties, *k*, in that region. The *k* runs from $k = 1, \ldots, Kj$ for each region. We use 2004 Rural Urban Continuum Codes to separate counties to metro vs. rural (nonmetro) areas. Then we generate “relative regional earnings” for all nonmetro counties and typological areas with respect to the metro areas,

6. $$rM_{tj} = \log\left(\frac{r_{tkj}}{r_{tkM}}\right),$$

and with respect to the US,

7. $$rU_{tj} = \log\left(\frac{r_{tkj}}{r_{tkU}}\right),$$

Where $rM_{tkj}$ stands for the relative regional earnings of region *j* with respect to $r_{tM}$, the metro earnings as defined in Equation 5 at time period *t*. Likewise, $rU_{tkj}$ stands for the relative regional earnings of Region *j* with respect to $r_{tU}$, the US earnings as defined in Equation 5 at time period *t*. Here $j$ = {nonmetro counties, farming areas, mining areas, manufacturing areas, government dependent areas, service areas, retirement areas and no-specialty areas}.

The standard testing method of the stochastic convergence is to check the order of integration in a variable such as our relative earnings concepts above. If there is convergence between two regions under study, their relative earnings should be integrated of order zero, i.e. it should be stationary. This is the rejection of unit root hypothesis in the testing process. This type of tests is commonly known as the unit root tests as their null hypotheses assume the presence of unit root. There are alternative tests which start out with the assumption of stationarity. They are known as the stationarity tests. However, for all practical reasons, they serve the same purpose, thus, in this paper; we use these two naming conventions interchangeably. There are several unit root/stationarity tests in the literature. A large volume of literature employs the Augmented Dickey Fuller (ADF) test (Dickey and Fuller 1979; Said and Dickey 1984; and MacKinnon 1991, 1996). The ADF assumes that the variable has unit root. As mentioned above, if a relative earnings variable is found to contain unit root, we reject the convergence between the average earning levels of two regions. The test equation in ADF with a constant and trend in data is

8. $$\Delta z_t = \alpha + \beta z_{t-1} + \phi TT_t + \sum_{i=1}^{p} \gamma_i \Delta z_{t-i} + \varepsilon_t$$

Where $z$ is the dependent variable to be tested for unit root/stationarity, $TT$ is the time trend, $\Delta$ is the difference operator, and $p$ represents the optimum lag length to obtain the white noise errors. The optimum lag lengths are chosen according to Schwarz (1978). The null hypothesis is $\beta = 0$ vs. the alternative, which is $\beta < 0$ [4].

However, it is also known that Dickey-Fuller type tests have low power in distinguishing between the null and alternative hypotheses, especially when there is trend in data. According to Hobijn, Franses and Ooms (1998), the stationarity is more likely than non-stationarity for the data in many cases. Furthermore, ADF tends not to reject the null hypothesis more often with roots in the close neighborhood of the unit circle. A solution to the drawbacks of ADF is offered by Kwiatkowski, Phillips, Schmidt, and Shin (1992), where their test (KPSS) employs the stationarity as its null hypothesis. The KPSS is thus more reliable in testing trended data compared to ADF as the former reverses the place of the null and alternative hypotheses of the latter. The KPSS is considered as one of the most powerful tests for stationarity (Ibrahim 2004). This test is based on the residuals from the least squares regression of the original data against the constant, time trend and the optimum number of lags of the dependent variable. Like the ADF test, the optimum lag lengths are chosen according to Schwarz (1978). An LM test is constructed where the cumulative residual function deflated by the number of observations and an estimator of the residual spectrum at frequency zero is contrasted against the KPSS critical values. In this paper, we present the results of both tests for the sake of comparison. Besides, Kwiatkowski, Phillips, Schmidt, and Shin (1992) consider their test and the ADF test to be complementary. Thus, they recommend that both tests be reported.

In general, the biggest drawback of the individual data based stationarity tests is that they are usually designed for large data sets, that is, most of their results are asymptotically valid. Obviously with data spanning only 1969-2004 period, we face a sample size problem. To resolve this issue, panel unit root tests are recommended in the literature as they have higher power than unit root tests based on individual time series such as ADF and KPSS. With so many counties in all typological areas in the US over a 36 year period, we have quite a large data set. There are many variants of these types of unit root tests. We use Levin, Lin and Chu (2002) or LLC, Breitung (2000) or B, Im, Pesaran and Shin (2003) or IPS, Hadri (2000) or Hadri as well as Fisher-type tests using ADF, ADFP, and PP tests (Maddala and Wu 1999; Choi 2001) or PP[5]. By using a large variety of the tests we have a more robust conclusion regarding the convergence or lack thereof among the regions under various statistical alternatives. For example, all these tests with the exception of Hadri (2000) start off with the null hypothesis of non-stationarity (non-convergence) in terms of our models. The null hypothesis of Hadri (2000) is the stationarity. Hence, the panel based tests would be a replica of our individual variable based tests because in both cases we employ the unit root and stationarity as the null hypotheses. Additionally, LLC, B and Hadri assume a common AR structure for all of the variables whereas IPS, ADFP and PP allow for different AR

[4] Note that this is the empirical version of the stochastic convergence test equation derived above. For comparison, $z$ in this equation represents the $lny_t$ in the equation above.

