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A SPATIAL ANALYSIS OF CREATIVE CLASS WORKER GROWTH CONVERGENCE IN US COUNTIES

Bhawani Mishra*, Shriniwas Gautam, and Thomas G. Johnson

Office of Social and Economic Data Analysis (*OSEDA*)
University of Missouri, Columbia
e-mail: mishrab@umsystem.edu
*Corresponding author

Biographical notes

Bhawani Mishra is a Research Associate in Office of Social Economic Data Analysis (OSEDA) at the University of Missouri, Columbia, USA, where he does research related to health, poverty, and economic development. Prior to this position, he worked in agricultural development field for more than a decade. His current research interests include economic development, poverty, food security, efficiency measurement, health care costs, and spatial econometrics.

Shriniwas Gautam is a Postdoctoral Scientist at the World Vegetable Center based in Thailand and is involved in monitoring and evaluation of center's vegetable postharvest research and development activities that focus on improving the vegetable value chains in developing countries. He also has several years of experience (1993 to 2003) in agricultural development in Nepal. His research interests include agricultural marketing and value chains, impact evaluations, and regional disparities in basic services like healthcare access and technology adoption and concentration of poverty and have published in these areas.

Thomas G Johnson is a Professor Emeritus, University of Missouri-Columbia. He was formerly the Frank Miller Professor of Agricultural and Applied Economics, and professor in the Harry S Truman School of Public Affairs at the University of Missouri. His recent research areas include the causes and consequence of rural economic development, fiscal and economic impact analysis, local government finance, renewable energy, rural entrepreneurship, broadband, land use and rural transportation. He has studied rural policy issues in Canada, Ukraine, the European Union, and Korea.

Abstract. The Creative Class Workers (CCWs), a special group of human capital, are not uniformly distributed across geographic locations. The CCWs are the most innovative and dynamic group of human capital and play important role in regional economic growth. Therefore, it is important to understand the distribution of CCW growth across regions and time. This study examines the CCWs growth convergence of CCWs across US counties. Due to the spatial autocorrelation, the conditional spatial error model turns out to be the best fit model to examine the $\boldsymbol{\beta}$-convergence. The conditional spatial error model estimates about 58 years required to cover the gap of CCWs growth among the US counties. Due to spatial autocorrelation, the neighboring counties help shorten the convergence by 19.8 years. The result also finds evidence of $\boldsymbol{\sigma}$-convergence but not in all Rural-Urban Continuum Code (RUCC) county groups. The $\boldsymbol{\beta}$-convergence analysis by RUCC groups shows different convergence rates.

Keywords: Creative class workers, Convergence, Spatial model**.**

JEL Codes: R12, O15, C31

1. INTRODUCTION

Like many economic activities, human capital is not distributed equally across geographical locations. The Creative Class Workers (CCWs), a special type of human capital, is not also distributed uniformly across the counties in the US. Since CCWs have strong relationship with regional economic growth, retaining and attracting CCWs in any location is becoming one of the regional development strategies (Florida, 2002a). Although the role of human capital in economic development has long been recognized by other economists as well, but Florida (2002a) specifically pinpoints the role of this special class of human capital in economic growth of cities. The creative class workers include people from technology, art and culture, professional and managerial, and educating and trainings professions. This special class of human capital creates 'meaningful new forms' through their creativity (Florida, 2003). Florida (2002a) classified CCWs into creative core class and non-core creative class based on the level of creativity. The creative core class includes scientists and engineers, university professors, poets and novelists, artists, entertainers, actors, designers, analysts, researchers, editors, writers, and opinion makers. The non-core creative class group includes people who work in a wide range of knowledge intensive industries and engage in solving problems. These people generally require a higher education to perform their functions. People who work in high-tech, financial services, legal, and health profession, and business management fall into this non-core creative class category. Florida also used the term super creative class to denote scientists, engineers, artists, musician, and designers who are highly creative even within creative core class workers. Not all locations are equally attractive to CCWs. These workers prefer the locations with "3Ts", i.e. Talent, Tolerance, and Technology (Florida, 2002a). In addition to that location specific urban amenities such as theater, recreation center, restaurants, education and other location specific characteristics also play role on attracting or retaining CCWs in any location.

Using the convergence theory, this study investigates a research question, whether the gap between lower CCW growth regions and higher CCW growth regions converge in the future. In other word, whether the regions currently lagging behind in CCWs growth will ever be able to catch the region with higher CCWs growth. If it catches to higher CCW growth regions, how long it will take to reach that level. These are the questions this study has addressed. Both $\boldsymbol{\beta}$-convergence and **σ**-convergence examined by accounting spatial autocorrelation to understand role of neighboring counties in CCWs growth. The convergence literature is rich in income convergence, but not in human capital convergence. In summary, this study focuses on two areas. Firstly, it extends the traditional method of convergence analysis by incorporating spatial dimension in the model to examine the growth convergence of CCWs. Secondly, realizing the diversity among the counties this study also examine the CCW growth convergence by county groups and also examined the spatial distribution pattern of CCW growth in counties in the 48 contiguous US states.

2. LITERATURE REVIEW

The CCWs, a sub-group of human capital, include creative and innovative people like scientist, engineers, professors, poets and architects, health care professionals, business managers, lawyer, designer, artist, and musician (Florida, 2003). These workers have higher level of creativity than other group of human capital and play positive role regional growth and development. Richard Florida specifically describes the functions and roles of CCWs in the economic growth in urban areas. CCWs integrate new ideas, new businesses, and new technologies which could lead to regional economic growth (Florida, 2003). The literature review section divided into three parts. In the first part, the income convergence literature is reviewed. In the second part, literature about human capital convergence is reviewed. In the third part, this study discussed about the location characteristics and factors that play role in attracting and retaining CCW in any location.

2.1. Income convergence

The concept of economic convergence has been extensively discussed in the economic literature. Income convergence described in two ways. First, convergence can occur when income of poor regions grow faster and catches the rich regions in per capita income (Rey & Montouri, 1999). This kind of convergence is also known as **β**-convergence. In the many studies following cross-sectional model is employed to estimate **β**-convergence. The negative **β-**coefficient shows the evidence of **β-**convergence.

$$\ln\left(\frac{Y_{i,t+k}}{Y_{i,t}}\right) = \alpha + \beta ln\left(Y_{i,t}\right) + \varepsilon_{it}$$

Barro & Sala-i-Martin (1992) has found the evidence of income convergence among the 48 contiguous U.S states in their seminal paper. The diminishing returns to capital plays a role in bringing regions' convergence (Barro & Sala-i-Martin, 1991). Barro & Sala-i-Martin (1992) also described the concepts of absolute and conditional convergence based on the inclusion and exclusion of control variables in the model. The absolute convergence takes place when poorer areas grow faster than richer ones without considering other characteristics of regions; whereas the conditional convergence explains the convergence among regions by controlling other factors (Barro & Sala-i-Martin, 1992). The absolute income convergence is estimated by regressing the growth in per capita GDP from its initial level for a set of cross-sectional data; whereas conditional convergence includes other control variables along with the initial level of GDP (Barro & Sala-i-Martin, 1992). The conditional convergence is the better way to analyze convergence if economies differ substantially in terms of preferences and technologies (Barro & Sala-i-Martin, 1992).

Other form of convergence could be **σ**-convergence, which examines the decline of cross-sectional dispersion over the time (Barro & Sala-i-Martin, 1991). The coefficient of variation is used to examine **σ**-convergence (Bernard & Jones, 1196; Carlino & Mills, 1996). Both convergence measures are important because **β**-convergence parameter does not necessarily imply **σ-**convergence (Wolff, 2014). Barro and Sala-i-Martin (1992) further states that necessary condition for the existence of **σ**-convergence is the existence of $\boldsymbol{\beta}$-convergence, not necessarily the opposite.

2.2 Human capital convergence

As stated earlier, the role of human capital in economic growth has long been recognized by many economists. The countries with greater initial stocks of human capital are likely to introduce new goods and services rapidly and grow faster (Romer, 1989). Further, a higher human capital stock in any country or region makes to absorb the new products or ideas (Nelson & Phelps, 1966). Barrow (1991) examines initial human capital and real per capita GDP with the real per capita growth rate of GDP and found that the initial human capital shows positive coefficient whereas initial real per capita GDP has negative coefficient (Barro R. , 1991). But the country or region with higher initial capital experience diminishing returns in its capital, therefore lagging country or region tends to grow faster and catches up higher growth country or region (Barro R. , 1991; Barro & Sala-i-Martin, 1991).

