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DIVERSITY AND REGIONAL ECONOMIC GROWTH: EVIDENCE FROM US COUNTIES

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This study examines the relationship between economic growth and diversity for US counties over the period 1990-2007. The existing literature provides conflicting conclusions on the relationship between diversity and growth, based on theoretical arguments as well as empirical analysis. A conditional growth model is estimated through spatial econometric techniques which account for the role of location and spatial dependence in the regional economic growth process. The results suggest economic diversity has a positive impact on economic growth.

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1. INTRODUCTION

There are many theoretical arguments that suggest growth and economic diversity are intrinsically linked, yet such arguments can be found both in support of and in opposition to economic diversity. Empirical investigations of the relationship between diversity and growth provide similarly ambiguous conclusions. Attaran (1986, p. 45) defines economic diversity as “the presence in an area of a great number of different types of industries” or “the extent to which economic activity of a region is distributed among a number of categories”. Proponents of economic diversity suggest that diverse economies are less susceptible to volatility associated with the business cycle and are therefore able to avoid serious fluctuations in employment and income (Hackbart and Anderson, 1975; Dissart, 2003). This notion suggests that diversity acts as an “averaging” process in which different sectors are able to reemploy displaced workers from other sectors (Frenken *et al*., 2007). In turn, the stability related to diversity within a region may facilitate growth in productivity and income. On the other hand, economic theory suggests that regional specialization fosters employment growth by exploiting a

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comparative advantage for certain forms of production. However, Malizia and Ke (1993) define diversity as not the absence of specialization but the presence of multiple specializations and sectors with strong inter-industry linkages.

Jacobs (1969) argues that economic diversity within a region promotes technological innovation through knowledge and technology spillovers across sectors in a single geographic location. Empirical support for Jacobs externalities is provided by a number of studies, such as Feldman and Audretsch (1999). Alternatively, economic theory suggests that regional specialization may facilitate economic growth through returns to agglomeration in the form of Porter and MAR (Marshall-Arrow-Romer) externalities. Porter (1990) suggests that regional specialization fosters innovation through local competition in which firms compete for scarce resources. Alternatively, Glaeser *et al*. (1992) argue that absolute regional specialization, or a spatial monopoly, may be more efficient in the production of goods and services than perfectly competitive firms.

It is not surprising to see that empirical studies of the relationship between economic diversity and economic growth at the regional level offer conflicting results. For example, Attaran (1986) demonstrates that economic diversity is *not* related to per capita income growth at the US state level, yet Attaran and Zwick (1987) find a positive correlation between economic diversity and per capita income growth at the county level in Oregon. A similar phenomenon has been documented for employment growth in Great Britain by Bishop and Gripaios (2010) and in the Netherlands by Frenken *et al*. (2007).

This study examines the link between regional economic diversity (measured by employment patterns) on county level income growth over the period 1990-2007. The period is selected to represent a reasonable window to examine long-run growth strategies. As Wagner (2000, p. 2) states, "...short-run policies are aimed at promoting growth and long-run policies are aimed at promoting stability with growth". That is, the potential for growth increases as stability and diversity increase. The aim is to revisit the existing studies by applying spatial econometric techniques which more accurately capture the role of location and account for spatial dependence in the economic growth process.

2. THE EMPIRICAL GROWTH MODEL

The theory of economic growth is a constantly evolving field, and a number of critical drivers of economic growth have been suggested by the literature. Solow (1956) demonstrated the importance of physical capital and labor, and Mankiw *et al*. (1992) later added human capital as a major determinant of economic growth. In the years following this seminal work, a vast literature has expanded the traditional growth model to include other important factors. Our empirical growth model explains growth in real per capita income at the US county level as a function of economic diversity and a set of variables drawn from the existing literature. The conditional growth model is expressed:

$$g = \alpha S + \beta m_0 + Z\varphi + \varepsilon \, , \quad \varepsilon \sim N(0, \sigma^2 I) \, , \tag{1}$$

where g is the vector of average annual growth rates as measured by the log difference of per capita income between the ending period 2007 and initial year of 1990; m_0 is the vector of log per capita income in 1990; Z contains the variables which maintain the constant steady state of each economy; S is a unit vector; and ε is the vector of errors.

