Local Economies and Economic Growth, Does Location Matter? A Spatial Analysis in the Great Lakes Region

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Abstract

We examine the growth rates of county per capita personal income in the five-state region of the Great Lakes using data between 2010 and 2018. Our analysis reveals a clustering of slow-growing counties mostly in Illinois and relatively fast-growing counties in Indiana, Michigan, Ohio, and Wisconsin. Using spatial regressions, we find evidence suggesting relatively low levels of human capital and innovation drive growth in the initial period of expansion, whereas high levels of human capital and a business environment conducive to entrepreneurship drive growth towards full employment. Location of counties does matter for income growth. Between 2016 and 2018, we find significant negative spillover effects of Some College on local growth while business conditions conducive to entrepreneurs had positive spillover effects. Our results imply that there is value to a regional approach to economic development policy, coordinating local policies across independent, adjacent jurisdictions.

1 Introduction

Regional economies experience differential growth rates across space and time. In the five-state Great Lakes region, the average annual per capita personal income growth rate grew at a rate of 1.96 percent between 2010 and 2018. During this time, counties in Illinois experienced the lowest growth rate at 1.49 percent while counties in the neighboring state of Indiana grew at a higher rate of 2.01 percent, and counties in adjacent state of Wisconsin grew at 2.03 percent. Counties in Michigan exhibited the highest growth rate in the region at 2.23 percent, higher than adjacent state Ohio to the South, with 2.13 growth rate. In the more recent period, between 2016 and 2018, the Great Lakes region in general experienced a higher growth rate of 2.24 percent relative to 1.86 percent growth in the period following the Great Recession between 2010 and 2016. Michigan counties experienced the highest growth rate between 2010 and 2016, whereas the lowest growth rate was registered by counties in Illinois over this same period. Meanwhile, Ohio had the highest growth rate among all the states between 2016 and 2018 at 2.53 percent. Ohio's neighbor to the north, Michigan, grew at 2.24 percent, while its neighbor to the west, Indiana, grew at 2.10 percent. The variation in the growth rates across the counties in the region could be due to economic or demographic characteristics, human capital, the business environment, and/or location of these counties relative to each other. The spatial dimension upon which these interrelationships take place allows us to determine whether fast-growing or slow-growing areas are clustered together or are randomly dispersed. The observed similarity and disparity in growth rates between adjacent states and between neighboring counties within a state would indicate location matters. In this study, we examine the spatial pattern, interactions, and dependence of these factors to explain the annual average per capita personal income growth using spatial regression analysis. Not accounting for spatial dependence where it exists can lead to unreliable statistical inference (LeSage and Pace, 2010) and thus, incorrect conclusions. Spatial analysis will allow us to estimate spillover effects which impact the overall marginal effects of predictor variables. If significant spillover effects are observed, this will imply there are benefits to be gained from pursuing a regional approach to economic development policy.

2 Literature Review

There is an abundance of research on the determinants of economic growth stemming from the seminal neoclassical growth theory (Solow, 1956) and endogenous growth theories (Romer, 1986) and Lucas Jr (1988). A wide range of economic, political, social, demographical, and institutional factors have been identified that influence economic growth (among others (Romer, 1990); (Barro, 1991); (Mincer, 1984)). (Artelaris et al., 2006) provide an extensive review of the literature on the determinants of economic growth. A more recent contribution to growth theory stems from the new economic geography theory (Krugman, 1991) which emphasizes the role of self-reinforcing effects of clustering in generating patterns in economic activity and income across space. As Tobler's first law of geography states, "everything is related to everything else, but closer things more so." This means that what happens in one region is related to what happens in neighboring regions. In other words, spatial relationships matter. As such, (Rey and Janikas, 2005) contend for the incorporation of spatial effects in the analysis of regional incomes over time. Studies on regional growth have subsequently incorporated spatial effects and confirm that space does matter. For example, (Ertur et al., 2006), in examining European regional convergence process, found a strongly significant spillover effect—the average growth rate of neighboring regions positively affected per capita GDP of a given region.

In studying regional resilience in the European Union in the aftermath of the 2008 economic crisis, (Annoni et al., 2019) conclude that location matters. They identified two distinct spatial regimes, a core and a periphery, and found that determinants of growth and spillover effects differ across the two. In the core regime, domestic growth is spurred by better institutions, higher shares of investment, and specialization in higher value-added sectors. Investment also induced positive spillover effects. In the peripheral regime, domestic growth is positively affected by lower shares of lower-secondary educational attainment and higher shares of tertiary educational attainment. Tertiary education also induced a positive spillover effect. Specific to the US, (Garrett et al., 2007) find an overall positive spatial correlation in income growth rates across neighboring states, although the extent of spatial correlation varies significantly by region— correlations were highest for Northeastern and Southern states and lower for Midwestern and Western states. (Hall et al., 2019) examine the impact of economic freedom (utilizing the Economic Freedom of North America (EFNA) index) on income levels across U.S. states utilizing spatial panel data analysis accounting for spatial spillovers. They find that a 10% increase in economic freedom is associated with a 5% increase in real per-capita gross state product. (Wiseman, 2017) likewise investigated the relationship between economic freedom and income growth and inequality across U.S. states controlling for spatial dependence, particularly for the top 10% and bottom 90% of the income distribution, and finds an overall positive relationship, albeit with larger income growth rates in the bottom 90% relative to the top 10%.

A few other studies have examined economic growth across U.S. counties controlling for spatial dependence. (Rupasingha et al., 2002) assess the contribution of social and institutional variables on growth rates of per capita income across U.S. counties. They find ethnic diversity and higher levels of social capital contribute to faster economic growth rates while higher levels of income inequality are associated with lower growth rates. (Hammond and Tosun, 2011) analyze the impact of fiscal decentralization on U.S. county real income growth and find special-purpose governments significantly impact growth for metropolitan counties while general-purpose governments significantly impact non-metropolitan counties. (Monchuk et al., 2007) also examine regional economic growth at the county level. They employ mapping to identify growth spots but utilize OLS rather than spatial regression in their modeling and found that amenities, state and local tax burdens, population, the amount of agricultural activity, and demographics impact economic growth. Focusing on a specific region in the U.S., (Gebremariam et al., 2011) use a spatial simultaneous equations approach to examine determinants of employment, income, and migration in Appalachia between 1990 and 2000 and find spatial correlation in error terms implying a random shock into the system spreads across the region. They conclude that rather than treating all locations equally, concentrating public development investments in centers will yield a greater return.