Kyriacou (1991) has also examined the relationship between the human capital and growth of output. The author regressed per capita income growth at the county level with initial per capita income and initial human capital levels. Kyriacou (1991) found that the coefficient on initial per capita income is negative and significant; whereas in initial human capital stock the coefficient is positive and significant. The result suggests that the countries that are behind in growth cannot converge with economically more advanced countries unless they have relatively abundant levels of initial human capital stock (Kyriacou, 1991).

Sab and Smith (2002) specifically examined the human capital convergence using data across nations. These authors used life expectancy, the infant survival rate, and the average stocks of total and of secondary years of schooling as a source of human capital. These authors found that countries are converging in terms of health and education levels.

2.3 Location characteristics for CCWs

Florida (2002a) explained that cities with "3T's" i.e. talent (talented/educated/skilled population), tolerance (a diverse community), and technology (technological infrastructure) are attracting factors of CCWs. But later, another factor "Territory Assets" (another "T") is added to the list making "4T". The 'Territory Assets' includes housing, climate, education, health care, transportation, dis-amenities (crime, weather), and economic growth[1]. Additionally, Florida (2003) stated that the urban amenities such as restaurants, theatres, museums and other natural environment also play an important role in attracting CCWs in any location. Urban amenities that includes personal service industries such as restaurants, theatres and museums demand geographical closeness between producer and consumer (Glaeser, Kolko, & Saiz, 2001). In other word, these amenities are local specific and non-tradable therefore consumers can only enjoy when they are in that particular location. Cities provide higher quality lifestyle amenities to CCWs than in rural areas; therefore the concentration of CCWs is higher in cities than rural areas despite being less favorable in term of rents, and other expenses in the rural areas (Florida, 2002a). CCWs valued more to urban amenities[2]; therefore they will be willing to accept a less favorable mix of rents and wages to live in larger cities to enjoy more urban amenities (Dalmazzo & de Blasio, 2010). Within the CCW, some group of CCW have stronger attachment to the urban amenities than others. The

[1] This information is obtained from Martin Prosperity Institute http://martinprosperity.org.
[2] In this study we used the terms urban amenities, local amenities, and life style amenities are used interchangeably.

Bohemian[3] CCW group is footloose that does not have strong locational preferences (Wojan, Lambert, & McGranahan, 2007). In the rural areas, natural amenities play a key role in increasing concentration of CCWs; however they plays little role on attracting CCW in urban areas (McGranahan & Wojan, 2007).

Since the CCW growth process does not follow administrative boundary, therefore the growth neighboring counties likely to affect the CCW growth in a county in addition to the urban amenities within the country boundary. In other word, the CCW growth shocks originated in any county can spillover into surrounding counties (Rey & Montouri, 1999). Realizing this fact, some authors have used spatial model to examine the growth convergence (Arbia, Basile, & Salvatore, 2002; Dall'erba & Gallo, 2008; Gyawali, Fraser, Burkenya, & Schelhas, 2008; Rey & Montouri, 1999). McGranahan & Wojan (2007) have also find the negative coefficient of initial level of CCW in their study. They also examined convergence by diving data into different quarters.

In addition to these location specific amenities, CCWs prefer non locational characteristics such as flexible working environment and flexible dress codes (Florida, 2003). These workers themselves create an open, dynamic, personal and professional urban environment to increase their quality of life (Florida, 2003). Places that can maintain a mix of these favorable locational and non-locational amenities are able to attract and retain CCWs over time (Florida, 2002b).

3. CONCEPTUAL FRAMEWORK

The concept of income growth convergence applied to examine the CCW growth convergence. Richard Florida does not specifically mentioned convergence or divergence of CCWs' growth across the locations. However, his theory explains that the locations with higher quality lifestyle amenities able to attract more CCWs than locations. Therefore, Florida is implicitly referring a divergence of CCWs' growth. The location choosing behavior of people can be explained by the utility maximization theory. The general premise of utility maximization is that people have tendency to maximize their utility with given combination of goods and services under income constraint. Roback (1982) model shows that how a person make decision based on the constraint.

$$U_{ic} = W_C - R_C + A_C + e_{ic}$$

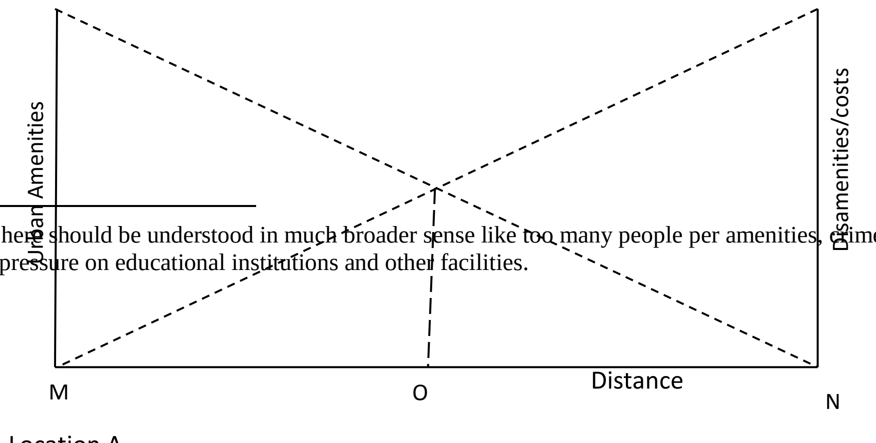
Where W_c is the nominal wage in location c; R_c is the cost of housing; A_c is a measure of local amenities; and e_{ic} represents worker i idiosyncratic preferences for location c. A large e_{ic} means that worker i is particularly attached to a location c due to family connections or birth attachment to the location, holding constant real wage and amenities. Ricard Florida emphasized

[3] Bohemians include people who work in arts, design, entertainment and media occupations.

that CCWs put greater weight on local amenities than nominal wage and housing costs. This is particularly because CCWs can earn higher wages in any location. With this assumption in the equation left out only local amenities and idiosyncratic preferences are major determining factors of choosing a particular location by the CCWs. Even idiosyncratic preferences such as family and birthplace connections have also little impact on these CCWs. At the end, the local amenities are the major determining factor of location choice for CCWs. Local amenities are basically non-tradable commodities and cannot be traded across locations. These commodities are also non-exclusive and non-rivals goods and services can only be consumed by the residents of a particular location.

Usually CCWs are in the high income bracket; therefore for the simplicity we assumed no income constraint. With that assumption there is higher demand for location A, more and more CCWs come this location until the dis-utility (created by congestions[4]) exceeds utility received by being close to the location A. Congestion occurs in two ways. Firstly, CCWs that are already in location A attract more CCWs on that location thereby increasing more CCWs per locational amenities. Secondly, the concentration of CCWs in location brings more jobs and business growth which ultimately bring more people (other than CCWs) in the location A thereby again increasing other forms of congestions such as higher costs of livings, crime, traffic as well. Increasing congestions likely to reduce the attractiveness of a location A for CCWs. Additionally, the concentration of CCWs in location A has a spillover effect on the CCW growth rate of its adjacent locations such as B and C.

The boundaries of CCWs concentration around the location A can be explained using following figure (Figure 1). The point M is the urban center of location A (Figure 1). The left axis shows the urban amenities for the point M and the right axis shows the dis-amenities that arises from being farther from the point M. As said before, point M has the highest urban amenities by being close to the city center. As more and more CCWs move to point M of location M costs/dis-amenities starts rising. At the point O, costs/dis-amenities surpass the utility received by being close to the point M (Figure 1). So, the boundary for the location A will be within the distance of MO. The distance MO could be the outside the region’s administrative boundaries such as county boundaries.



[4] Congestion here should be understood in much broader sense like too many people per amenities, crime and traffic, higher housing costs, higher pressure on educational institutions and other facilities.

Figure 1: Boundaries of creative class workers' growth.