One of the key properties of (1) is known as (conditional) beta convergence. Beta convergence implies that the growth rate of an economy will be positively related to the distance that separates it from its own steady state. The process occurs when a negative relationship exists between the growth rate of (real) per capita income and the initial level of (real) per capita income (see Baumol, 1986). Consequently, poor economies would grow faster than rich economies. Thus, when Z is fixed, β is expected to be negative and statistically significant. Considering that the model in Equation (1) is non-spatial, then the parameter β is fixed and the convergence rate or speed of convergence is given as $b = -\ln(1+\beta)/T$.[1] The amount of time for economies to fill half of the separation between the economy and its steady state is called the half life and is calculated as $\tau = -\ln(2)/\ln(1+\beta)$. In the long run, regions are expected to converge to an equilibrium or steady-state. Regions with similar initial endowment/characteristics may converge to the same equilibrium, and form what is known as “convergence clubs”.

The earliest studies of economic growth examined differences between countries at the national level, but the regional science literature provides a number of studies on economic growth at the sub-national level. Regional growth studies address smaller spatial units, such as states, counties in US, NUTS regions in Europe, districts and provinces, or small artificially created grid cell data. Regional analysis of economic growth has also spurned the development of specialized quantitative methods designed to account for the spatial dimensions of higher resolution, spatially referenced data.

It has been consistently demonstrated that the spatial dimensions of regional economic data can impact the results and interpretation of empirical growth models (Abreu *et al*., 2005). As a result, spatial econometric methods have been used in an increasing number of studies (see, Abreu *et al*., 2005, for a meta-analysis of these developments). Spatial econometrics provides a formal econometric methodology in which the true factors at the origin of spillovers are proxied by geographical distance, and the spatial process carries the advantages of being exogenous. Rey and Janikas (2005) note that technology spillovers, labor migration, and commodity flows, among other factors of production, can tie neighboring economies and their economic conditions together. Further, the authors note that the administrative boundaries used in quantitative growth studies may not represent the true boundaries of the economic

[1] Meta-analysis of Abreu *et al*. (2005) suggests that cross-country level convergence rate is commonly observed in the neighborhood of 2%.

processes, and as a result, the measurement error will induce spatial autocorrelation.

Spatial econometric techniques have been accepted in part because of their ability to capture important aspects of regional economies, such as human capital spillovers, technology diffusion across regions, and other important locational externalities (see Temple, 1999a,b; Fingleton and Lopez-Bazo, 2006; Ertur and Koch, 2006, 2007). Further, Magrini (2004) argues that empirical studies should explicitly account for spatial interaction effects given the larger degree of openness of regional interaction compared to cross- country studies. Wagner (2000) also stresses the importance of spatial econometric methods when modeling the relationship between diversity and growth.

The leading spatial econometric models augment a regression equation to explicitly account for the spatial aspects of the data, typically through either the dependent variable or the regression error.[2] The spatial lag model captures spatial dependence in the regressand by including spatially weighted values of the dependent variable on the right hand side of the equation (Anselin, 1988). Alternatively, spatially related omitted or unobservable variables may lead to correlated disturbance terms (Anselin, 1988). In which case, the spatial error model provides an appropriate specification.