In our study, we specifically explore the spatial patterns of per capita income growth across counties in the Great Lakes States between 2010 and 2018. First, we use per capita personal income data from the BEA as our measure of economic growth, similar to (Rupasingha et al., 2002). Most studies use GDP per capita for growth (e.g., (Hall et al., 2019)) and total or per capita income (e.g., (Monchuk et al., 2007); (Wiseman, 2017); and (Hammond and Tosun, 2011)). Personal income data from BEA includes wages and salaries, Social Security and other benefits, dividends and interests, business ownership, and other sources. In a sense, we measure economic well-being and tells us how local workers and businesses are performing in a county.

Second, we identify spatial patterns between 2010 and 2018 through spatial autocorrelation analysis. Consequently, the spatial analysis of economic growth (well-being) in the decade following the Great Recession is a novel contribution of this study. Third, we examine the human capital, innovation, and business environment effects on per capita personal income growth by utilizing spatial econometrics models. We use specific components of the Innovation Index 2.0 (Slaper et al., 2016).[1], rather than the global index, as explanatory variables, to capture human capital, innovation, and business conditions. We exploit the amount of disaggregated information and data available that makes up the global index. This allows us to provide a more nuanced understanding of the determinants of growth within the spatial area. Finally, our study provides a valuable resource for a more detailed understanding of regional economic development issues as we focus on smaller economic entities (i.e., local economies) in a given region—counties in the Great Lakes States of the U.S. The Great Lakes States are known as the industrial heartland of America and best known globally for its manufacturing prowess. (Magrini, 1998) posits that concentration of manufacturing activities is detrimental to economic growth since it impedes the existing research sector's ability to "develop superior technological competence in research and to attract other researchers (page 7)." Thus, the Great Lakes States provide an empirical case to study if the effects of different levels of human capital, innovation, and business environment on economic growth extend to predominantly manufacturing-based local economies.

3 Data and Methods

Our empirical analysis uses county-level data of per capita personal income growth between 2010 and 2018 for the Great Lakes States. The Census Bureau classifies this region as East North Central and includes the states of Illinois, Indiana, Michigan, Ohio, and Wisconsin. Our data is cross-sectional with annual average growth rate of real per capita personal income (AAGRPCI) between 2010 and 2018 as the dependent variable.[2] The per capita personal income data are from the Bureau of Economic Analysis (BEA) and are transformed to real terms using Midwest CPI (1982-84 base year) from the Bureau of Labor Statistics (BLS). The explanatory variables included in our study are economic and demographic data collected for 2010 and 2016 from the Census Bureau, and the county-level human capital, innovation, and business condition variables expressed as sub-indexes collected from the Innovation Index 2.0 developed by the Indiana Business Center at Indiana University. Further, we break down our analysis into two separate periods, (1) 2010 to 2016, and (2) 2016 to 2018, for two practical reasons. First, there was a change in administration in the White House in 2017 which likely introduced a structural break. We performed a Chow test for structural break and confirmed that the coefficients for the two time periods are statistically different.[3] Second, the breakdown also allows us to examine growth following a major economic downturn (2010 – 2016), and then further into recovery and expansion (2016 – 2018). A closer look at the annual growth rate reveals growth oscillating between 2010 and 2015, peaking at 3.26 percent in 2015, then dipping to 1.3 percent in 2016, and steadily increasing with a growth rate of 2.77 percent in 2018. A paired t-test for the difference in means for the average growth rate from 2010-2016 and from 2016-2018 verified a significantly faster growth rate in the latter period.[4] These separate time periods are analyzed using two different dependent variables. In the first model, the annual per capita personal income growth rate computed between 2010 and 2016 is used as the dependent variable and a set of explanatory variables from 2010. The second model uses the annual per capita personal income growth rate between 2016 and 2018 as the dependent variable with the same set of explanatory variables from 2016. For comparison purposes, we likewise analyze growth rates for the full time period between 2010

[1] Technical details of how all indexes and sub-indexes are calculated are fully discussed in Slaper et al. (2016).

[2] Mean of the series of annual growth rates.

[3] F statistic = 5.71 with p-value = 0.

[4] t-statistic = -5.04 with p-value = 0.

and 2018 with a set of explanatory variables from 2010.

3.1 Spatial Autocorrelation Analysis

We begin our study with spatial autocorrelation analysis of our dependent variable AAGRPCI. This allows us to discern patterns such as clustering, randomness, or dispersion. Specifically, we identify and test for the presence of spatial autocorrelation. We map AAGRPCI for the three time periods to allow a visual inspection of the data and then proceed to test for global spatial autocorrelation with Moran's I. Moran's I statistic ranges from − 1 to + 1 indicating intensity of spatial dependence. Values close to -1 indicate dispersion, while values close to +1 indicate a cluster.

The Moran's I statistic for spatial autocorrelation is given as:

$$\mathrm{I} = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where, z_i is the deviation of an attribute for feature 'i' from its mean $x_i - \bar{X}$, $w_{i,j}$ is the spatial weight between county 'i' and 'j', n is equal to the total number of counties, and So is the aggregate of all spatial weights. The spatial weight matrix used is a contiguity matrix where two spatial units share a common border, defined as those that share a common edge or a common vertex.

Moran's I only indicates the presence of global spatial autocorrelation and does not provide information on the specific locations of spatial patterns. Moreover, it is possible to find local clusters even if there is no global clustering. Thus, our next step is to find local clusters, i.e., local spatial autocorrelation. The Local Indicators of Spatial Association (LISA) is used to identify areas in the region where real per capita personal income growth is strongly positively or negatively correlated (Anselin, 1999).

3.2 Spatial Regression Analysis

In the context of this study, spatial dependence means that per capita personal income growth of a county is influenced by growth of neighboring counties. In the presence of spatial dependence, spatial econometrics models need to be employed. Before we specify such models, we first identify our explanatory variables and discuss our motivation for their inclusion.