Rauch (1993) also pointed out that cities with higher average levels of human capital have higher wages and higher land rents. Consequently, growth of the CCWs in such locations likely to reach to some sort of saturation point for that particular time due to dis-utility created by the congestions. However, these locations can attract CCWs further in the future if they can add or improve the amenities in those locations. Meanwhile, other locations, which are less attractive at the beginning, will likely to start attracting some CCWs when the first location reaches to some sort of saturation point. This suggests that in the long run, locations once unattractive to the CCWs will start competing with attractive locations. Attractiveness of locations includes the combination of several factors such as industries, improved infrastructure, entertainments, natural amenities, research and development, government policy, educational institutions, even working culture of company and many other factors. This would then contribute to the growth of the CCWs in locations that were less attractive in the past. Over the time such competition among the counties would result the convergence in CCWs growth. However, locations with very low urban amenities are less likely to converge unless these locations improve their urban amenities.

4. DATA AND MATHODS

4.1. Data

The convergence research literature includes studies in which the unit of analysis ranges from cities, counties to countries (Barro & Sala-i-Martin, 1992; Drennan & Lobo, 1999; McGranahan & Wojan, 2007; Niebuhr, 2001; Chatterji & Dewhurst, 1996). This study uses county as a unit of analysis. The data on CCWs by county is taken from the Economic Research Service (ERS)[5] of the U.S. Department of Agriculture. In addition to that we have used USDA's Rural-Urban Continuum Codes (RUCCs) county classification of year 2003 is used to examine the CCW growth convergence. The counties in RUCC1 to RUCC3 represent urban counties and the counties in RUCC4 to RUCC9 represent the rural counties (Table 1).

[5] Economic Research Service of US Department of Agriculture.

Table 1: Description of Rural-Urban Continuum Codes.

Code	Description
RUCC1	County in metro area with 1 million population or more
RUCC2	County in metro area of 250,000 to 1 million population
RUCC3	County in metro area of fewer than 250,000 population
RUCC4	Nonmetro county with urban population of 20,000 or more, adjacent to a metro area
RUCC5	Nonmetro county with urban population of 20,000 or more, not adjacent to a metro area
RUCC6	Nonmetro county with urban population of 2,500-19,999, adjacent to a metro area
RUCC7	Nonmetro county with urban population of 2,500-19,999, not adjacent to a metro area
RUCC8	Nonmetro county completely rural or less than 2,500 urban population, adjacent to metro area
RUCC9	Nonmetro county completely rural or less than 2,500 urban population, not adjacent to metro area

Source: USDA.

Our analysis includes 3,108 counties from the 48 contiguous US states. Out of 3108 counties, 1085 (35%) counties are metro counties and 2023 (65%) counties are non-metro counties based on 2003 year's definition (Table 2). Similarly, the urban counties groups RUCC1, RUCC2, and RUCC3 comprise 13.3, 10.4 and 11.3 percentages of the total counties respectively. The rural counties groups RUCC4 to RUCC9 comprises 7, 3.2, 19.6, 14.2, 7.5, and 13.6 percentages respectively.

Table 2: Distribution of counties by RUCC county groups.

County groups	Number of counties	Percent of total counties
Rural	2023	65.1%
Urban	1085	34.9%
RUCC1	413	13.3%
RUCC2	322	10.4%
RUCC3	350	11.3%
RUCC4	218	7.0%
RUCC5	101	3.2%
RUCC6	609	19.6%
RUCC7	440	14.2%
RUCC8	232	7.5%
RUCC9	423	13.6%
Total Counties	**3108**	**100%**

Source: USDA.

4.2. Methods

The main objective of this study is to examine the CCW growth convergence and the spatial CCW growth pattern between 1990 and 2000 in counties of 48 contiguous U.S. states. McGranahan and Wojan (2007) also estimated negative $\boldsymbol{\beta}$-coefficient on the initial creative class employment share and analyzed the data by quarters. Due to diversity among the counties, we have used all counties, RUCC groups, and rural and urban county groups to make comparative analyses of CCW growth convergence. In addition, we estimated conditional spatial models to examine $\boldsymbol{\beta}$-convergence of CCW growth due to the potential spatial autocorrelation. Finally, this study also compares competitive models to estimate the CCW growth convergence.

4.2.1 $\boldsymbol{\beta}$-convergence without spatial dependence

The concept of $\boldsymbol{\beta}$-convergence is that lagging regions grow faster than other regions and eventually catch up with the rich regions. To test $\boldsymbol{\beta}$-convergence numerous studies have employed a cross-sectional specification (without considering the omitted variable problem) as follows:

$$\mathbf{ln}\left(\frac{\mathbf{y_{i,t+k}}}{\mathbf{y_{i,t}}}\right) = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{ln}\left(\mathbf{y_{i,t}}\right) + \boldsymbol{\varepsilon_{it}} \qquad (1)$$

Where, $y_{i,t}$ is the number of creative class workers in the county i, in year t, α and $\boldsymbol{\beta}$s are the parameters to be estimated, and $\boldsymbol{\varepsilon}_{it}$ is a stochastic error term. To support the convergence hypothesis a negative $\boldsymbol{\beta}$-coefficient is required. The negative coefficient of $\boldsymbol{\beta}$ suggests that the growth rate of CCWs over t years is negatively correlated with the starting number of CCWs. This version of the model specification makes absolute convergence, whereas when the model includes other variables in addition to the initial value then the model becomes conditional convergence. Generally, if the differences among the locations in the study is minor then absolute convergence model can be appropriate to examine growth convergence. In this study, we estimated an Ordinary Least Square (OLS) conditional convergence model as follows:

$$\mathbf{ln}\left(\frac{\mathbf{y_{i,t+k}}}{\mathbf{y_{i,t}}}\right) = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{ln}\left(\mathbf{y_{i,t}}\right) + \boldsymbol{\beta_2}\mathbf{D} + \boldsymbol{\varepsilon_{it}} \qquad (2)$$

Other variables are as described before but D represents a dummy variable for metro and non-metro counties. The annual rate of $\boldsymbol{\beta}$-convergence can be obtained from the equation $\boldsymbol{\delta}$= -ln(1-β)/T, where, T denotes the number of years between the initial and the final year of observation. Another common indicator used to characterize the speed of convergence is the half-life $\boldsymbol{\tau}$, which explains that time require to vanish half of gap between among the locations. This time can be obtained from the expression: $\boldsymbol{\tau}$=ln(2)/β. We also examine $\boldsymbol{\sigma}$-convergence using the coefficient of variation in addition to $\boldsymbol{\beta}$-convergence .

4.2.2 $\boldsymbol{\beta}$-convergence with spatial lag and error terms

The CCW growth likely to have spillover effect on the adjacent counties. Besides, lifestyle amenities of a counties likely to affect CCW growth in adjacent counties. Therefore, we also examine the evidence of spatial autocorrelation using Moran's I statistics. The positive spatial autocorrelation indicates high or low value of random variables tend to cluster together in a space and negative spatial autocorrelation indicates high and low values cluster near the surrounding geographical locations (Anselin, 1988). The spatial autocorrelation is modeled by means of a functional relationship between a variable and error term, i.e. spatial lag and spatial error respectively (Anselin, 1988). Here are the general form and reduced form of the spatial lag model:

$$\boldsymbol{y} = \boldsymbol{\rho W y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \qquad (3)$$

$$\mathbf{y} = (\mathbf{I_n} - \boldsymbol{\rho}\mathbf{W})^{-1}\mathbf{X}\boldsymbol{\beta} + (\mathbf{I_n} - \boldsymbol{\rho}\mathbf{W})^{-1}\boldsymbol{\varepsilon} \qquad (4)$$

$$\boldsymbol{\varepsilon} \sim \mathbf{N}(\mathbf{0_{n\times1}}, \boldsymbol{\sigma}^2\mathbf{I_n})$$

where y is a n by 1 vector of observations on the dependent variable, Wy is the corresponding spatially lagged dependent variable for weight matrix W, X is a n by k matrix of observations on the explanatory variables, $\boldsymbol{\varepsilon}$ is a n by 1 vector of error terms, ρ is the spatial autoregressive parameter, and β is a k by 1 vector of regression coefficients.

A second way to incorporate spatial autocorrelation in a regression model is through the disturbance terms. The most common specification is a spatial autoregressive process in the error terms:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (5)$$

i.e., a linear regression with error vector $\boldsymbol{\varepsilon}$ and

$$\boldsymbol{\varepsilon} = \boldsymbol{\lambda}\mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu} \qquad (6)$$

Where λ as the spatial autoregressive coefficient for the error lag Wu and $\boldsymbol{\varepsilon}$ is the error term. After putting value of μ in the first model the equation can be rewritten as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \boldsymbol{\lambda}\mathbf{W})^{-1}\boldsymbol{\varepsilon} \qquad (7)$$

Equation 3 is known as spatial lag model and equation 7 is known as a spatial error model.