The paper starts with an estimation of the a-spatial model in (1) and later uses the spatial diagnostics tests (Lagrange Multipliers) to identify the appropriate spatial process. The spatial process could be a model with spatial lag or spatial error process, or a combination of both called "spatial autoregressive model with autoregressive disturbances" (SARAR) (see Kelejian and Prucha, 1998). The SARAR model is mathematically expressed as follows:

$$g = \alpha S + \rho W g + \beta m_0 + Z\varphi + \varepsilon \,, \quad \varepsilon = \lambda W \varepsilon + u \,, \tag{2}$$

and, the spatial lag and error process, (which are nested in the SARAR) are given respectively as:

$$g = \alpha S + \rho W g + \beta m_0 + Z\varphi + \varepsilon \,, \tag{3}$$

$$g = \alpha S + \beta m_0 + Z\varphi + \varepsilon \,, \quad \varepsilon = \lambda W \varepsilon + u \,, \tag{4}$$

where W is a spatial weight matrix, u is a vector of errors assumed to be normally distributed with mean zero a constant variance, all other terms are defined as in Equation (1).

The spatial structure of regions is defined by the spatial weights matrix W. The

[2] Spatial aspects of the data may also be modeled in the independent variables. This is known as cross-regressive model.

matrix W is binary and its element w_{ij} take value 1 when regions i and j are neighbors and 0 otherwise. By convention, a region cannot be a neighbor to itself, so the diagonal elements w_{ii} are zero. The specification of the weight matrix depends on the spatial units and the subject under investigation. The weight matrix is exogenously defined. Several specifications are possible, with the most commonly used being the distance-based weights and the contiguity weights (rook or queen). The distance weight matrix is developed based on the geographical distance between the midpoints (centroides) of the spatial units (regions for example). Two regions are considered neighbors when the geographical distance (arc or Euclidian distance) between them is less than a threshold distance. Elements of the distance weight matrix therefore take value 1 when regions are neighbors and 0 when they are not. The threshold distance is chosen in such a way to guaranty all counties have at least one neighbor. The definition of contiguity weight considers that regions are neighbors when they are contiguous through their borders based on the rook or queen criteria.

The sign of the unknown spatial lag parameter ρ indicates the nature of spatial dependence. Positive values of ρ suggest that, on average, regions are positively affected by growth in neighboring locations. The second spatial autoregressive process in the disturbance terms ε also includes the exogenous spatial weights matrix W and an unknown spatial parameter λ. The remaining error u is assumed to retain the standard properties in regression analysis and is also assumed to be free of remaining spatial dependence.

Given that the model in Equation (2) and (3) contains a spatial autoregressive component, the interpretation of the coefficients involves computing measures of direct, indirect and total effects (see LeSage and Pace, 2009). The direct effect represents the average impact of a change in the explanatory variable in each of the spatial units (counties) on the dependent variable at the same location. The indirect effect measures the average impact of a change in the explanatory variable in each location (counties) on the dependent variable in different locations.

The reduced form of the SARAR model in Equation (2) is given as:

$$g = (I - \rho W)^{-1}[\alpha S + \beta m_0 + Z\varphi + (I - \lambda W)^{-1} u], \qquad (5)$$

where, I represents the unity diagonal matrix, and all other terms are defined as previously. Using this reduced form, the marginal effect of a change in an explanatory variable Z_i is given as:

$$\frac{\partial g}{\partial Z_i} = \left(I - \rho W\right)^{-1} \varphi_i, \qquad (6)$$

where φ_i represents the coefficient corresponding to Z_i.

3. MEASURING ECONOMIC DIVERSITY

To test for the effects of economic diversity, the model includes several measures which capture the distribution of employment across a set of sectors - called *entropy indices*. Entropy indices were first introduced to economic analysis by Garrison and Paulson (1973) and have been used in several studies of employment stability, such as Attaran (1986) and Malizia and Ke (1993). Jacquemin and Berry (1979) use entropy indices to measure the diversity of the product mix within firms, and Hackbart and Anderson (1975) use a time series of entropy indices to measure the effects of diversification. Entropy measures of diversity have been used in employment growth models in numerous studies, including Duranton and Puga (2000), Bishop and Gripaios (2010), and Frenken *et al*. (2007).