Our main variables of interest are the human capital, innovation, and business environment determinants of growth. Human capital and innovation are both key sources of economic growth in the endogenous growth models. (Romer, 1990) argues that the initial level of human capital, i.e., literacy, has a role to play in explaining output growth while (Mincer, 1984) posits the growth of human capital is both a condition and consequence of economic growth. There are a multitude of empirical studies that confirm this theoretical relationship (see, e.g., (Barro, 1991); (Mankiw et al., 1992); (Papageorgiou, 2003)). Innovation, through its role in increasing productivity and growth by increasing the use of technology, can likewise play an important role in economic development. It facilitates the creation and development of new products and processes. The same can be said for business environment, through its role in fostering firm growth.

We use a subset of the components of the 2016 Innovation Index 2.0 to measure human capital, innovation, and business environment. The headline index combines five categorical indexes organized thematically which themselves are built up from several measures that are also categorized thematically. These include (1) human capital and knowledge creation; (2) business dynamics; (3) business profile; (4) employment and productivity; and (5) economic well-being.

To proxy levels of education that capture human capital and its accumulation—from literacy all the way through highly educated and specialized human capital—we use a subset of category (1) which includes: high school attainment, population ages 18-24 (High School); some college, population age 25+ (Some College); associate degree, population age 25+ (Associates); bachelor's degree, population age 25+ (College); and graduate degree, population age 25+ (Graduate).

To capture innovation activities, we use a subset of category (4)—Patents—which is a sub-index that includes the following measures: change in average patenting rate, patent diversity and patents by institution type. This variable will capture current innovation and predict future developments. We also use the Business Dynamics Index (BDI) (component 2) of the global index to capture creative destruction measures. This component includes core indexes for establishment formation, establishment dynamics, venture capital dollar measures and venture capital count measures.

Table 1: Summary Statistics for Non-Index Related Variables

Variable (Date)	Definition (Unit of Measure; Data Source)	Great Lakes (n = 437)	Illinois (n = 102)	Indiana (n = 92)	Michigan (n = 83)	Ohio (n = 88)	Wisconsin (n = 72)
		Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
AAGRPCI (2010-2018; Model 1)	Annual average growth rate of real per capita personal income (Percent; Authors' calculations from BEA data)	1.96 (0.73)	1.49 (0.75)	2.01 (0.84)	2.23 (0.62)	2.13 (0.59)	2.03 (0.53)
AAGRPCI (2010-2016; Model 2)	Annual average growth rate of real per capita personal income (Percent; Authors' calculations from BEA data)	1.86 (0.94)	1.25 (0.99)	1.99 (1.06)	2.22 (0.78)	1.99 (0.73)	2.01 (0.68)
AAGRPCI (2016-2018; Model 3)	Annual average growth rate of real per capita personal income (Percent; Authors' calculations from BEA data)	2.24 (1.15)	2.24 (1.47)	2.10 (0.82)	2.24 (1.20)	2.53 (1.22)	2.08 (0.76)
PCPI (2010)	Per capita personal income ($; BEA)	36325.88 (5727.0)	38159.41 (5355.17)	35370.08 (5313.44)	33668.78 (5100.27)	35324.52 (5901.59)	38690.35 (5517.63)
PCPI (2016)	Per capita personal income ($; BEA)	40421.69 (6901.84)	40973.04 (6695.40)	39708.34 (6221.02)	38448.96 (6713.24)	39786.74 (7284.52)	43602.27 (6758.18)
UR (2010)	Unemployment rate (Percent; BLS)	10.94 (2.34)	9.88 (1.52)	10.71 (1.70)	13.34 (2.45)	11.43 (2.06)	9.39 (1.83)
UR (2016)	Unemployment rate (Percent; BLS)	5.34 (1.41)	6.07 (1.10)	4.47 (0.76)	6.02 (1.60)	5.52 (1.47)	4.41 (1.01)
Metro	Metro county (=1 if Metro, 0=non-metro; Census Bureau)	0.40 (0.49)	0.39 (0.49)	0.48 (0.50)	0.31 (0.47)	0.43 (0.50)	0.36 (0.48)
AAPGR (2010-2018)	Annual average population growth rate (Percent; Authors' calculations from Census Bureau data)	-0.16 (0.55)	-0.55 (0.54)	0.01 (0.59)	-0.13 (0.49)	-0.09 (0.48)	0.03 (0.37)
AAPGR (2010-2016)	Annual average population growth rate (Percent; Authors' calculations from Census Bureau data)	-0.20 (0.57)	-0.53 (0.57)	-0.04 (0.62)	-0.19 (0.55)	-0.12 (0.48)	-0.06 (0.42)
AAPGR (2016-2018)	Annual average population growth rate (Percent; Authors' calculations from Census Bureau data)	-0.03 (0.63)	-0.59 (0.50)	0.17 (0.58)	0.09 (0.52)	0.001 (0.56)	0.30 (0.40)
POV (2010)	Poverty rate (Percent; Census Bureau)	14.49 (4.16)	13.53 (4.11)	13.88 (3.62)	16.68 (4.09)	15.32 (4.24)	13.12 (3.71)
POV (2016)	Poverty rate (Percent; Census Bureau)	13.43 (4.3)	13.66 (4.13)	12.83 (3.55)	15.11 (3.77)	13.71 (4.34)	11.51 (3.46)

Economic policies and macroeconomic conditions set the stage within which growth takes place and are therefore also important determinants of economic growth. This includes the conditions for which investment—which is a fundamental determinant of growth in both neoclassical and endogenous growth models—becomes attractive. We use the Business Profile Index (BPI) (component 3) of the global index to capture the impact of business conditions and resources available to entrepreneurs and businesses. This category includes core indexes for foreign direct investment attractiveness, connectivity, dynamic industry profile, and proprietorship. In addition, clustering of firms and economic activities provide self-reinforcing effects that yield agglomeration economies (benefits) from shared intermediate inputs and labor pooling. We utilize Industry Performance Index (IPI), a subset from category (4) of the global index to gauge location desirability for industries that help fuel economic growth. This includes measures for cluster diversity, cluster strength and cluster growth factor.[5] To complete the set of explanatory variables related to macroeconomic conditions, baseline per capita real income (PCPI) and unemployment rate (UR) are included in the model.