[5] Panel unit root tests are straight forward extensions of the individual unit root tests, though not exactly identical to them. More detailed discussion including the test equations employed is omitted here for the sake of brevity. However, interested reader is referred to the references listed in the paper.

coefficients in each series. The exogenous variables used in all tests are the individual effects and individual linear trends. As in the individual unit root tests, the lag lengths are automatically selected based on the Schwartz information criterion. We employ the Newey and West (1994) bandwidth selection using Bartlett kernel (Andrews 1991; Dyer and Keating 1980).

The variables for the panel tests are reconstructed by slightly modifying the variables defined above as

5'. $$r_{tj} = \frac{y_{tj}}{p_{tj}}$$

Where $r_{tj}$ stands for average earnings of each county in each region at period $t$. The $y_{tj}$ represents total earnings of each county in each region at the same period, and $p_{tj}$ is the full and part-time employment of region $j$ at time $t$. The $j$ = {rural, farming, mining, manufacturing, government dependent, service, retirement and no-specialty areas}. The way this variable is calculated for the metro areas and US remains the same. Therefore, we have

6'. $$rcM_{tj} = \log\left(\frac{r_{tj}}{r_{tkM}}\right),$$

and with respect to the metro areas, and

7'. $$rcU_{tj} = \log\left(\frac{r_{tj}}{r_{tkU}}\right),$$

With respect to the US average. Here the $rcM_{tj}$ ($rcU_{tj}$) stands for the relative average earnings of region $j$ with respect to $r_{tkM}$ ($r_{tkU}$), the average metro (US) earnings as defined in Equation 5 at time period $t$.

## 3. Empirical Results

As mentioned before, we initially conduct unit root tests on the relative regional earning variables generated above using ADF and KPSS tests. It is well known that these tests may be quite sensitive to the lag length used in carrying out the procedure (Kwiatkowski, Phillips, Schmidt, and Shin, 1992)[6]. Since this type of data might be highly correlated over time, the inclusion of too few lags in the tests would seriously bias the results due to the remaining autocorrelation in the data. On the other hand, including too many lags has its own shortcomings in terms of reduced power of the tests. In the absence of a clear guidance, however, one may start off with a larger lag structure rather than the smaller one as this is found to be preferred via Monte Carlo experiments. Ng and

[6] Some authors, however, dictate the lag length in these tests. Hammond (2006), for example, imposes the lag structure rather than testing for an optimal lag length. This might be because of the short span of his data.

Perron (2001) recommend starting with a relatively larger model and reducing the lag length based on some criterion. Schwert (1989) proposes a rather ad hoc choice of the lag length, which is $\left\{\text{integer}\left[12(N/100)^{0.25}\right]\right\}$ where N is the number of observations in the series. Alternatively, one may use an information criterion such as AIC (Akaike information criterion) and/or SIC (Schwarz (1978) information criterion). Hobijn, Franses and Ooms (1998) recommend the use of the automatic lag length selection procedure developed by Newey and West (1994) to improve the performance of the original KPSS test. Therefore, we allow the lag length to be optimally chosen with the help of Schwarz (1978) information criterion. We include a constant and time trend in all estimations as dictated by the graphs of the variables.

The results of the tests are presented in Tables 2 and 3. Table 2 gives the stationarity/unit root tests of the regions with respect to the metro areas and Table 3 presents the same analysis with respect to the USA average. Admittedly, delineating regions by the 2004 Rural-Urban continuum code may be problematic. Should it be the beginning code, rather than the end? According to Isserman (2001), a sizable portion of rural growth has occurred in areas reclassified as metropolitan over time. The implication is that if classification is redone according to rural codes from the early 1970s, we might find still stronger evidence of convergence. Therefore, we also conduct these tests based on a typology classification which corresponds to somewhat the middle date of the data sample, i.e. 1980. Our results largely consistent with the more recent classification of 2004 typology. These results are available from the corresponding author upon request.

As shown in Table 2, the overall comparison where we compare nonmetro areas altogether against metro areas, ADF test finds no convergence between the nonmetro and metro areas, whereas KPSS finds the opposite, though with a small margin. Both tests agree that average earnings of mining and retirement dependent counties do not converge to average earnings of the metro areas. They also agree that average earnings of service dependent areas do not differ from the metro average income. However, they disagree on the remaining variables. While ADF tests claim that there is no convergence between farming and metro areas, between manufacturing and metro areas, and between no specialty and metro areas; KPSS tests claim just the opposite. It is important to note here that the non-stationarity (and thus non-convergence) of manufacturing areas with respect to the metro areas according to the KPSS test is only marginally true at the 5% level of significance. This inference disappears once we adopt 10% level of significance whose critical value is 0.119. Likewise, no specialty areas tend to converge to the metro areas once we adopt a 10% level of significance for the ADF test whose critical value is -3.2047. In the case of government dependent income areas, while ADF test points to a convergence, the KPSS reverses this result.