Ignoring spatial autocorrelation leads to serious model mis-specifications in which spatial interdependencies (Abreu, DeGroot, & Florax, 2005; Rey & Montouri, 1999). Under such condition, Ordinary Least Square (OLS) cannot produce Best Linearly Unbiased Estimators (BLUE). The consequences of ignoring the spatial autocorrelation are depend on the model types. If the spatial autocorrelation occurs on the dependent variable, the result will be biased and inefficient due to omitting a significant explanatory variable (Anselin, 1988). But if the spatial autocorrelation on the on side error, the result will be unbiased, but inefficient, therefore t –test and f-test are misleading (Anselin, 1988). In order to incorporate the effect of neighboring counties, a spatial weight matrix was created based on the Queen Contiguity matrix. The GeoDa[6] software is used to estimate the both spatial models such as spatial lag and spatial error models.

We estimated the following form of the conditional convergence spatial lag model in order to correct spatial autocoorealtion problem at the dependent variable .

$$\mathbf{ln}\left(\frac{\mathbf{y_{t+T}}}{\mathbf{y_t}}\right) = \boldsymbol{\alpha_0} + \boldsymbol{\beta}\mathbf{ln}(\mathbf{y_t}) + \boldsymbol{\alpha_2}\mathbf{D} + \boldsymbol{\mu} \qquad (9)$$

In order to correct the error, spatial autocorrelation is incorporated in the spatial error model as following:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (10)$$

$$\boldsymbol{\varepsilon} = \boldsymbol{\lambda}\mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu} \qquad (11)$$

where

$$\boldsymbol{\mu} \sim \mathbf{N}(\mathbf{0}, \boldsymbol{\sigma}^{\mathbf{2}}\mathbf{I})$$

Equation 11 can be simplified as follows

$$\boldsymbol{\mu} = (\mathbf{I} - \boldsymbol{\lambda}\mathbf{W})^{-\mathbf{1}}\boldsymbol{\varepsilon} \qquad (12)$$

Where, μ is iid and $\boldsymbol{\lambda}$ is a spatial autoregressive parameter and $W\varepsilon$ is the weighted average of the errors in adjacent counties. By putting equation 12 into equation 10 we get the following reduced form equation.

$$\mathbf{ln}\left(\frac{\mathbf{y_{t+T}}}{\mathbf{y_t}}\right) = \boldsymbol{\alpha_0} + \boldsymbol{\beta}\,\mathbf{ln}(\mathbf{y_t}) + \boldsymbol{\alpha_2}\mathbf{D} + (\mathbf{I} - \boldsymbol{\lambda}\mathbf{W})^{-\mathbf{1}}\boldsymbol{\varepsilon} \qquad (13)$$

5. RESULTS AND DISCUSSION

The summary statistics show higher variation in 2000 than 1990 (Table 3). The average number of CCWs increased in 2000 than 1990 in all of county groups. The difference of average number of

[6] GeoDa is a spatial analysis software tools. The details of application of the software can be found here at http://geodacenter.asu.edu/.

CCW is huge between rural and urban counties in both years. But the variation between maximum and minimum of CCW numbers was higher in urban counties.

Table 3: Descriptive statistics for CCWs.

County group	Year	Obs	Average	Std. Dev.	Min	Max
RUCC1	2000	413	48811.3	92744.9	275	1087880
RUCC1	1990	413	38825.9	81008.6	231	1047920
RUCC2	2000	322	18931.4	23603.8	318	151211
RUCC2	1990	322	15011.0	19108.4	201	138813
RUCC3	2000	350	7633.2	6867.8	139	31656
RUCC3	1990	350	6015.2	5358.4	68	24921
RUCC4	2000	218	5256.8	3007.7	1124	24679
RUCC4	1990	218	4248.2	2424.8	875	22960
RUCC5	2000	101	4446.9	2289.3	1227	12668
RUCC5	1990	101	3677.7	1666.4	1224	9786
RUCC6	2000	609	1619.4	1085.7	128	6608
RUCC6	1990	609	1268.7	829.9	140	5716
RUCC7	2000	440	1312.5	925.7	187	7332
RUCC7	1990	440	1069.8	715.2	144	5673
RUCC8	2000	232	631.7	590.0	34	5177
RUCC8	1990	232	476.9	430.5	29	3933
RUCC9	2000	423	382.5	357.6	9	3070
RUCC9	1990	423	298.2	252.9	4	2382
Rural	2000	2023	1713.9	2026.4	9	24679
Rural	1990	2023	1373.1	1623.2	4	22960
Urban	2000	1085	26660.5	61408.5	139	1087880
Urban	1990	1085	21174.2	53063.7	68	1047920
All counties	2000	3108	10422.7	38207.2	9	1087880
All counties	1990	3108	8285.6	32760.1	4	1047920

Source: ERS/USDA.

Note: Two counties are not included in the analysis due to unavailability of data.

We also examined the relationship between CCWs growth and real per capita income growth. As expected, there is a positive relationship between real per capita income [7] growth and CCWs growth all counties and urban counties only (Figure 2). However, the relationship is much stronger in metro counties than rural counties.

[7] Per capita personal income data were taken from Bureau of Economic Analysis (BEA) and adjusted to 2000 price.

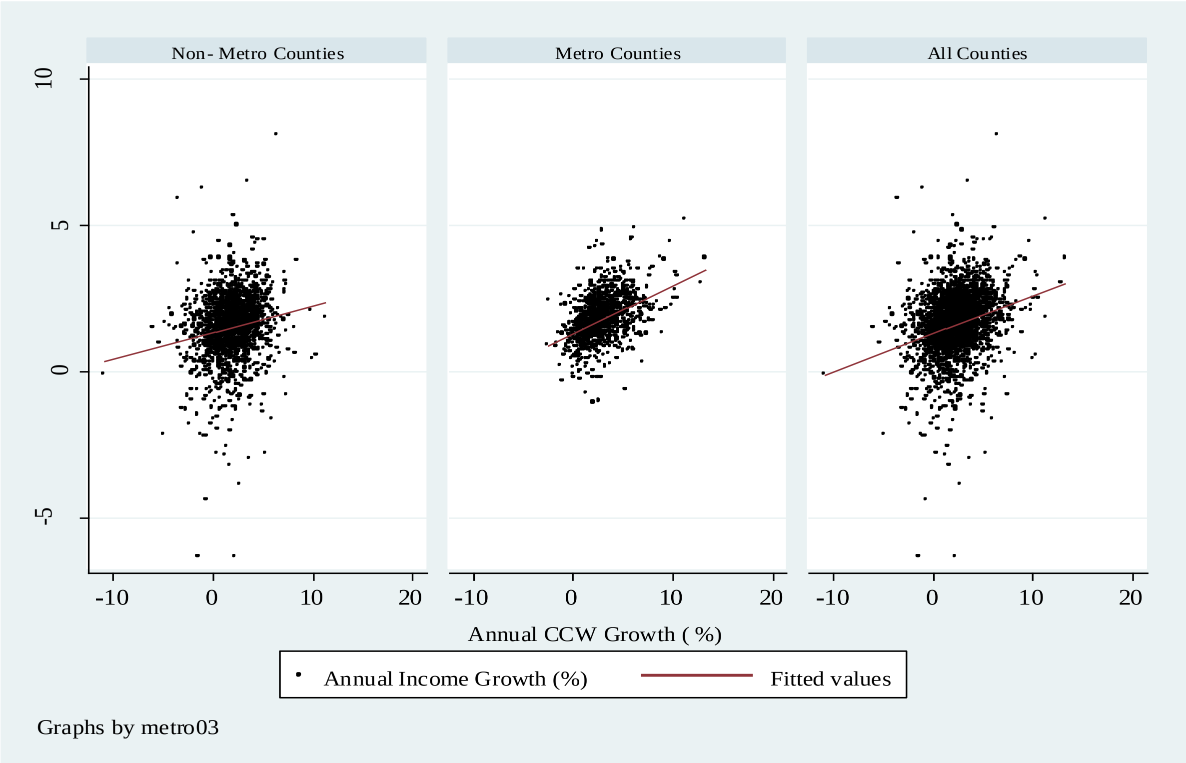


Figure 2: Relationship between CCWs' growth with real income growth.