There are a number of formulations of entropy indices (Wagner, 2000). To examine the robustness of the results, the model is estimated using three of the leading diversity indices: Ogive (O_i), Herfindalh (H_i), and Shannon (S_i).

$$O_i = \sum_{s=1}^{S_i} \frac{\left[\left(\frac{e_{si}}{e_i}\right) - \frac{1}{S_i}\right]^2}{\frac{1}{S_i}}, \tag{7}$$

$$H_i = \sum_{s=1}^{S_i} \left(\frac{e_{si}}{e_i}\right)^2, \tag{8}$$

$$A_i = -\sum_{s=1}^{S_i} \left(\frac{e_{si}}{e_i}\right) \ln\left(\frac{e_{si}}{e_i}\right), \tag{9}$$

where S_i is the total number of industries in region *i*, e_{si} is employment in industry *s* in region *i*, and e_i is the total employment in region *i*.

Smaller values of the Ogive and Herfindahl indices suggest greater levels of diversity, and larger values are associated with more specialized economies (Wagner, 2000). The benefits of regional economic diversity are therefore supported when the associated coefficients are statistically significant and negative. The same conclusion can be inferred by a positive coefficient for the Shannon index, as smaller values of this index suggest less diverse economies. All of the measures presented assume a standard of equiproportional level of economic activity in all industries (Wagner, 2000). In addition, the measures are static and therefore do not capture diversification effects.

4. DATA

The models described above explain the growth rate in per capita income between 1990 and 2007 at the county level as a function of the initial level of per capita income, a set of economic and demographic control variables, and a measure of economic diversity. All of the control variables are measured in the year 1990 and are expressed in logarithmic form.

The dataset contains observations for 3,074 counties in the lower 48 states of the U.S., for the years 1990 and 2007. Per capita income data were obtained from the Bureau of Economic Analysis (BEA), and the series was expressed in real values using the regional consumer price index from the Bureau of Labor Statistics (BLS) (2007=100). Table 1 presents summary statistics for the real per capita income (RPCI) for 1990 and 2007, as well as the imputed growth rate, at the county level. In addition, the growth rate by county is shown in Figure 1. The growth rate is presented by quartile in which darker colors are associated with higher levels of real per capita income growth over the period 1990-2007. The map indicates that high growth counties are concentrated in Southern, as well as Central Mountain counties. This observation adheres to expectations that poor economies exhibit faster growth rates when compared to rich economies.

Table 1. Data Summary

Variable	Mean	Std. Dev.
Growth	0.227	0.127
Real per capita income 1990	24,032.100	5,649.860
Real per capita income 2007	30,259.600	8,036.990
Gini	0.419	0.038
Housing	53,833.500	35,447.000
Amenities	0.052	2.288
	Proportion	
Metropolitan	35%	
Race other	2%	
Race black	9%	
Race Hispanic	5%	
High school grad	34%	
Some college	16%	
Associate’s degree	5%	
Bachelor’s degree	9%	
Graduate degree	4%	

Age 5 to 14	15%	
Age 15 to 17	4%	
Age 18 to 64	58%	
Age 65 or over	15%	
Diversity Index	Mean	Std. Dev.
Ogive	0.081	0.110
Herfindalh	0.129	0.072
Shannon	2.436	0.254