Qualitatively speaking, a similar rundown on the results between the regions and the whole US (including the overall comparison), as shown in Table 3, also arrives at the same conclusions. In other words, if a test claims that there is (not) convergence between a specific region and the metro areas of the US, there is (not) a similar convergence between that region and the US average. This would mean that the metro and the US earnings should be pretty closely associated with each other.

The panel unit root test results are presented in Table 4. The immediate observation we make from Table 4 is that there is a perfect correlation between the US based and metro based tests. In other words, if a region's average earnings with respect to the US average earnings are found to be stationary (non-stationary) by a certain test, then that region's average earnings with respect to the metro average earnings are also found to be stationary (non-stationary). This is a confirmation of the results obtained above via individual unit root tests. Additionally, at the 5% level of significance, all the tests whose null hypothesis is non-stationary reject the null in favor of the alternative hypothesis for all regions. Hadri (2000) tests, too, rejects its null hypothesis, but its conclusion is the non-stationarity or the existence of the unit root in data. Overall, based on panel unit root tests; there is an indication of convergence of average earnings in nonmetro counties in the US.

## 4. Discussion

The debate on the per capita income/earnings convergence among US regions, variously defined, continues to generate an energetic interest for both policy makers and researchers. This is because the findings may have both policy and research implications. Obviously, a per capita income divergence among regions would necessitate compensating policy measures to reduce differences (Miller and Genc 2005). This may lead to an increased burden, say of taxes, of the relatively well-off regions while the residents of the worse-off areas may enjoy a windfall, which may be politically difficult to deal with.

In this paper, we look at a relatively recent US economic data on non-metro wages and earnings to investigate the convergence question. Although we do not have all of our findings completely supporting the convergence argument, especially in the cases of mining and retirement, it is fair to say that we find an indication that in the recent history the per capita earnings in the non-metropolitan areas tend to converge to a US and a metropolitan earnings average. Without citing the immense literature in this field, we take comfort in the fact that we are in good company per our claim such as Carlino and Mills (1993) and Loewy and Papell (1996), which studied similar issues by comparable methods. That is to say, the research on stochastic convergence in the time series domain. Directly comparable papers with opposing findings to ours are Alvi and Rahman (2005) and Hammond (2006) among many others.

Alvi and Rahman (2005) test convergence among the BEA regions and fail to find convergence, thus reversing the Carlino and Mills (1993) and Loewy and Papell (1996) findings. The main argument of Alvi and Rahman (2005) is that technology drives income divergence among the BEA regions. Interestingly, Drennan, Lobo and Strumsky (2004)[7] cite the lack of a major technological breakthrough in the recent past as the cause of divergence. Lim (2003) shows that technology is not a statistically significant variable in determining the income convergence among US metropolitan areas in 1990-1999. Furthermore, "after controlling for structural characteristics determining metropolitan economic growth," Lim (2003) "finds significant evidence of convergence for the period." Our findings are also in line with the conclusions obtained by Strazicich and Lee (2006) where they employ panel data methods with the allowance of heterogeneous multiple structural breaks in testing for the stochastic convergence.

Additionally, lumping together metropolitan and non-metropolitan areas, as in Alvi and Rahman (2005), rather than treating them separately, as we do in this study, may

[7] We should note that Drennan, Lobo and Strumsky (2004) search the sigma convergence.

bring about the so-called “aggregation bias.” As a matter of fact, Byrne and Fiess (2007) discover such problem in inflation rates among Euro area countries where the aggregate national inflation rates diverge, disaggregate inflation rates tend to converge. Therefore, we believe that the aggregation biases results toward divergence.

Lastly, we conjecture that the main culprit behind the Hammond (2006) result is that he ignores the major concern regarding the selection of lag lengths in his tests. All in all, we are convinced that our findings are robust in pointing to a convergence among relative regional per capita incomes in the US in the recent history, at least when proper statistical tests are employed in the search.

## 5. Conclusions

Despite the policy significance and the renewed interest in interregional income and earnings convergence, there is only a very few studies that explicitly consider convergence in nonmetro counties in the US. Those too are limited to within nonmetro convergence. In this paper we seek to test for stochastic convergence of average earnings in nonmetro areas (both towards a metro average and the US average) utilizing various time-series techniques. More importantly, we use USDA classified county typologies to group nonmetro counties into various economic development categories and test for stochastic convergence of those typologies with average earnings of metro counties on one hand and the US national average earnings on the other.