Table 2: Summary Statistics for Innovation Index 2.0-related Variables

Variable	Definition	Great Lakes	Illinois	Indiana	Michigan	Ohio	Wisconsin
		Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
High School	High school attainment, population ages 18-24	118.30 (36.81)	125.01 (34.93)	97.26 (32.44)	113.27 (39.67)	123.99 (32.86)	134.39 (33.59)
Some College	Some college, population ages >25	106.53 (34.99)	130.32 (31.34)	85.00 (20.37)	135.67 (30.70)	79.26 (20.20)	100.11 (25.14)
Associates	Associate degree, population ages >25	126.23 (36.01)	133.98 (38.56)	109.2 (32.47)	125.42 (30.49)	115.00 (31.10)	151.67 (30.99)
Bachelors	Bachelor's degree, population ages >25	102.61 (39.66)	105.07 (39.39)	92.31 (35.64)	103.49 (40.11)	97.26 (40.20)	117.78 (39.60)
Graduate	Graduate degree, population ages >25	104.65 (36.92)	103.28 (38.93)	99.40 (33.27)	110.04 (40.28)	104.65 (37.91)	107.04 (32.95)
Patents	Sub-index includes measures of patenting rate, patent diversity and patents by institution type	90.79 (45.99)	76.33 (52.75)	92.38 (43.22)	90.10 (44.46)	98.30 (44.98)	100.83 (37.42)
BDI	Business dynamic index for establishment formation, establishment dynamics, venture capital $ and venture capital count measures	53.81 (15.57)	50.92 (14.68)	52.69 (13.64)	55.77 (17.54)	56.83 (17.87)	53.37 (12.93)
BPI	Business profile index includes core indexes for foreign direct investment attractiveness, connectivity, dynamic industry profile and proprietorship	76.93 (13.17)	71.12 (11.81)	81.88 (14.38)	77.73 (11.51)	80.68 (12.87)	73.34 (11.51)
IPI	Industry performance index includes measures for cluster diversity, cluster strength and cluster factor growth	103.78 (20.31)	104.83 (38.93)	110.514 (20.74)	98.83 (19.51)	99.50 (20.18)	104.66 (18.33)

The values in the table are indexes extracted from 2016 Innovation Index 2.0. The index scores a county on a continuous scale and scaled to a maximum of 200 with ranking preserved, i.e., higher index values are indicative of outcomes more conducive to growth.

We also include a binary variable that explicitly captures relative location and its impact on economic growth—Metro. Metro counties are classified using the Census Bureau definition, i.e., a core area containing a

[5] Cluster diversity quantifies whether the area is relatively concentrated in just a few industries. Cluster strength measures the degree to which clusters dominate the employment in the area. Cluster factor growth measures percent of employment growth in the area that can be attributed to strong clusters. Overall, industry clusters can create an environment of increased rivalry that can lead to higher pressures to innovate.

large population nucleus, together with adjacent communities that have a high degree of economic and social integration with that core.[6] To the extent that the Metro variable captures market size, labor force source and agglomeration economies, we expect Metro counties to exhibit faster growth than non-metro counties. Urban concentration is typically deemed to lead to faster growth. On the other hand, agglomeration diseconomies might be more dominant which may slow growth in Metro counties, particularly if adjacent to non-metro counties.

The last set of explanatory variables account for demographic factors. These include annual average population growth rate (AAPGR) and poverty rate (POV) that can likely have a negative impact on growth. Solow (1956) provides a theoretical explanation for a negative relationship between population growth and output per capita growth—rapid population growth leads to smaller amounts of capital per worker slowing economic growth. Finally, to control for unmeasured sources of state-level heterogeneity within the region, we include state dummy variables. Illinois (IL) is the reference group.

All explanatory variables, except AAPGR, are measured at the beginning of the period (or close to the beginning) to avoid endogeneity issues.[7] The summary statistics, including definitions, units of measure and sources, for the dependent variable and all non-index related explanatory variables are presented in Table 1. All data related to Innovation Index 2.0 are valued at an index rate and are presented in Table 2.[8]

3.3 Spatial Regression Model

The presence of spatial autocorrelation in regression models violates the independence of errors assumption and leads to unreliable statistical inference (LeSage and Pace, 2010). Spatial regression explicitly includes spatial information related to the data. There are two main types of spatial regressions: (1) spatial lag model or spatial autoregressive model (SAR), and (2) spatial error model (SEM). The spatial lag model is appropriate when the issue is spatial dependence, i.e., values observed at one location depend on the values of neighboring observations at nearby location (LeSage and Pace, 2009). The spatial error is appropriate when spatial heterogeneity is the issue, i.e., lack of spatial stability of relationships from incorrect functional form, omitted variables, and other forms of misspecifications, leading to error terms with non-constant variance (Anselin, 1999). The spatial arrangements of units in the sample, specified in the weights matrix W, is an important component of spatial regression models. As previously indicated, we utilize a contiguity-based spatial weights matrix where neighboring counties are defined as those who share a common edge or a common vertex.

The spatial lag model (SAR) (LeSage and Pace, 2010) incorporates the spatial effects through the inclusion of a spatially lagged dependent variable in the regression model specified as:

$$Y = \rho WY + X\beta + \varepsilon \tag{2}$$

where, WY is a spatially lagged dependent variable for weights matrix W, ρ is the spatial coefficient, $X$is a vector of explanatory variables as discussed above, and ϵ is a vector of i.i.d. error terms. An extension of the SAR is the Spatial Durbin Model (SDM) (LeSage and Pace, 2010) where spatially lagged independent variables are included in the model, in addition to the spatially lagged dependent variable. The SDM model is specified as:

$$Y = \rho WY + X\beta + \gamma WX + \varepsilon \tag{3}$$

where γWX represent a weighted average of surrounding values of the independent variables, capturing any spillovers that may be present.

[6] At least 50,000 in a city or contain a Census Bureau-defined urbanized area (UA) or have a total population of at least 100,000.

[7] Innovation Index 2.0 is only available for 2016. The beginning periods for the three time periods (2010-2018, 2010-2016, and 2016-2018) in the study are 2010 and 2016.