We also examined relationship between per capita income growth and CCW growth by RUCC county groups. The relationship between per capita income growth and CCW growth is stronger for urban county groups (RUCC1, RUCC2, and RUCC3) than rural counties groups (RUCC4 to RUCC9), which indicate the weak relationship between CCW growth and income growth (Figure 3). The relationship is still positive for rural county groups suggests that possible positive role of CCW on income growth.

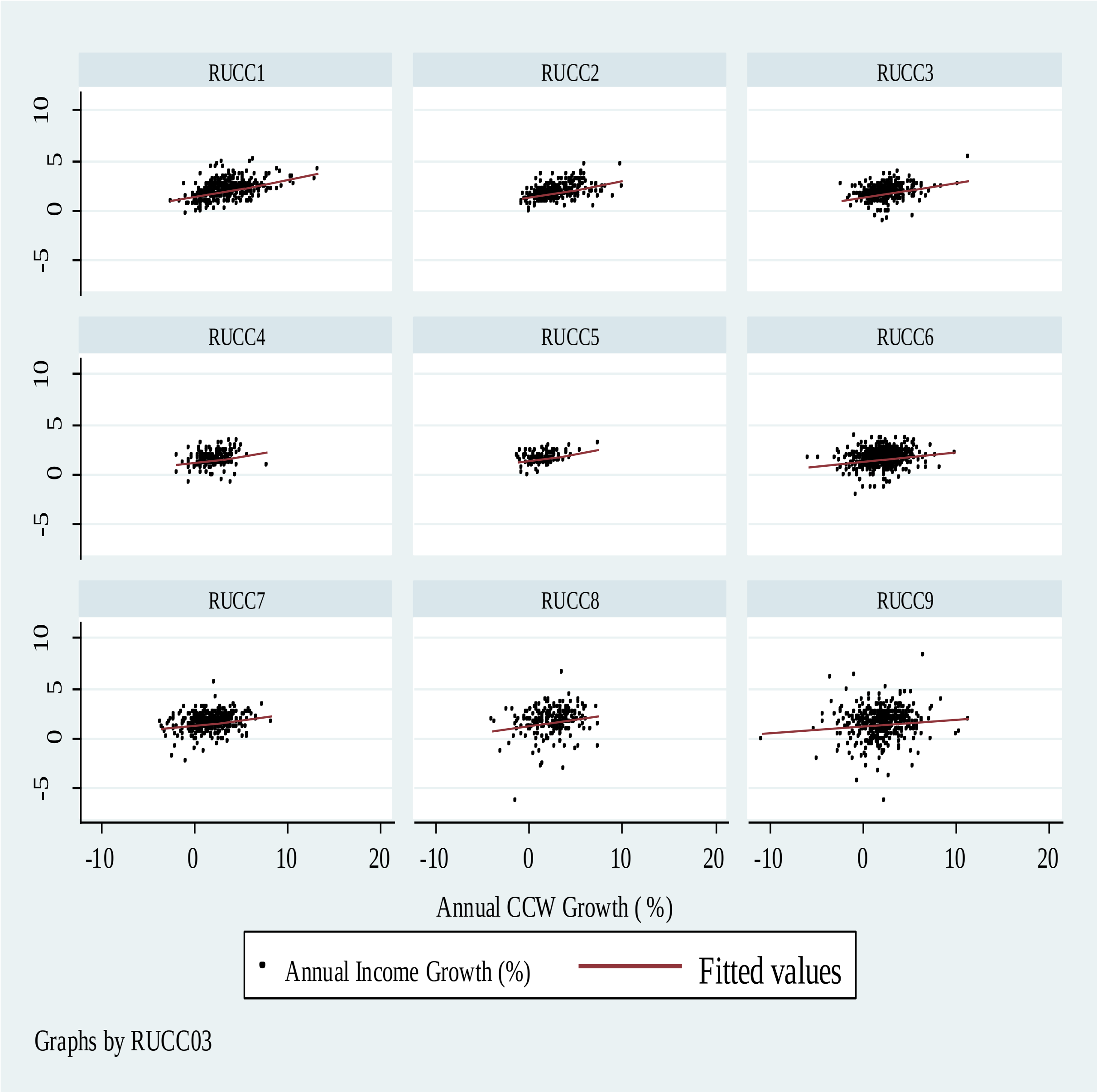


Figure 3: Relationship between CCWs' growth with real income growth by RUCCs.

The growth rate[8] of CCWs, which is a dependent variable in the model, is calculated using logarithmic value of CCW number for each county between 1990 and 2000. The Table 4 shows the top and bottom ten counties in CCWs annual CCW growth over ten-year period. Out of ten highest growth counties, four counties are in Colorado, three are in Georgia, two are in South Dakota and one is in Idaho. Surprisingly, the third and seventh highest growth counties are the most rural counties (RUCC 9). Out of the ten lowest growth counties, three are in Texas, two each in Montana and Nebraska, and one each from in Alabama, Kentucky and North Carolina. All counties on the

[8] Growth rate is calculated as $Growth = \frac{1}{T} ln\left(\frac{y_{t+T}}{y_t}\right)$ where T is time period .

bottom ten ranked had negative growth are rural counties. In total, there are 266 counties with negative annual CCW growth rates between 1990 and 2000.

Table 4: Top and bottom ten counties CCW growth rate from 1990 to 2000.

Bottom ten counties					Top ten counties				
FIPS	**County**	**State**	**Growth %**	**RUCC**	**FIPS**	**County**	**State**	**Growth %**	**RUCC**
30069	Petroleum	MT	-10.79	9	13117	Forsyth	GA	13.38	1
01011	Bullock	AL	-5.82	6	08035	Douglas	CO	12.92	1
31183	Wheeler	NE	-5.21	9	16081	Teton	ID	11.44	9
31009	Blaine	NE	-4.82	9	46127	Union	SD	11.4	3
48283	La Salle	TX	-4.63	6	13223	Paulding	GA	10.67	1
30109	Wibaux	MT	-4.19	9	13085	Dawson	GA	10.58	1
37095	Hyde	NC	-4.17	9	08053	Hinsdale	CO	10.48	9
48229	Hudspeth	TX	-3.92	8	08039	Elbert	CO	10.45	1
48311	McMullen	TX	-3.64	8	08093	Park	CO	10.39	1
21075	Fulton	KY	-3.56	7	46083	Lincoln	SD	10.27	3

Source: Calculated from ERS/USDA data.

A map of CCWs' annualized growth between 1990 and 2000 is presented in the Figure 4. The map shows higher growth counties are in the Mountain and South-western states. Major counties in bigger metropolitan cities like Los Angeles, New York, Washington DC have a modest CCW growth rates. Negative growth of CCW mainly observed in the Southern states (Figure 4).

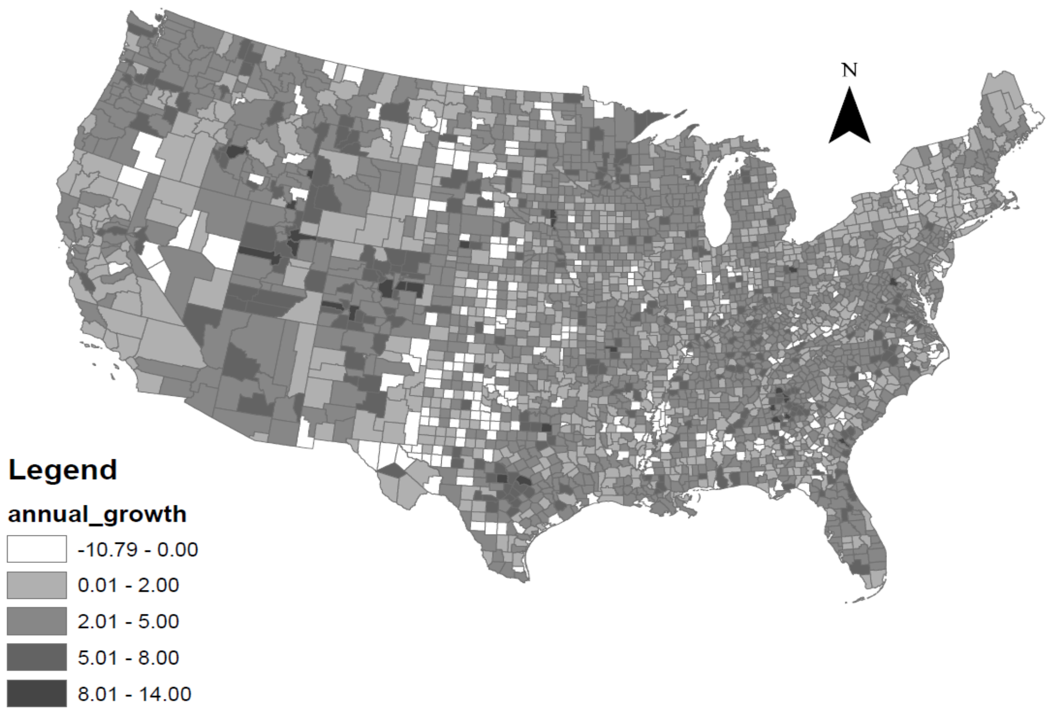


Figure 4: Annualized growth of CCWs between 1990 and 2000 .