A battery of individual as well as panel based tests is conducted on our definitions of earnings concepts in search of convergence. Individual unit root tests show that nonmetro counties as a single group and mining, retirement and service dependent areas average earnings do not converge to the average earnings of the metro areas as well as the US average, irrespective of the unit root/stationarity test employed. However, test results disagree on the convergence of earnings of other county types to either the metro average or the US average earnings. Alternatively, we employ the panel unit root tests which are shown to be substantially more powerful than individual unit root tests. Overall, we can say that, these tests present an indication of convergence for the average earning levels in nonmetro areas irrespective of whether one takes the metro income average as the comparison criterion or the US national average. Therefore, our results do not agree with the conclusions reached by previous studies that focus on nonmetro convergence.

The general consensus is that rural manufacturing-dependant counties are at a disadvantage in the face of increasing globalization, decreasing investment, and decreasing exports from these counties. Therefore one could expect divergence of earnings between these counties and metro counties in general or national average. But our test results are almost unanimous about convergence of these counties with metro counties and national average. Rural mining counties’ earnings were expected to diverge from metro counties and national average due to slow economic growth and lower earning capacities in these counties. However, our results point towards a general convergence of these counties with metro and national averages. One reason may be that most of these counties are major recipients of various federal funding. For example, most of Appalachian counties are dominated by mining and receive relatively high levels of federal funding through the Appalachian Regional Commission (ARC) and the Tennessee

Valley Authority (TVA). This trend could continue with the boom in the mining industry, including oil and gas. The reason that farming counties are catching up with metro counties or national average may not be due to higher earnings from traditional farming activities but may be due to new economy in these areas such as recreation and tourism. Earnings convergence in retiree-dependent nonmetro counties (characterized by high levels of in-migration among those 60 years or older) implies that jurisdictions that promote retiree-attraction as an economic development policy can push their earnings toward a metro or national average.

**References**

Alvi E. and H. Rahman. "US Regional Income and Technology: A Unit-Root and Cointegration Study." *Topics in Macroeconomics*, 5, 1(2005), Article 11.

Andrews, D.W.K. "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." *Econometrica* 59(1991): 817-858.

Beaulieu, L.J. "Creating Vibrant Communities & Economies in Rural America. Southern Rural Development Center, 2002, Available at www.duc.auburn.edu/edi/links/ vibrant_ communitiessrdc.pdf.

Ben-David, D., R.L. Lumsdaine, and D.H. Papell. "Unit Roots Postwar Slowdowns and Long-run Growth: Evidence from Two Structural Models." *Empirical Economics* 28(2003): 303-319.

Bernard, A.B. and S.N. Durlauf "Convergence in International Output." *Journal of Applied Econometrics* 10, 2(1995), 97-108.

Bernard, A.B. and S.N. Durlauf "Interpreting Tests of the Convergence Hypothesis" *Journal of Econometrics* 71(1996), 97-108.

Borts, G.H. "The Equalization of Returns and Regional Economic Growth." *American Economic Review* 50(1960): 319-347

Borts, G.H., and J.L. Stein. *Economic Growth in a Free Market*. Columbia University Press: New York , 1964.

Breitung, J. "The Local Power of Some Unit Root Tests for Panel Data," in: B. Baltagi (ed.), *Advances in Econometrics*, Vol. 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels, JAI Press: Amsterdam, 2000, 161-178.

Byrne J. P. and N. Fiess "Euro Area Inflation: Aggregation Bias and Convergence." *Working Paper*, University of Glasgow, Glasgow, UK, (October, 10, 2007).

Carlino, G., and L. Mills. "Are U.S. Regional Incomes Converging? A Time Series Analysis. *Journal of Monetary Economics* 32(1993): 335-346.

Carlino, G. and L. Mills. "Convergence and the U.S States: A Time Series Analysis." *Journal of Regional Science* 36(1996a): 597-616.

Carlino G. A. and L. Mills. "Testing Neoclassical Convergence in Regional Incomes and Earnings." *Regional Science and Urban Economics* 26(1996b), 565–590.

Carvalho, V. M. and A. C. Harvey. "Convergence in the Trends and Cycles of Euro-Zone Income."*Journal of Applied Econometrics* 20(2005): 275-289.

Choi, I. "Unit Root Tests for Panel Data." *Journal of International Money and Finance* 20(2001):249-272.

De La Fuente, A. "The Empirics of Growth and Convergence: A Selected Survey." Centre for Economic Policy Research, London, CEPR Discussion Paper No. 1275, 1995.

De La Fuente, A. "What Kind of Regional Convergence?" Centre for Economic Policy Research,London, CEPR Discussion Paper No. 1924, 1998.

Dickey, D. A. and W. A. Fuller. “Distribution of the Estimators for Autoregressive Time Series with a Unit Root.” *Journal of the American Statistical Association*, 74(1979): 427-431.

Drennan, M., J. Lobo and D. Strumsky. “Unit Root Tests of Sigma Income Convergence Across Metropolitan Areas of the U.S.” *Journal of Economic Geography* 4(2004): 583–595.