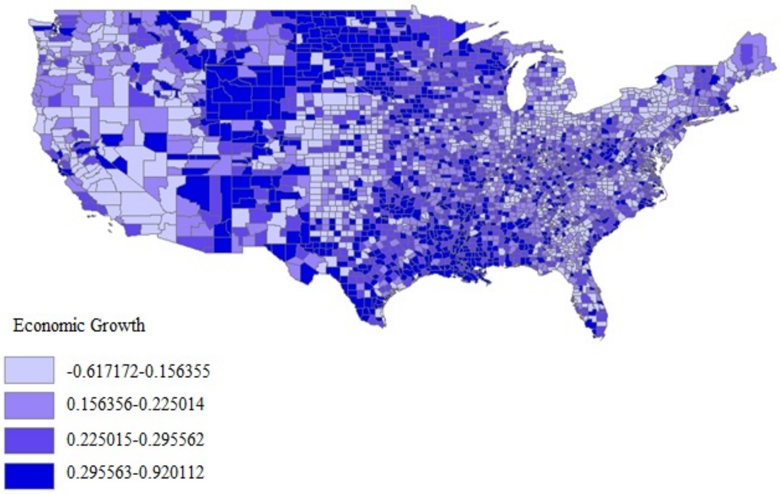

Figure 1. Economic Growth by Quartile, 1990-2007

Employment diversity is calculated using data disaggregated to two-digit North American Industry Classification System (NAICS) industries for the initial period 1990. The data were estimated by Economic Modeling Specialists Inc. (EMSI).[3] Table 2 reports the mean and standard deviation of the proportion of employment for each class across all 3,074 counties. The diversity measures are summarized in Table 1 and shown by quartile in Figure 2. The figure suggests that diverse counties are clustered around major metropolitan areas and along the coasts.

[3] EMSI is a privately held company based in Idaho. More information about EMSI can be obtained from the company's website at http://www.economicmodeling.com/company/. The EMSI employment data combines covered employment provided by the Quarterly Census of Employment and Wage (QCEW) with total employment data from the Regional Economic Information System (REIS).

Table 2. Employment Classes and Diversity

Class	Proportion
Agriculture, forestry, fishing, and hunting	17.49
Mining	1.97
Utilities	0.54
Construction	9.13
Manufacturing	8.70
Wholesale trade	2.44
Retail trade	12.09
Transportation and warehousing	3.75
Information	1.29
Finance and insurance	3.37
Real estate and rental and leasing	4.18
Professional, scientific, and technical services	4.50
Management of companies and enterprises	0.60
Administrative and support and waste management and remediation services	3.68
Education services	1.55
Health care and social assistance	7.94
Arts, entertainment, and recreation	1.83
Accommodation and food services	6.28
Other services (except public administration)	7.83
Public administration	0.83

The empirical conditional growth model includes a number of explanatory variables drawn from the literature to control for structural differences across observations, also reported in Table 1. The conditioning variables include a number of demographic variables related to education, age, and racial composition for the base year 1990, obtained from the US Census Bureau. Reviews of the role of human capital in empirical growth analysis are provided by Savvides and Stengos (2009) and Temple (1999a). Five categories of human capital variables are considered in the growth model: percentage of county population with High school degree, some College degree, Associate's degree, Bachelor's degree, Graduate degree. We expect that these categories of educational attainment will have different effects on income growth. The motivation for including these educational categories is also supported in the literature.