The equation 1, which is unconditional OLS and without considering the spatial autocorrelation, shows the divergence trend against the initial level of CCWs while including all counties (Figure 5). The divergence result while taking all counties together support Richard Florida's implicit assumption of divergence in CCWs' growth. This result suggests that the CCW growth inequality between the counties will increase in the future. However, by taking only metro counties, the result shows the clear trend of convergence (Figure 5). This means that lagging metro counties are able to catch other metro counties in the future in CCWs.

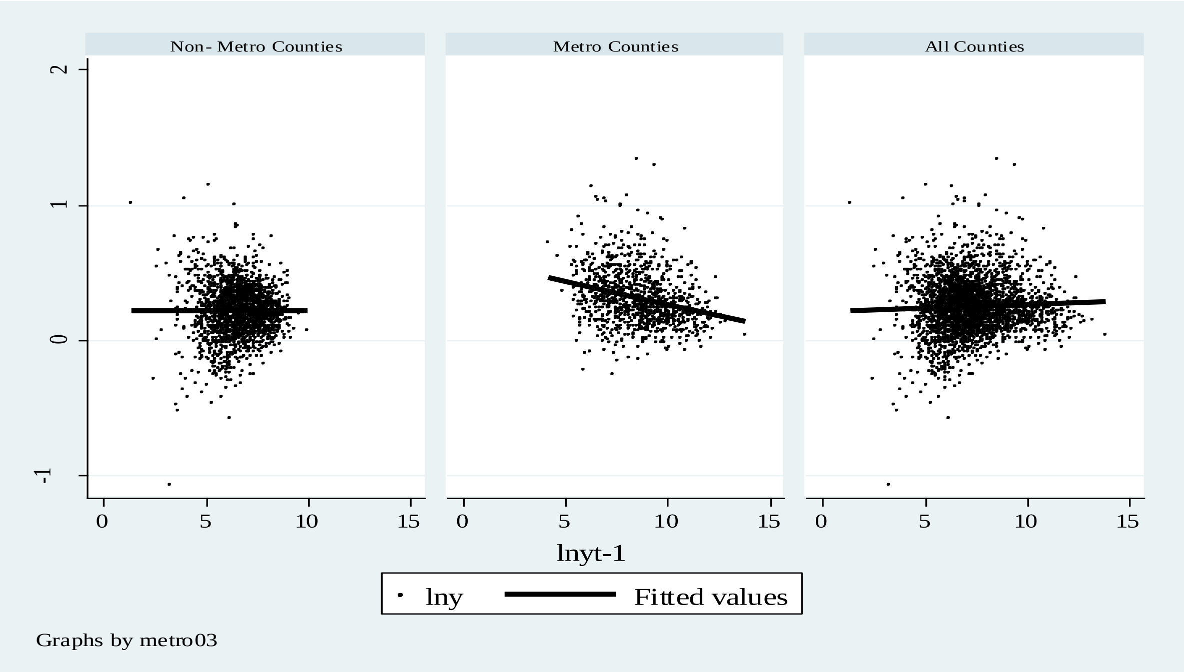


Figure 5: Relationship between annual growth rates and initial level of CCWs.

In addition to graphical relationship, we also estimated the absolute convergence models. The **β**-coefficient of absolute convergence model while including all counties has positive value that indicates no convergence. But the absolute convergence models for rural and urban counties separately show the negative **β**-coefficient indicating convergence. These three absolute convergence models are aspatial models. However, **β**-coefficient for non-metro counties is not statistically significant (Table 5).

Table 5: Estimation of absolute convergence model.

	All counties	Non-metro	Metro
Intercept	0.2096209	0.21129	0.60009[N]
	(0.0164406)	(0.0252305)	(0.0316656)
lnyt-1	0.0046036	-0.0001962[N]	-0.0338972
	(0.0021802)	(0.0037381)	(0.0035866)
N	3108	2023	1085

Note: N along with coefficient indicates not significant and values in the parenthesis indicate the standard error.

We have also examined relationship between level of CCWs in 1990 and CCW growth between 1990 and 2000 by RUCC county groups. As moving from RUCC1 to RUCC9 relationship between CCW number in 1990 and CCW growth goes from downward sloping to slight upward sloping relationship (Figure 6). The upward sloping trend starts from RUCC4 and ends at RUCC9. These RUCC4 to RUCC9 groups comprises rural counties.

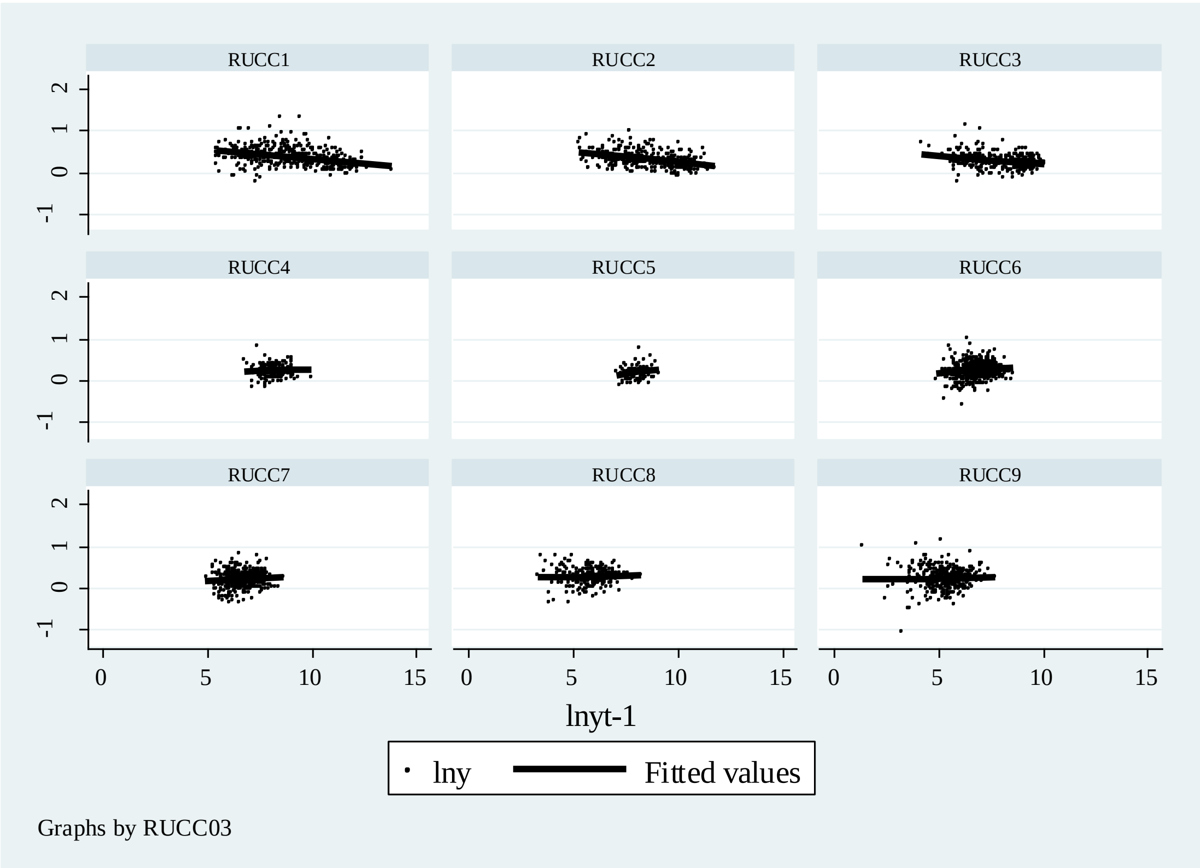


Figure 6: Relationship between annual growth rates and CCW numbers in 1990 by RUCC.