[8] The index scores a county on a continuous scale and scaled to a maximum of 200 with ranking preserved, i.e., higher index values are indicative of outcomes more conducive to growth. For a complete definition of indexes and formulas for calculation, refer to Slaper et al. (2016).

The spatial error model (SEM) (LeSage and Pace, 2010) incorporates spatial effects through the error terms specified as:

$$\begin{aligned} Y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W \varepsilon + \mu \end{aligned} \tag{4}$$

where ϵ is a vector of error terms spatially weighted using weights matrix W, λ is the spatial error coefficient, X is vector of explanatory variables as discussed above, and μ a vector of i.i.d. errors.

These spatial regression models are estimated through maximum likelihood as the inclusion of WY on the right-hand side of the SAR introduces simultaneity bias while error terms in the SEM are spatially dependent. The final specification of our empirical models follow (Annoni et al., 2019) in their use of the SDM to examine regional growth in the EU. They use the argument proposed by (LeSage and Fischer, 2008) who contend that the combination of spatial dependence in the error terms in the OLS model and the existence of an omitted spatially dependent variable(s) that is(are) correlated with an included variable(s) in applied regional regression models make the SDM specification a natural choice. To test the appropriateness of the SDM for our data, we use the technique provided by (Anselin, 2005) which employs a series of Lagrange Multiplier (LM) tests to choose whether results from OLS cannot be rejected. We find that the OLS model is rejected in favor of SAR and SER, and the SAR in favor of the SER.[9] As a last step, we use the standard Likelihood Ratio (LR) test to examine if the SDM can be simplified to the SAR. The results indicate SDM is the best model to describe our data.[10] Thus, the empirical SDM specification of our growth models is:

$$Y = \rho WY + \beta_k X_k + \gamma_k W X_k + \varepsilon \tag{5}$$

where Y is the average annual growth rate of personal per capita income (AAGRPCI) for the periods under analysis (2010-2018; 2010-2016; and 2016-2018); W is the contiguity-based spatial matrix; X_k are a set of K explanatory variables as identified earlier. The SDM specification allows for growth rates to depend on its own set of county characteristics in the region (captured by β_k), on the same set of characteristics in neighboring counties in the region (captured by γ_k), and on the level of spatial dependence across county growth rates in the region (captured by ρ).

4 Results

4.1 Spatial Autocorrelation Analysis

The mean of average annual growth of real per capita personal income (Table 1) across all counties in the Great Lakes States region between 2010 and 2018 was 1.96 percent. Growth following the Great Recession (2010-2016) was statistically significantly slower at an average of 1.86 percent and increased to 2.24 percent in the more recent period between 2016 and 2018 (paired t-test with p-value = 0). Among these 5 states, counties in Illinois had relatively slower growth rates between 2010 and 2018. According to the Illinois Policy Institute, Illinois underperformed and lagged the rest of the US (except Mississippi) due to state income tax policies (higher taxes), numerous regulations, and prospects of more tax hikes to pay for debt leading to firms ignoring to invest in the state.

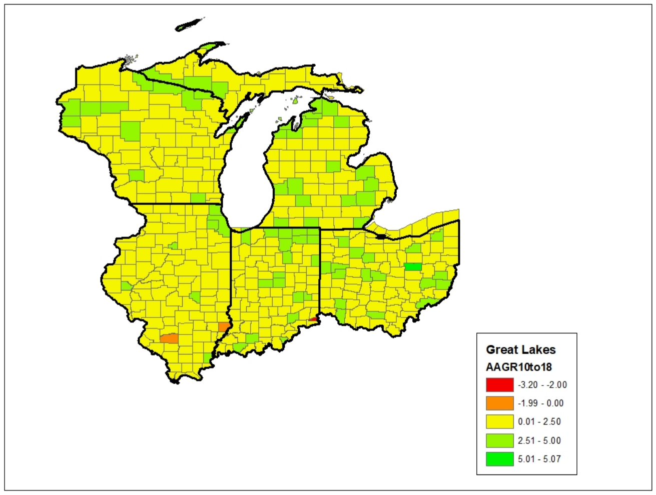
Figure 1 displays the spatial distribution of local per capita personal income growth across the Great Lakes States region between 2010 and 2018. A visual inspection of the mapped data reveals some clustering with more distinct pockets of slow-growth counties (color coded with yellow) in Illinois and more scattered fast-growth counties (color coded with two shades of green) in the four other states, but still with traces of

[9] For both 2010-2018 and 2010-2016 time periods, both spatial lag and spatial error models were significant. The robust tests help identify what type of spatial dependence may be at work. The robust test for spatial lag is still significant while insignificant for spatial error. Thus, it is appropriate to use the spatial lag model (Anselin, 2005). For the period between 2016 and 2018, results are not as conclusive. Both robust tests for spatial lag and spatial error are insignificant but the initial test on spatial lag was more significant than spatial error. Hence, we also choose spatial lag for this period.

[10] LR = 33.804, p=value = 0.0000 for the period 2010-2018; LR = 30.65, p-value = 0.0000 for the period 2010-2016; and LR = 22.512, p-value = 0.0000 for the period 2016-2018.

clustering. These observed spatial clustering is confirmed by the Moran's I statistic of 0.244 (p-value = 0) indicating a positive spatial autocorrelation of neighboring/adjacent counties with similar growth rates.

Figure 1: Spatial Distribution of Per Capita Personal Income Growth Rates between 2010 and 2018



A breakdown of 2010 and 2018 time periods into 2010 to 2016 and 2016 to 2018 reveal a slightly different pattern (Figure 2). We observe stronger clustering between 2010 and 2016 compared to the more recent growth between 2016 and 2018. This is supported with a larger (positive) Moran's I statistic of 0.266 (p-value = 0.014) for the period 2010 to 2016 compared to a Moran's I of 0.170 (p-value = 0) for the period 2016 to 2018. The data suggests a stronger spatial association of average per capita personal income growth across counties in the period following the Great Recession.