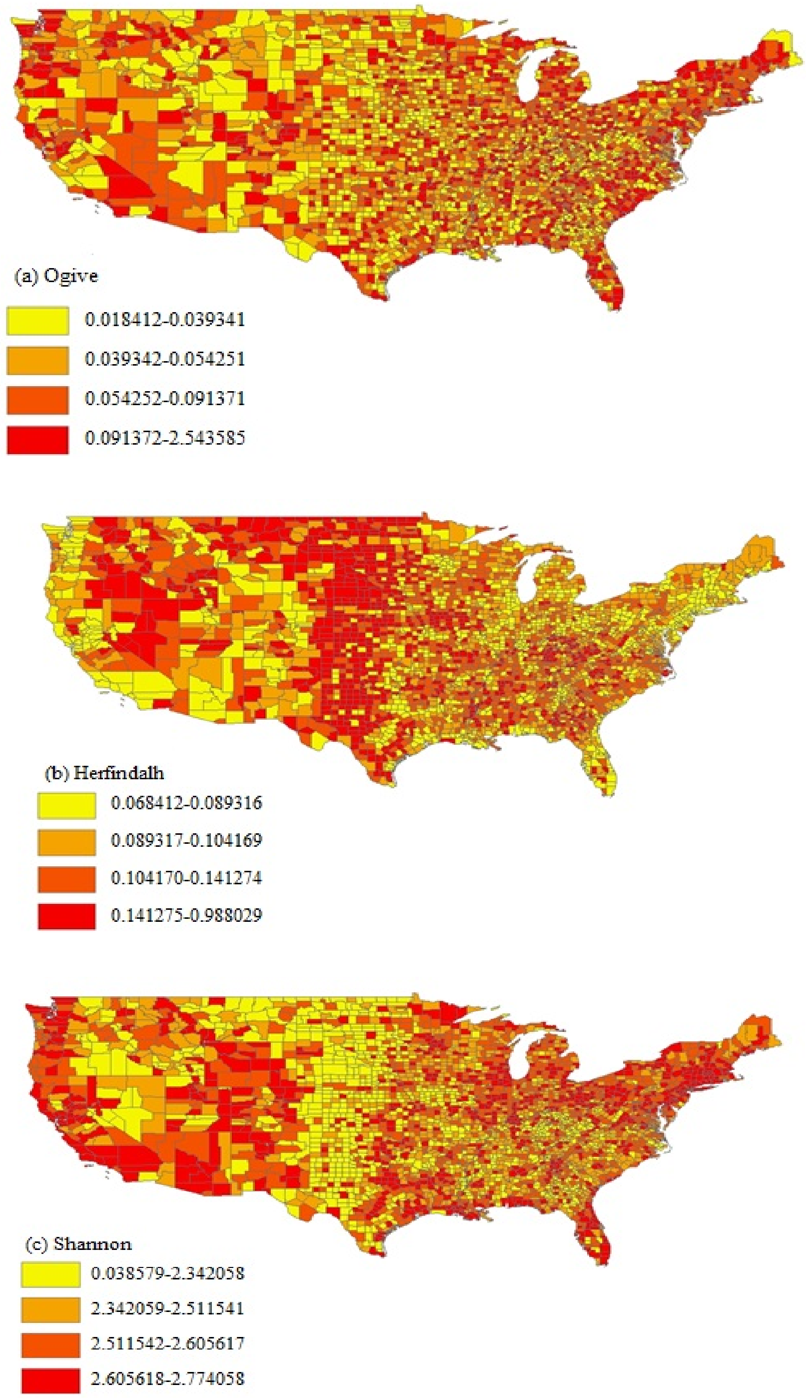

Figure 2. Employment Diversity by Quartile, 1990

For instance, Higgins *et al*. (2006) have shown that the category of bachelor degree and higher specifically has a profound effect on economic growth. The inclusion of age categories in the growth model is also supported in the literature (see for instance, Canton *et al*., 2002; Poterba, 1996; Nahuis *et al*., 2000). In our model, we consider four age categories: Age 5 to 14, Age 15 to 17, Age 18 to 64, Age 65 and over. These age cohorts were kept as defined by the US Census Bureau. Our empirical growth model also includes a measure of income inequality. The findings on the inequality-growth link are very controversial. A negative or positive relationship is often claimed. In some studies the two forms of relationships are also observed. For instance Khalifa and Hag (2010) used a panel of annual data on 70 countries over the period 1970 to 1999, and found that there is a threshold income per capita below which the relationship between growth and inequality is negative and above which it is positive. Other studies found that the relationship is different for rich and poor countries. Dehghan (1995) found a positive relationship between inequality and growth for low income countries and a negative relationship for high income countries. A meta-analysis from De Dominicis *et al*. (2008) shows that the findings on the inequality-growth link depend on estimation method, data quality and sample coverage. Various measures of inequality are also used in the literature, which may also have some implication on the results obtained. Following Fallah and Partridge (2007) on a similar study, we consider the GINI coefficient to measure the family level income inequality in each county. It is expressed as:

$$GINI = 1 - \sum_{i=0}^{M-1} \left(\frac{Y_i + Y_{i+1}}{Y} \right) \left(\frac{n_{i+1} - n_i}{N} \right), \tag{10}$$

where M is the number of income categories, Y_i is the aggregate income in group i, Y is the aggregate family income in the county, n_i is the number of families in category i, and N is the total number of families in the county.