Dyer, D. D. and J. P. Keating. “On the Determination of Critical Values for Bartlett's Test.” *Journal of the American Statistical Association* 75(1980): 313-319.

Hammond, G. W. “Metropolitan/non-metropolitan divergence: A spatial Markov chain approach.”*Papers in Regional Science* 83 (2004): 543–563.

Hammond, G. W. “A Time Series Analysis of US Metropolitan and Non-Metropolitan Income Divergence.” *Annals of Regional Science* 40(2006): 81-94.

Hadri, K. “Testing for Stationarity in Heterogeneous Panel Data.” *Econometrics Journal* 3(2000): 148-161.

Henry, M.S. “The Rural Economic Gap: Fact or Fiction?” In: Barkley DL (ed) Economic Adaptation: Alternatives for Non-Metropolitan Areas. Westview Press: Boulder, CO, 1993.

Hobijn, B., P. H. Franses, and M. Ooms. “Generalizations of the KPSS-Test for Stationarity,” *Econometric Institute Report*, no. 9802/A (January). Available at http://www.eur.nl/few/ei/papers, 1998.

Ibrahim, A. “A Complementary Test for the KPSS Test With an Application to the US Dollar/Euro Exchange Rate.” *Economics Bulletin* 3(2004): 1−5.

Im, K. S., M. H. Pesaran and Y. Shin. “Testing for Unit Roots in Heterogeneous Panels.” *Journal of Econometrics* 115(2003): 53-74.

Isserman, A. M. “Competitive Advantages of Rural America in the Next Century.” *International Regional Science Review* 24(2001), 1, 38-58.

Kusmin, L., J. Redman and D. Sears. *Factors Associated with Rural Economic Growth*. Technical Bulletin 1850, USDA Economic Research Service, Washington D.C., 1996.

Kwiatkowski, D., P.C.B. Phillips, P. Schmidt, and Y. Shin. “Testing The Null Hypothesis of Stationary Against the Alternative of a Unit Root.” *Journal of Econometrics* 54(1992): 159-178.

Levin, A., C.F. Lin and C. Chu. “Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties.” *Journal of Econometrics* 108(2002): 1-24.

Lim, U. “Knowledge Spillovers, Agglomeration Economies, and Regional Economic Growth in the U.S. Metropolitan Areas,” The 50th Annual North American Meetings of the *Regional Science Association International*, Philadelphia, Pennsylvania, (November 20-22, 2003).

Loewy, M.B. and D.H. Papell. “Are US Regional Incomes Converging? Some Further Evidence.” *Journal of Monetary Economics* 38(1996), 587-598.

MacKinnon, J. G. “Critical Values for Cointegration Tests.” Chapter 13 in: R. F. Engle, Granger, C.W.J., (eds.), *Long-Run Economic Relationships: Readings in Cointegration*, Oxford: Oxford University Press, 1991.

MacKinnon, J. G. “Numerical Distribution Functions for Unit Root and Cointegration tests.” *Journal of Applied Econometrics* 11(1996): 601-618.

Maddala, G. S. and S. Wu. “A Comparative Study of Unit Root Tests with Panel Data and A New

Simple Test." *Oxford Bulletin of Economics and Statistics* 61(1999): 631-652.

Miller J. R. and I. H. Genc. "Alternative Regional Specification and Convergence of US Regional Growth Rates." *Annals of regional Science* 39(2005): 241-252.

Newey, W. and K. West. "Automatic Lag Selection in Covariance Matrix Estimation." *Review of Economic Studies* 61(1994): 631-653.

Ng, S. and P. Perron. "Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power." *Econometrica* 69(2001): 1519-1554.

Nissan, E. and G. Carter. "Spatial and Temporal Metropolitan and Nonmetropolitan Trends in Income Inequality." *Growth and Change* 30(1999):407-29.

Quah, D. "Galton's Fallacy and Tests of the Convergence Hypothesis." *Scandinavian Journal of Economics* 95(1993): 427–443.

Reeder, R.J. Retiree-Attraction Policies for Rural Development. Economic Research Service, USDA, 1998. Available at //www.ers.usda.gov/publications/aib741/ AIB741a.PDF.

Renkow, M. "Income Non-Convergence and Rural-Urban Earnings Differentials: Evidence from North Carolina." *Southern Economic Journal* 62(1996): 1017-1028.

Romer, D. *Advanced Macroeconomics*, McGraw Hill, New York, 1996.

Rupasingha A., S. J. Goetz and D. Freshwater. "Social and Institutional Factors as Determinants of Economic Growth: Evidence from the United States Counties." *Papers in Regional Science* 81(2002): 139–155.

Said, S.E. and D. A. Dickey. "Testing for Unit Roots in Autoregressive Moving Average Models of Unknown Order." *Biometrika* 71(1984): 599-607.