We estimated the **β**-convergence using absolute convergence aspatial models for each RUCC county group. The results show the convergence only for urban county groups (RUCC1, RUCC2, and RUCC3). The **β**-coefficients for RUCC4 to RUCC9 are positive, which means there is no convergence between 1990 and 2000 (Table 6). The **β**-coefficients of RUCC5, RUCC8, and RUCC9 are not statistically significant.

Table 6: Examining the β-convergence by RUCC classification.

	RUCC1	RUCC2	RUCC3	RUCC4	RUCC5	RUCC6	RUCC7	RUCC8	RUCC9
Intercept	0.75021	0.73773	0.54353	0.14526N	-0.35958N	-0.06805^{N}	-0.00293^{N}	0.22939	0.20032

	RUCC1	RUCC2	RUCC3	RUCC4	RUCC5	RUCC6	RUCC7	RUCC8	RUCC9
	(0.05188)	(0.05735)	(0.05514)	(0.15819)	(0.27696)	(0.07744)	(0.09141)	(0.09592)	(0.07205)
lnyt-1	-0.04322	-0.05063	-0.03546	0.00713^{N}	0.06477^{N}	0.04156	0.02695	0.00458^{N}	0.00265^{N}
	(0.00557)	(0.00649)	(0.00672)	(0.01918)	(0.03408)	(0.0111)	(0.01344)	(0.01622)	(0.01322)
N	413	322	350	218	101	609	440	232	423

Note: N along with coefficient indicates not significant and values in the parenthesis indicate the standard error.

5.1 Spatial analysis of CCW growth

The CCW growth in any county likely to have spillover effect. Therefore, we also examined the spatial autocorrelation using the Moran's I scatter plot. In addition we also prepare the cluster map to the distribution of CCW growth in US counties. The GeoDa software is used for Moran's I analysis, which produces a scatter plot, and clustered map. The Moran's I scatter plot gives a significant value of 0.270, indicating autocorrelation of the CCW growth among the counties (Figure 7). The horizontal axis shows the CCW growth and the vertical axis represents the lagged CCW growth using the queen weight matrix. The Moran's I Scatter plot have four quadrants which represents high-high, high-low, low-high, and low-low growth rates of county and its adjacent counties. These four quadrants relationship between of the value a county and its neighboring counties. For example, the upper right quadrant represents the high–high that means higher average CCW growth value surrounding by the counties with higher average CCW growth values.

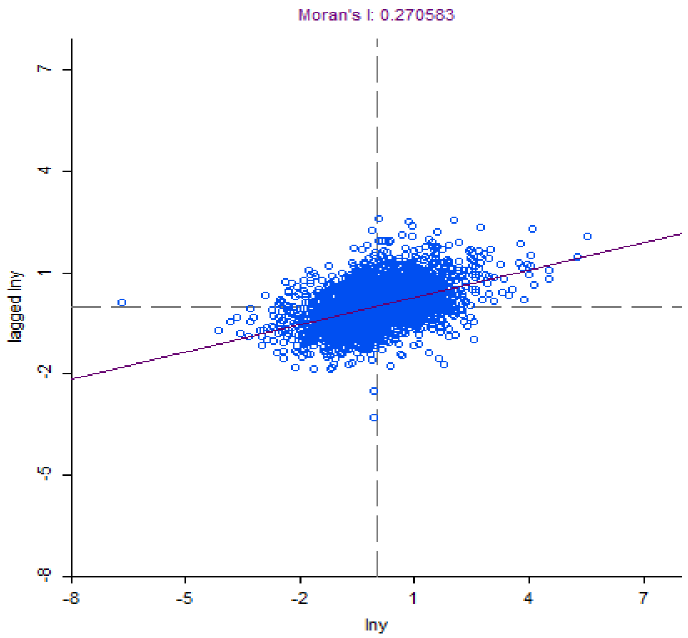


Figure 7: Moran's I scatter plot of all counties.

A Local Indicators of Spatial Association (LISA) cluster map is prepared to examine the distribution of significant cluster values. The LISA cluster map basically identify cluster values by comparing with the values of neighboring counties. The LISA cluster map shows Arizona, Colorado, Minnesota, Texas around San Antonio, Georgia (Atlanta) as high- high clusters. This means these red color counties have above average CCW growth and shares the boundaries with counties that have above average CCW growth (Figure 8). Similarly, North-West Texas and Southern portion of Oklahoma, Northern New York, Maine, and Vermont, North-west portion of Kansas and south-west portion of Nebraska, middle portion of Louisiana and Mississippi have low-low clusters. High-low and low-high cluster spread across the around high-high and low-low clusters.

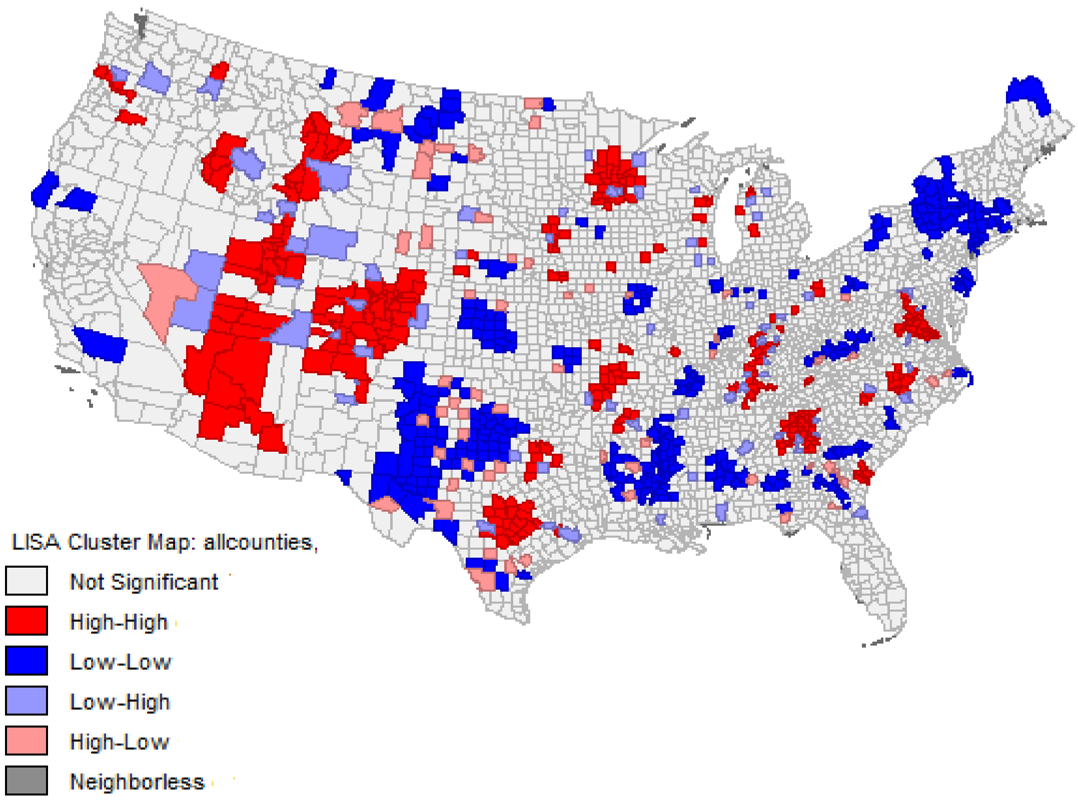


Figure 8: LISA cluster map of CCW growth.

To examine $\boldsymbol{\beta}$-convergence, three conditional convergence models with and without considering spatial autocorrelation are also estimated. The results of each model are presented below (Table 7). Each is these models are compared by the Akaike's Information Criterion[9] (AIC) to find out the best fit model.

[9] AIC is calculated as $AIC = n.ln\left(\frac{SSE}{n}\right) + 2p$ where n is observations, SSE is sum of squared errors and p is number of independent variables.

The Model 1, which is conditional Ordinary Least Square (OLS) aspatial model, has shown the presence of $\boldsymbol{\beta}$-convergence, and has the lowest R-square and higher AIC value. The coefficient for log of initial value has a negative sign and is significant at less than one percent level of significance indicates the presence of convergence. The speed of convergence is 0.18 per cent per year. This implies that it will take a county about 38.7 years to eliminate half of the initial gap from its steady state (Table 7).