The model also contains a binary explanatory variable to control for structural differences across metropolitan and nonmetropolitan counties (as defined by the US Department of Agriculture). As Wagner (2000) suggests, the structure of metropolitan counties will differ from rural counties due, in part to competitive advantage.

5. RESULTS

To examine the role of economic diversity in a regional growth context, the conditional growth model is estimated for the period 1990-2007. The model is first estimated using Ordinary Least Squares (OLS) and a set of specialized Lagrange multiplier tests are applied to select the appropriate spatial specification. The spatial estimation defines neighboring relationships using a normalized first-order queen contiguity weights matrix. In such a case, the non-zero elements take the value of 1 for counties which share a common border, and the matrix is then row-normalized such that the elements $\sum w_{ij} = 1$ for each row *i*. The weights matrix was selected because it captures spillover relationships for all neighboring locations (as well as higher-order neighbors through spatial multiplier effects).[4] The spatial diagnostic tests (Moran's I, and Lagrange Multipliers) of the OLS estimations are all statistically significant. Following the specification strategy outlined in Anselin *et al*. (1996), the spatial lag process was deemed appropriate in all cases.[5] Thus, we proceed to estimate the spatial lag model using maximum likelihood in the specifications involving the three types of diversity indexes.

Table 3. Spatial Diagnostic Tests

	Ogive	Herfindahl	Shannon
LM Error	650.20***	616.60***	607.90***
LM Lag	722.80***	694.80***	686.20***
Robust LM Error	0.09	0.43	0.40
Robust LM Lag	72.74***	78.66***	78.72***
SARAR	722.9***	695.60***	686.60***

Note: *** indicates significance at the 1%.

Table 4 reports the empirical results for each of the three diversity measures: Ogive, Herfindalh, and Shannon Indexes. The estimates appear quite robust; the sign and significance of the coefficients for each control variable are generally consistent across all equations.

The results suggests a positive and significant relationship exists between economic growth and a number of control variables in the equation, including, percentage of bachelor's degree holders, and proportion of population between 5 and 14 years old, 18 years old and above. The metropolitan indicator variable is significant and positive in all models, which suggests that metropolitan counties, on average, experienced higher levels of growth than non-metro countries over the study period. All models support the presence of beta-convergence, with a negative, statistically significant coefficient for the initial level of income. The spatial autoregressive coefficients ρ is also statistically different than zero across all equations. The positive spatial lag coefficient suggests that county level economic growth is positively related to growth at its neighbors. The observance of positive spillovers effects of growth across US regions support previous findings.

[4] The results were consistent across other definitions of weight matrix such as distance based matrices.

[5] The Lagrange Multiplier (LM) lag and error are statistically significant, but the robust version of the LM error is not.

Table 4. Empirical Growth Model Results.