Schwarz, G. "Estimating the Dimension of a Model." *The Annals of Statistics*, 6(1978): 461-464.

Schwert, W. "Stock Volatility and Crash of '87." *Review of Financial Studies* 3(1989): 77-102.

Solow R. M. "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics* 70(1956): 65–94.

Swan, T. W. "Economic Growth and Capital Accumulation." *Economic Record* 32(1956): 334-361.

Strazicich, M. C. and J. Lee "Are Regional Incomes Converging in the U.S.? Evidence from Panel Unit Root Tests with Heterogeneous Structural Breaks." *Working Paper*, Appalachian State University, (July 26, 2006).

Tomljanovich, M. and T. Vogelsang. "Are U.S. Regions Converging? Using New Econometric Methods to Examine Old Issues." *Empirical Economics* 27(2002): 49-62.

Vohra, R. "Convergence (Divergence) and the U.S. States." *Atlantic Economic Journal* 26(1998): 372-378.

Webber, D.J., P. White and D. O. Allen. "Income Convergence Across US states: An Analysis Using Measures of Concordance and Discordance." *Journal of Regional Science* 45(2005): 565-589.

On line Annex at the journal Website: http://www.usc.es/economet/aeid.htm

**Table 1. 2004 County typology codes**

| | |
|---|---|
| Farming-dependent | Based on two thresholds—farm earnings accounting for an annual average of 15 percent or more of total county earnings during 1998-2000 or farm occupations accounting for 15 percent or more of all occupations of employed county residents in 2000. |
| Mining | Based on the industry accounting for an annual average of 15 percent or more of total county earnings during 1998-2000. |
| Manufacturing | Based on accounting for an annual average of 25 percent or more of total earnings during the 3 years. |
| Services | Based on 45 percent or more of average annual labor and proprietors' earnings derived from services (SIC categories of retail trade; finance, insurance, and real estate; and services) during 1998-2000. |
| Federal/State government | Based on the industry accounting for an annual average of 15 percent or more of total county earnings during 1998-2000. |
| Nonspecialized | Counties that are not classified as dependent upon any of above industries |
| Retirement destination | Counties that had number of residents 60 and older grew by 15 percent or more between 1990 and 2000 due to in-migration. |

Source: Economic Research Service, USDA.

**Table 2. Optimum UR tests for relative regional income with respect to metro areas**

| **Variables** | **Tests** | **Null** | **Lag** | **Stat** | **5%CV** | **I(0)** |
|---|---|---|---|---|---|---|
| **Rural** | ADF | UR | 0 | -3.5201 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1340 | 0.1460 | Y |
| **Farming** | ADF | UR | 0 | -3.2741 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.0728 | 0.1460 | Y |
| **Mining** | ADF | UR | 0 | -2.4898 | -3.5485 | N |
| | KPSS | No UR | 4 | 0.1575 | 0.1460 | N |
| **Manufacture** | ADF | UR | 1 | -2.9289 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1406 | 0.1460 | Y |
| **Government** | ADF | UR | 0 | -3.8296 | -3.5443 | Y |
| | KPSS | No UR | 4 | 0.1846 | 0.1460 | N |
| **Service** | ADF | UR | 6 | -4.7435 | -3.5742 | Y |
| | KPSS | No UR | 3 | 0.0575 | 0.1460 | Y |
| **Retirement** | ADF | UR | 0 | -2.8410 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1654 | 0.1460 | N |
| **NoSpecialty** | ADF | UR | 0 | -3.5413 | -3.5443 | N |
| | KPSS | No UR | 2 | 0.1058 | 0.1460 | Y |

Sample 1969-2004. “ADF” is the Augmented Dickey-Fuller tests with a constant and a time trend. “KPSS” tests are the $\eta_\tau$ tests in Kwiatkowski et al. (1992). The null hypothesis of each test is mentioned under the “Null” column. “Lag” stands for the optimum lag length for the ADF test and the Newey-West bandwidth using Bartlett kernel for KPSS. “Stat” is the test statistic as computed by the relevant test. “5%CV” shows the 5% critical values. The critical values for ADF are obtained from MacKinnon (1991, 1996) and for KPSS from Kwiatkowski et al. (1992, p166, Table 1). “I(0)” indicates whether the tested variable is found to be stationary “Y” or not “N”.