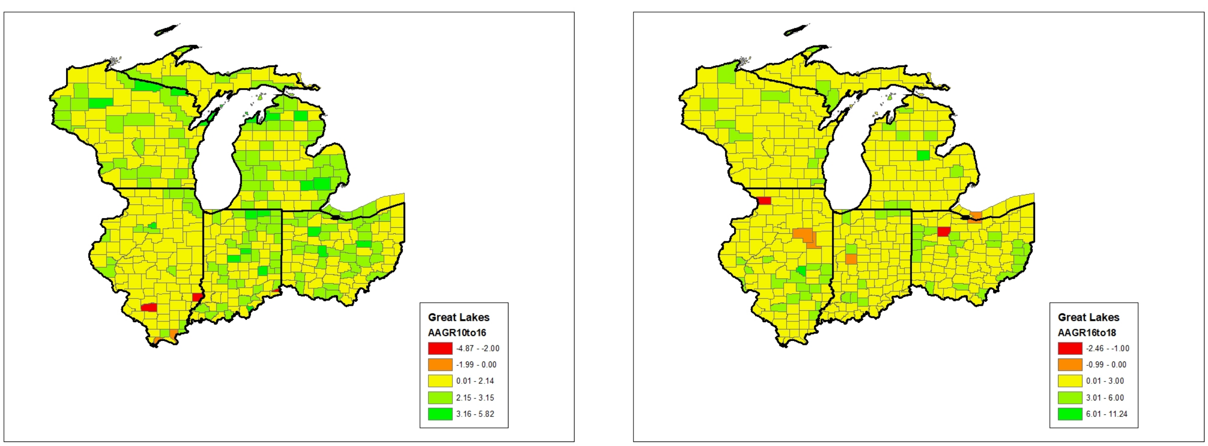


Figure 2: Spatial Distribution of Per Capita Personal Income Growth Rates, 2010-2016 and 2016-2018

Moran's I confirms global spatial dependence. The next set of LISA Cluster Maps (Figures 3, 4 and 5) identify the location of specific clusters that statistically contribute to a positive or negative global spatial autocorrelation. The LISA Significance Map assigns the LISA score for each county by determining its individual contribution to the global Moran's I and whether the value is statistically significant or not is assessed by comparing the actual value to the value calculated for the same location using a Monte Carlo randomization procedure. If an actual LISA score is among the top 0.1 percent (or one percent or five percent) of scores associated with that location under randomization, then it is judged statistically significant at the 0.001 (or 0.01 or 0.05) level (Anselin, 1995).

Between 2010 and 2018 (Figure 3), 95 out of the 437 counties in the region exhibited significant clustering. Specifically, 52 counties were in the low-low cluster (slow-growth), 27 counties in the high-high cluster (fast-growth). The low-low cluster includes counties with slow growth rates adjacent to each other, while high-high cluster includes counties with high growth rates adjacent to each other. Majority of low-low counties are clustered in Illinois which supports the fact that it is struggling to put people back to work after the Great Recession. According to (Lucci, 2016), there are 110,000 fewer Illinoisans working than before the recession began. In addition, the state is lagging in recovering high-quality, full-time jobs, and a significant part of the job recovery has been driven by part-timework. The high-high clusters are in Indiana, Michigan, and Ohio. The high-high cluster of counties in Indiana are those that border Michigan to the North, which are manufacturing hubs supplying motor vehicle parts to the auto industry in Michigan and the U.S. There are 16 counties in Figure 3 that exhibited negative local spatial autocorrelation (7 counties in the low-high cluster and 9 counties in the high-low cluster). The low-high cluster indicates a county with slow growth rate surrounded by at least one county with higher growth rate (twice the growth rate) and a common border, while high-low cluster indicate a county with high growth rate surrounded by at least one county with low growth (half the growth rate) and a common border. In the low-high cluster of counties in Ohio, a few low growth counties were rural, Appalachian and a few others were metro counties that were underemployed with low labor market participation rates that did not completely recover after the Great Recession. In the high-low cluster of counties in Illinois, the high growth counties were rural and adjoining to metro counties that exhibited high growth rate relative to adjacent counties that had low or negative growth rate.

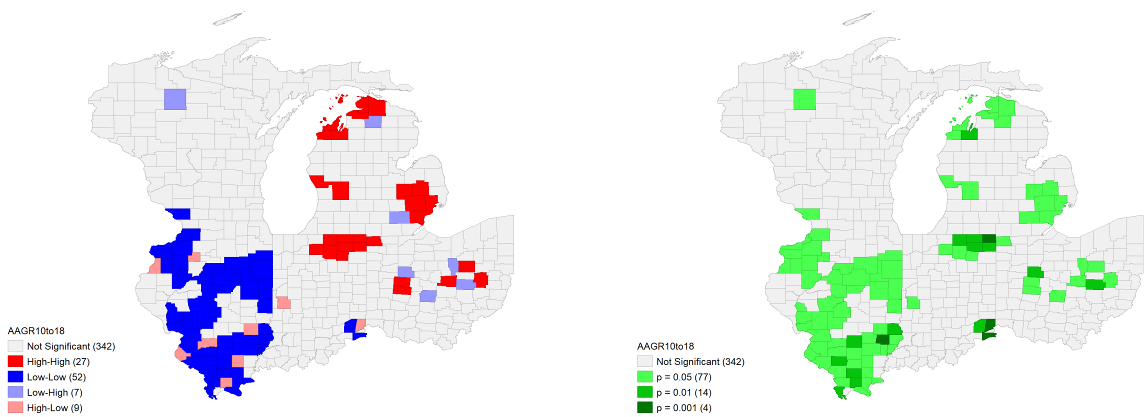


Figure 3: LISA Cluster Map and LISA Significance Map for Per Capita Personal Income Growth Rates between 2010 and 2018

The maps in Figures 4 and 5 (LISA Cluster and Significance Maps), which break down the overall time into two-periods (2010-2016 and 2016-2018) display a pattern consistent with the results from the global measure of spatial dependence (Moran's I) reported earlier. Around 22 percent of counties in the region showed local clustering between 2010 and 2016 compared to 16 percent between 2016 and 2018 (98 counties vs 70 counties). There are more counties in the low-low cluster (50 out of 98) relative to the high-high cluster (25 out of 98) between 2010 and 2016. Between 2016 and 2018 however, roughly the same number of counties were in clusters exhibiting positive spatial autocorrelation (29 out of 70 in high-high and 25 out of 70 in low-low). The pattern of clusters between 2016 and 2018 is relatively distinct compared to the earlier period. Many of the high-high clusters are in Illinois and Ohio. In Illinois, counties in the low-low cluster following the Great Recession were in the high-high cluster by 2016-2018, indicating a more recent spur of growth. These results suggest that Illinois lagged in the quality of jobs recovered from immediately after the Great Recession and has caught up much later with their regional neighbors. (Ajilore, 2020) sums up in his report that after the Great Recession, lack of jobs, loss of services, lack of startups and entrepreneurial activities, and state tax policies have contributed to the slow recovery in rural America.