Other two models, model 2 and model 3, are conditional spatial models. The model 2, which is spatial lag model, also shows the negative significant $\boldsymbol{\beta}$-coefficient. The speed of convergence is 0.18 percent per year. This implies that it will take about 38.8 years to eliminate half the initial gap from its steady state. The AIC value is less than the OLS model indicating a better fit model than OLS model. The R- square is higher than OLS model.

The Model 3, the spatial error model, also has the negative significant $\boldsymbol{\beta}$-coefficient. The speed of convergence and estimated years to remove the half of initial gaps are 0.24 percent and about 28.8 years respectively. AIC for this model is the lowest therefore suggest the best fit model among the all. This best fit model suggests that strong spillover effect from adjacent counties (Table 7).

All of the conditional models suggest the presence of convergence of CCWs growth among the US counties. The best fit model shows that it requires about 58 years for lower growth counties to catch up higher growth counties. The results also suggest that the neighboring counties playing important role in removing the gap among counties. The adjacent counties help to shorten the convergence by 19.8 years. This study provides two key messages: a) evidence of convergence, and b) positive role of neighboring counties in reducing the gap of CCW level among the counties.

Table 7: Estimation of models.

	OLS	**Spatial lag**	**Spatial error**
	Model 1	**Model 2**	**Model 3**
Intercept	0.329095**	0.228917**	0.377998**
	(0.016998)	(0.01667)	(0.01888)
log (initial number)	-0.017913**	-0.01788**	-0.02404**
	(0.002467)	(0.00227)	(0.00255)
Dummy (metro=1, non-metro=0)	0.12892**	0.11062**	0.114023**
	(0.00872)	(0.00805)	(0.00843)
Rho		0.44819**	
		(0.0211)	
Lambda			0.49591**
			(0.02136)
R-square	0.06394	0.21109	0.22733
N	3108	3108	3108

AIC	-1493.52	-1919.24	-1956.32
Annual speed of convergence (δ)	**-0.00181**	**-0.0018**	**-0.00243**
Year to fill half of the gap (τ)	38.7	38.8	28.8

Note: a) ** indicates significant at less than 1 percent level of significance.
b) Figure in the parenthesis indicates the standard error of the coefficient.

The **β**-convergence is a necessary but not sufficient condition for **σ**-convergence (Young, Higgins, & Levy, 2008). Therefore, we also examined **σ**-convergence across the time in addition to **β**-convergence. The results of **σ**-convergence estimations show that there is a decrease in dispersion, measured by the coefficient of variation, over time between 1990 and 2000 (Table 8). This result further strengthen the convergence of CCW growth.

Table 8: Estimation of σ–convergence.

Estimate	Year 1990	Year 2000
Average	8263.05	10399.52
Standard Deviation	32744.7	38196.45
Coefficient of Variation	3. 95	3.66

In addition the overall counties, we have also estimated nine separate conditional spatial error regression models using dummy variable of each RUCC category. The results show the evidence of **β**-convergence in each nine regression model (Table 9). However, earlier results of the absolute convergence model shows **β**-convergence only in urban county groups (RUCC1, RUCC2, and RUCC3). The regression model of RUCC1 shows that It will take about 42 years to fill the one-half of the gap of CCW numbers across counties with a convergence speed of 0.17 percent per year. This is the lowest number of years to fill the half of the gap between counties. Similarly, the conditional spatial error models for RUCC4 and RUCC5 show about 81 years to fill the one-half of the gap between the counties, which is the highest among all RUCC county groups.

Table 9: Spatial Error model estimation for each RUCC county group.

	RUCC1	RUCC2	RUCC3	RUCC4	RUCC5	RUCC6	RUCC7	RUCC8	RUCC9
Intercept	0.3417	0.325	0.3137	0.3072	0.3052	0.3261	0.3135	0.314	0.316
	(0.0185)	(0.0189)	(0.0189)	(0.0188)	(0.019)	(0.0192)	(0.0186)	(0.0196)	(0.0206)
log (initial number)	-0.0164	-0.0123	-0.0102	-0.0085	-0.0086	-0.0107	-0.0089	-0.0098	-0.01
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0025)
Dummy (if county belongs to RUCC=1, otherwise=0)	0.1423	0.0677	0.0213	-0.0478	-0.0242^{N}	-0.0317	-0.0481	-0.0086^{N}	-0.0083^{N}
	(0.0125)	(0.0119)	(0.0108)	(0.0122)	(0.0183)	(0.0081)	(0.0096)	(0.0124)	(0.0112)
Lambda	0.4959	0.5192	0.5188	0.5179	0.5133	0.5204	0.5054	0.518	0.5099
	(0.0214)	(0.0208)	(0.0208)	(0.0208)	(0.021)	(0.0208)	(0.0211)	(0.0208)	(0.0208)
R-square	0.22	0.2	0.19	0.19	0.19	0.19	0.19	0.19	0.19

	RUCC1	RUCC2	RUCC3	RUCC4	RUCC5	RUCC6	RUCC7	RUCC8	RUCC9
Log likelihood	955.39	908.69	894.52	900.23	893.46	900.24	905.09	892.83	892.29
N	3108	3108	3108	3108	3108	3108	3108	3108	3108
AIC	-1904.77	-1811.38	-1783.04	-1794.45	-1780.91	-1794.48	-1804.18	-1779.66	-1778.58
Annual speed of convergence (**δ**)	-0.00165	-0.00124	-0.00102	-0.00086	-0.00086	-0.00108	-0.0009	-0.00098	-0.00101
Year to fill half of the gap (**τ**)	42.4	56.2	68.2	81.3	80.6	64.7	77.8	70.8	69.3

Note: All coefficients are significant less the 5 percent level of significance except indicated by N.

We also use coefficient of variation to examine the **σ**-convergence for each RUCC group. Despite all RUCC groups have shown **β**-convergence in the earlier result, only RUCC1 and RUCC2 have shown the evidence of **σ**-convergence (Table 10).

Table 10: Estimation of σ–convergence by RUCC county groups.

	RUCC1	RUCC2	RUCC3	RUCC4	RUCC5	RUCC6	RUCC7	RUCC8	RUCC9
Average1990	38826	15011	6015	4248	3678	1269	1070	477	298
Average2000	48811	18931	7633	5257	4447	1619	1313	632	382
SD1990	80910	19079	5351	2419	1658	829	714	430	253
SD2000	92633	23567	6858	3001	2278	1085	925	589	357
COV1990	2.084	1.271	0.89	0.569	0.451	0.654	0.668	0.901	0.847
COV2000	1.898	1.245	0.898	0.571	0.512	0.67	0.704	0.932	0.934

Note: SD represents Standard Deviation and COV represents Coefficient of Variation.

6. SUMMARY AND CONCLUSIONS

The role of human capital in economic development has long been recognized. However, the positive role of the “creative class workers”, a special class of human capital, in economic development is brought into literature by Richard Florida. Due to the strong preferences of urban amenities, the CCW growth is not uniform across US counties. But the question arises whether counties that are lagging behind now able to fulfill the gap in the future. The Creative Class Theory does not explicitly mention convergence or divergence of CCWs growth, though implicitly assume divergence due to strong locational preferences. This study examines the CCW growth convergence in aggregate and by RUCC county groups. Besides, study also examine the distribution pattern of CCW growth in US counties. The absolute convergence model indicate convergence in metro counties as explained by Richard Florida. However, due to huge difference among the counties and spatial autocorrelation, the conditional spatial model to examine the CCW growth convergence. Due to the spatial autocorrelation, the conditional spatial error model is turn out to be the best fit model among other competitive models. The conditional spatial error model shows that about 58 years is required to close the gap among the counties with 0.24 percent annual convergence speed. The study also finds the **σ**-convergence among urban counties. The neighboring counties plays a significant positive role in closing the gap between the higher growth and lower growth counties. The results also show that all RUCC county groups shows **β**-convergence but not the **σ**-convergence. The conditional spatial error model shows that the RUCC1 require 85 years to close the gap rest of RUCC county groups requires more than 100 years. The RUCC4 and RUCC5 require the highest number years to close the gaps. The results of this study are consistent with the human capital convergence studies, but differs with the Creative Class Theory implicit assumption of divergence.

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