Variables	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	1.4351	0.3924***	1.1312	0.3891***	0.9820	0.3915**
RPCI90	-0.2037	0.0146***	-0.1917	0.0146	-0.1958	0.0145***
Gini	0.1023	0.0754	0.1267	0.0747*	0.1018	0.0747
Amenities	-0.0004	0.0010	-0.0012	0.0010	-0.0011	0.0010
Race other	-0.0005	0.0004	-0.0003	0.0004	-0.0003	0.0004
Race black	-0.0004	0.0002**	-0.0005	0.0002***	-0.0005	0.0002***
Race Hispanic	-0.0006	0.0002***	-0.0006	0.0002***	-0.0006	0.0002***
High school grad	-0.0004	0.0005	-0.0010	0.0005**	-0.0011	0.0005**
Some college	-0.0001	0.0007	-0.0011	0.0007	-0.0014	0.0007**
Associate’s degree	0.0001	0.0012	-0.0009	0.0012	-0.0011	0.0012
Bachelor’s degree	0.0091	0.0010***	0.0095	0.0010***	0.0095	0.0010***
Graduate degree	-0.0013	0.0013	-0.0034	0.0014**	-0.0036	0.0014***
Age 5 to 14	0.0117	0.0051**	0.0160	0.0050***	0.0160	0.0051***
Age 15 to 17	-0.0059	0.0053	-0.0030	0.0053	-0.0029	0.0053
Age 18 to 64	0.0067	0.0036*	0.0088	0.0036**	0.0087	0.0036**
Age 65 or over	0.0061	0.0034*	0.0090	0.0034***	0.0091	0.0034***
Metropolitan	0.0329	0.0049***	0.0281	0.0049***	0.0272	0.0049***
Rho (Wy)	0.5087	0.0207***	0.4984	0.0207***	0.4968	0.0207***
Ogive	- 0.0336	0.0175*				
Herfindalh			-0.2623	0.0298**		
Shannon					0.0740	0.0088***

Note: ***, **, * indicate significance at the 1%, 5% and 10% respectively.

Of greatest interest to the current study, the three economic diversity measures also provide consistent evidence that economic diversity supports economic growth at the county level. The results support those of Attaran and Zwick (1987) who studied county level growth in Oregon and are consistent with the theory that diversity supports growth posed by Jacobs (1969). As previously noted, there are a number of measures of economic diversity (see Wagner, 2000). By analyzing some of these diversity indices, the results demonstrate a robust and positive relationship between economic growth and diversity. Thus, one may conclude that economic diversity may be an appropriate target for regional policy makers.

Coefficients presented in Table 4 cannot be directly interpreted as marginal effects. Further transformations of these coefficients are needed in order to arrive at asymptotically valid marginal effects which account for spatial spillovers (see LeSage and Pace, 2009 for details). Table 5 shows the marginal effect of a 1% change if each of the diversity indexes on per capita income growth. The total marginal effect is decomposed into direct and indirect effect. On average, the direct effect is bigger than the indirect, and the Herfindalh index shows a higher impact than the other two indexes (in absolute value).

Table 5. Marginal Effects

Diversity Index	Total effect	Direct effect	Indirect effect
Ogive	-0.068	-0.035	-0.033
Herfindalh	-0.523	-0.277	-0.245
Shannon	0.146	0.078	0.068

Note: Values in the table represent averages for the 3074 counties.

6. CONCLUSIONS

In sum, this study suggests that economic diversity is associated with increased levels of economic growth. A number of existing studies, such as Dissart (2003) and Hackbart and Anderson (1975), have argued that increasing economic diversity is a relevant policy goal because diverse economies may be less susceptible to the volatility associated with business cycles. Because firms in a diverse economy have the ability to hire displaced workers from other industries, diverse regional economies are assumed to be more stable. This stability then facilitates regional economic growth.

Our study of county level growth patterns over the period 1990-2007 suggests that economic diversity provides a positive impact on economic growth. Further, the results are robust against multiple measures of economic diversity. The analysis employs modern spatial econometric methods which proxy the true factors of economic spillovers through an exogenous geographic construct.

Although the entropy indices employed in this study provide a quantifiable measure of the dispersion of activity, the model does not provide insight into the exact composition of each activity. For example, the model is unable to identify whether specific industries are associated with higher levels of economic growth. Identifying the exact composition, along with measures of dispersion, is a difficult task. Identifying an appropriate model which can include both sets of information is left for future research. It is also important to note that this study specifically addresses the role of diversity in the determination of economic growth. Other studies, such as O'Donoghue (1999) address economic *diversification*, i.e., changing levels of diversity through time. Given the appropriate sources of information, the study could be extended to examine the relationship between diversification and economic growth through a panel data approach. This work is left for future studies.

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