**Table 3. Optimum UR tests for relative regional income with respect to the US**

| Variables | Tests | Null | Lag | Stat | 5%CV | I(0) |
|---|---|---|---|---|---|---|
| **Rural** | ADF | UR | 0 | -3.4908 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1333 | 0.1460 | Y |
| **Farming** | ADF | UR | 0 | -3.2236 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.0755 | 0.1460 | Y |
| **Mining** | ADF | UR | 1 | -2.4584 | -3.5485 | N |
| | KPSS | No UR | 4 | 0.1558 | 0.1460 | N |
| **Manufacture** | ADF | UR | 0 | -2.8056 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1387 | 0.1460 | Y |
| **Government** | ADF | UR | 0 | -3.9671 | -3.5443 | Y |
| | KPSS | No UR | 4 | 0.1861 | 0.1460 | N |
| **Service** | ADF | UR | 6 | -3.9612 | -3.5742 | Y |
| | KPSS | No UR | 3 | 0.0514 | 0.1460 | Y |
| **Retirement** | ADF | UR | 0 | -2.7687 | -3.5443 | N |
| | KPSS | No UR | 3 | 0.1693 | 0.1460 | N |
| **NoSpecialty** | ADF | UR | 0 | -3.4921 | -3.5443 | N |
| | KPSS | No UR | 2 | 0.1035 | 0.1460 | Y |

Sample 1969-2004. “ADF” is the Augmented Dickey-Fuller tests with a constant and a time trend. “KPSS” tests are the $\eta_\tau$ tests in Kwiatkowski et al. (1992). The null hypothesis of each test is mentioned under the “Null” column. “Lag” stands for the optimum lag length for the ADF test and the Newey-West bandwidth using Bartlett kernel for KPSS. “Stat” is the test statistic as computed by the relevant test. “5%CV” shows the 5% critical values. The critical values for ADF are obtained from MacKinnon (1991, 1996) and for KPSS from Kwiatkowski et al. (1992, p166, Table 1). “I(0)” indicates whether the tested variable is found to be stationary “Y” or not “N”.