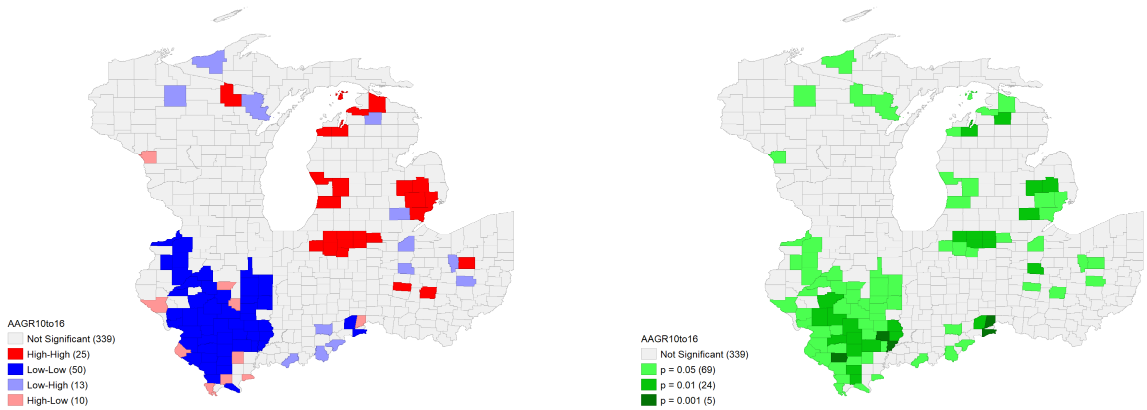


Figure 4: LISA Cluster Map and LISA Significance Map for Per Capita Personal Income Growth Rates 2010-2016

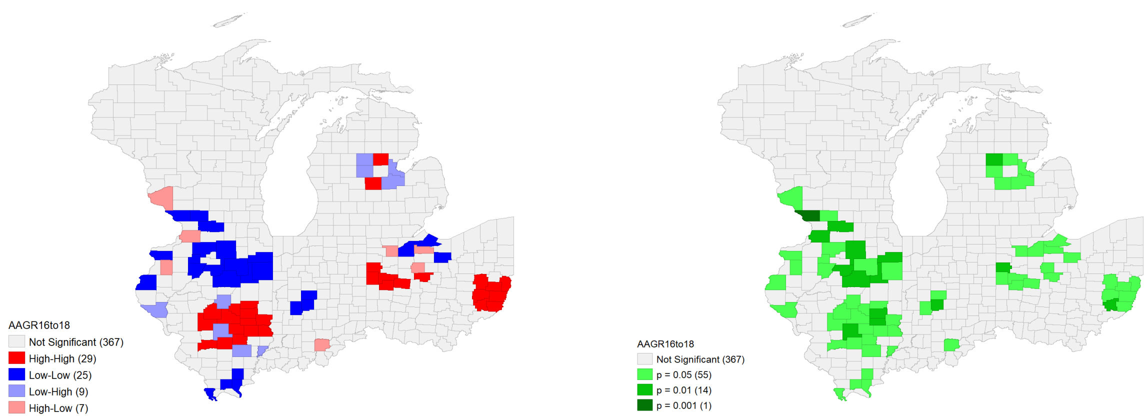


Figure 5: LISA Cluster Map and LISA Significance Map for Per Capita Personal Income Growth Rates 2016-2018

4.2 Spatial Regression Results

The spatial autocorrelation analysis revealed global positive spatial autocorrelation indicating per capita personal income growth across counties in the region are spatially dependent. This means that although growth varies across counties, clusters of similar growth rates are detected. As indicated earlier, we use the SDM specification to model local personal income growth which allows for spillover effects. These spatial spillovers arise due to impacts passing through neighboring counties and back to the county itself (LeSage and Fischer, 2008). Therefore, the impact on local income growth (total effects) from a change in explanatory variables is a combination of direct and indirect (spillover or neighborhood) effects. Table 3 present results of the SDM for the three time periods and include direct, indirect, and total effects that are averaged across all counties. The direct effect measures how much the growth rate changes in a county when a particular explanatory variable changes in that same county. This measure considers feedback effects that arise from a change in a county's explanatory variable on growth rates of neighboring counties in the system of spatially dependent counties (LeSage and Fischer, 2008). The indirect effect (or spillover effect) measures how changes in an explanatory variable at county 'j' affects growth at county 'i' ($i \neq j$). The total effect is the sum of direct and indirect effects and has two interpretations: (1) the average total impact on growth rates of the typical county arising from a change in an X variable in all counties in the region; and (2) total cumulative impact on growth rates of all other counties (on average) arising from one county's change in an