**Table 4. Panel unit root test**

| **Test** | **Null** | **US** | | | | **Metro** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Statistic** | **p** | **CS** | **T** | **Statistic** | **p** | **CS** | **T** | A/R | I(0) |
| **Rural** | | | | | | | | | | | |
| LLC | UR | -37.80 | 0.0000 | 1947 | 67078 | -39.21 | 0.0000 | 1947 | 67058 | R | Y |
| B | UR | -14.67 | 0.0000 | 1947 | 65131 | -15.20 | 0.0000 | 1947 | 65111 | R | Y |
| IPS | UR | -46.09 | 0.0000 | 1947 | 67078 | -47.6619 | 0.0000 | 1947 | 67058 | R | Y |
| ADFP | UR | 9196.33 | 0.0000 | 1947 | 67078 | 9350.4100 | 0.0000 | 1947 | 67058 | R | Y |
| PP | UR | 9507.89 | 0.0000 | 1947 | 68143 | 9632.3700 | 0.0000 | 1947 | 68143 | R | Y |
| Hadri | No UR | 59.66 | 0.0000 | 1947 | 70091 | 59.3417 | 0.0000 | 1947 | 70091 | R | N |
| **Farm** | | | | | | | | | | | |
| LLC | UR | -29.85 | 0.0000 | 367 | 12434 | -30.1375 | 0.0000 | 367 | 12390 | R | Y |
| B | UR | -20.30 | 0.0000 | 367 | 12067 | -19.7002 | 0.0000 | 367 | 12023 | R | Y |
| IPS | UR | -34.05 | 0.0000 | 367 | 12434 | -34.3281 | 0.0000 | 367 | 12390 | R | Y |
| ADFP | UR | 2532.83 | 0.0000 | 367 | 12434 | 2547.4100 | 0.0000 | 367 | 12390 | R | Y |
| PP | UR | 2763.87 | 0.0000 | 367 | 12845 | 2772.0600 | 0.0000 | 367 | 12845 | R | Y |
| Hadri | No UR | 21.86 | 0.0000 | 367 | 13212 | 21.6000 | 0.0000 | 367 | 13212 | R | N |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mine** | | | | | | | | | | | |
| LLC | UR | -6.45 | 0.0000 | 107 | 3592 | -6.7887 | 0.0000 | 107 | 3579 | R | Y |
| B | UR | -2.31 | 0.0103 | 107 | 3485 | -2.6129 | 0.0045 | 107 | 3472 | R | Y |
| IPS | UR | -4.55 | 0.0000 | 107 | 3592 | -5.0812 | 0.0000 | 107 | 3579 | R | Y |
| ADFP | UR | 304.67 | 0.0000 | 107 | 3592 | 320.7060 | 0.0000 | 107 | 3579 | R | Y |
| PP | UR | 290.03 | 0.0004 | 107 | 3745 | 297.8570 | 0.0001 | 107 | 3745 | R | Y |
| Hadri | No UR | 20.18 | 0.0000 | 107 | 3852 | 20.4089 | 0.0000 | 107 | 3852 | R | N |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Manufacturing** | | | | | | | | | | | |
| LLC | UR | -15.86 | 0.0000 | 565 | 19322 | -16.9051 | 0.0000 | 565 | 19293 | R | Y |
| B | UR | -1.84 | 0.0323 | 565 | 18757 | -2.4833 | 0.0065 | 565 | 18728 | R | Y |
| IPS | UR | -17.87 | 0.0000 | 565 | 19322 | -18.8933 | 0.0000 | 565 | 19293 | R | Y |
| ADFP | UR | 2226.0 | 0.0000 | 565 | 19322 | 2262.0800 | 0.0000 | 565 | 19293 | R | Y |
| PP | UR | 2230.3 | 0.0000 | 565 | 19775 | 2264.1700 | 0.0000 | 565 | 19775 | R | Y |
| Hadri | No UR | 40.17 | 0.0000 | 565 | 20340 | 40.0009 | 0.0000 | 565 | 20340 | R | N |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Gov't** | | | | | | | | | | | |
| LLC | UR | -10.00 | 0.0000 | 204 | 6918 | -10.7790 | 0.0000 | 204 | 6918 | R | Y |
| B | UR | -4.21 | 0.0000 | 204 | 6714 | -4.0683 | 0.0000 | 204 | 6714 | R | Y |
| IPS | UR | -11.52 | 0.0000 | 204 | 6918 | -12.7944 | 0.0000 | 204 | 6918 | R | Y |
| ADFP | UR | 791.84 | 0.0000 | 204 | 6918 | 839.8000 | 0.0000 | 204 | 6918 | R | Y |
| PP | UR | 764.84 | 0.0000 | 204 | 7140 | 783.4540 | 0.0000 | 204 | 7140 | R | Y |
| Hadri | No UR | 22.99 | 0.0000 | 204 | 7344 | 23.1913 | 0.0000 | 204 | 7344 | R | N |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Service** | | | | | | | | | | | |
| LLC | UR | -4.05 | 0.0000 | 110 | 3742 | -4.2157 | 0.0000 | 110 | 3732 | R | Y |
| B | UR | -4.20 | 0.0000 | 110 | 3632 | -4.5784 | 0.0000 | 110 | 3622 | R | Y |
| IPS | UR | -5.65 | 0.0000 | 110 | 3742 | -5.4293 | 0.0000 | 110 | 3732 | R | Y |
| ADFP | UR | 352.20 | 0.0000 | 110 | 3742 | 346.6610 | 0.0000 | 110 | 3732 | R | Y |
| PP | UR | 298.03 | 0.0004 | 110 | 3850 | 302.6660 | 0.0002 | 110 | 3850 | R | Y |
| Hadri | No UR | 17.31 | 0.0000 | 110 | 3960 | 17.0791 | 0.0000 | 110 | 3960 | R | N |
| **NoSpec** | | | | | | | | | | | |
| LLC | UR | -23.83 | 0.0000 | 594 | 20136 | -24.4625 | 0.0000 | 594 | 20105 | R | Y |
| B | UR | -11.90 | 0.0000 | 594 | 19542 | -12.2622 | 0.0000 | 594 | 19511 | R | Y |
| IPS | UR | -28.12 | 0.0000 | 594 | 20136 | -28.8866 | 0.0000 | 594 | 20105 | R | Y |
| ADFP | UR | 2988.73 | 0.0000 | 594 | 20136 | 3033.7500 | 0.0000 | 594 | 20105 | R | Y |
| PP | UR | 3160.77 | 0.0000 | 594 | 20790 | 3212.1600 | 0.0000 | 594 | 20790 | R | Y |
| Hadri | No UR | 34.20 | 0.0000 | 594 | 21384 | 33.9247 | 0.0000 | 594 | 21384 | R | N |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Retire** | | | | | | | | | | | |
| LLC | UR | -8.83 | 0.0000 | 266 | 9086 | -9.5733 | 0.0000 | 266 | 9073 | R | Y |
| B | UR | -5.64 | 0.0000 | 266 | 8820 | -6.2036 | 0.0000 | 266 | 8807 | R | Y |
| IPS | UR | -10.01 | 0.0000 | 266 | 9086 | -10.4846 | 0.0000 | 266 | 9073 | R | Y |
| ADFP | UR | 897.83 | 0.0000 | 266 | 9086 | 922.1500 | 0.0000 | 266 | 9073 | R | Y |
| PP | UR | 896.34 | 0.0000 | 266 | 9310 | 906.9060 | 0.0000 | 266 | 9310 | R | Y |
| Hadri | No UR | 27.50 | 0.0000 | 266 | 9576 | 27.3590 | 0.0000 | 266 | 9576 | R | N |

Sample 1969-2004. “Test” refers to the panel data unit root test employed. The “Null” is the null hypothesis of the test. In that column, “UR” stands for the existence of the unit root in data while “No UR” stands for the stationarity of the data. “CS” represents the number of cross sections in a specific region data. “Statistics” gives the test statistics of the panel data test as mentioned in the Test column. “p” is the p-value of the test. “T” gives the time series observations for the test. “A/R” represents the Acceptance or rejection of the test. A “Y” in the “I(0)” column shows that the data are found to be stationarity while an “N” in that column shows that they are found to be non-stationary.