Table 3: Impacts for the Spatial Durbin Model

Variable	Model 1 (2010-2018)			Model 2 (2010-2016)			Model 3 (2016-2018)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
High School	-0.002	0.006**	0.004	-0.002	0.006*	0.004	-0.001	0.008	0.007
Some College	0.001	-0.001	-0.0001	0.003	0.002	0.005*	-0.004*	-0.009*	-0.013***
Associates	-0.003***	0.0001	-0.003*	-0.005***	0.0002	-0.004**	0.001	0.001	0.001
College	0.003	-0.009*	-0.006	0.007**	-0.009	-0.002	-0.003	-0.009	-0.013
Graduate	0.003	0.007	0.009*	0.001	0.008	0.009	0.008**	-0.001	0.008
Patents	0.002*	0.003*	0.005**	0.002*	0.004*	0.006**	0.002	0.001	0.002
BDI	0.004*	0.008	0.013**	0.007**	0.010	0.017**	0.001	0.005	0.006
BPI	0.003	0.005	0.009	0.001	-0.003	-0.002	0.011**	0.026**	0.037***
IPI	0.001	0.005	0.006	0.001	0.007	0.008	0.001	-0.004	-0.004
PCPI (ln)	-1.650***	-0.403**	-2.053***	-2.045***	-0.457**	-2.502***	-1.575***	-0.470	-2.045**
UR	-0.019	0.075*	0.056*	-0.016	0.131***	0.116***	-0.054	-0.068	-0.122
Metro	-0.132*	-0.450**	-0.582***	-0.173*	-0.349	-0.522**	-0.038	-0.906**	-0.944**
AAPGR	-0.068	0.154	0.086	-0.159	0.371*	0.211	-0.241*	0.354	0.112
POV	-0.064***	0.004	-0.061***	-0.067***	-0.014	-0.081***	-0.083***	0.073*	-0.009
IN	0.005	0.086	0.091	-0.141	0.655	0.514	0.528	-1.899***	-1.372***
MI	0.636*	-0.460	0.176	0.622	-0.403	0.219	0.833	-1.401**	-0.568*
OH	0.218	-0.095	0.123	-0.179	0.620	0.441*	1.499**	-2.581***	-1.082**
WI	0.460	-0.061	0.399**	0.538	0.219	0.757***	0.442	-1.325**	-0.883**

Note: The dependent variable is the average annual growth rate of real per capita income (AAGRPCI) between 2010-2018, 2010-2016, and 2016-2018. Statistical significance with ***. **, and * referring to 1%, 5%, and 10%, respectively.

X variable. These two interpretations are numerically equal (LeSage and Fischer, 2008). As such, a richer set of results are obtained with the SDM. Overall, we find that spatial effects are important regardless of the time periods that we examined. Before fully discussing results, it is important to note a limitation with respect to variables capturing human capital, innovation, and business environment—sub-indexes that were culled from Innovation Index 2.0. As indicated earlier, these variables are only available for 2016, and as such, it is important to exercise caution in deriving sweeping conclusions with respect to these variables for Model 2 (2010-2016).[11]

Different levels of human capital are found to be a significant factor of growth in local economies. Since our education variables are indexes, the coefficients are interpreted as the percentage change in local growth associated with a 1-point change in the index variable. In the period between 2010 and 2018 (Model 1), the direct effect of a lower level of education (Associates degree) is negative on growth with no significant spillover effects. For a more specialized education (Graduate), the total effect on growth is significant and positive. On the other hand, it seems that a higher share of College graduates has a significant negative spillover effect—an increase in the index capturing share population 25 years and older with college education in county 'j' slows growth in surrounding counties (on average), perhaps capturing diminishing returns to education, or possibly the brain drain effect. More specific insights are revealed when we break down the time period. In the period following the Great Recession (Model 2; 2010-2016), the relevance of human capital as a growth factor is observed at both ends of the spectrum. On the lower end of education levels, the direct and total impacts of Associates degree are negative and significant, suggesting higher levels of Associates degree in a county slows growth in that county (direct effect), and that if all counties in the region raise their index level for Associates, the average impact on growth in the county is negative (total effect). Alternatively, the cumulative impact arising from a county raising its index level for Associates on growth of all other counties is negative (total effect). The direct impact of increasing the index for High School is not significant. However, the indirect effect is positive and significant. This result suggests that increased index for High School in neighboring counties increases growth in a county. The total impact of Some College on growth is positive and significant. On the higher end of education levels, the direct impact of increasing the index for College is positive and significant, consistent with the view of the positive impact of a higher level of human capital on growth. There is no observed significant impact on growth for the

[11] Note that all explanatory variables utilize values for the base year except AAPGR.

highest level of education (Graduate).

As the economy moves further into recovery (Model 3; 2016-2018) when the average income growth rate is higher, the direct, indirect, and total effects of Some College are all consistently negative and significant. These suggest we would see slower growth in counties experiencing higher levels of index for Some College. Although increased index levels for College have no significant impact on local growth, increased index levels for Graduate have a significant and positive direct effect.

Overall, we find different levels of human capital as captured by indexes for levels of education, are relevant predictors of economic development and well-being, even in a heavily manufacturing-based region that is typically associated with low levels of human capital. Even more important, while the direct impact of College is significant and positive in the period following the Great Recession (Model 2), it did not have a significant direct impact in the period further into recovery (Model 3). The reverse is observed for the direct impact of Graduate—not significant in Model 2, but positive and significant in Model 3. These results would suggest that perhaps more specialized human capital as captured by Graduate becomes valuable at a higher stage of income growth (Model 3 vs Model 2). Moreover, significant spillover effects are only observed for High School (Model 2) and Some College (Model 3). Our results are generally consistent with studies of spatial growth of regional economies in the EU (Annoni et al., 2019) and of state economies in the US (Hall et al., 2019). We also provide a more comprehensive insight as to the relevance of various levels of education and their impact at different stages of local income growth.

In addition to human capital, we find that innovation plays a relevant role in local income growth, consistent with the theoretical prediction and previous findings in the literature. More specifically, Patents (which capture current innovation and is predictive of future development) and BDI (Business Dynamic Index, which captures creative destruction and birth of new start-ups) had consistently significant positive direct and total effects on local income growth for the period between 2010 and 2018 (Model 1), and the period following the recession (Model 2; 2010-2016). Patents also showed significant positive spillover effects in Models 1 and 2. On the other hand, in the period between 2016 and 2018 (Model 3), BPI (Business Process Index, which captures business conditions and resource availability to entrepreneurs and businesses) showed significant positive direct, indirect, and total effects. The indirect impacts from BPI in nearby counties is slightly over twice the magnitude of the direct impact, suggesting a large spillover impact from BPI. The total impact is positive, with about seventy percent of this comprised of the spillover effects from BPI of neighboring counties. These findings suggest creative destruction is more important as the economy is initially recovering from a downturn (Model 2) and helps fuel income growth but tends to lose its significance as the economy grows further (Model 3). On the other hand, the premium for a supportive environment to foster entrepreneurship is higher when local economies are experiencing higher income growths. (Annoni et al., 2019) find investment, technological readiness, and business sophistication to be directly associated with regional growth.

The total impact of Metro counties showed consistently slower income growth over all time periods in the Great Lakes region. More specifically, the local average income growth rate in Metro counties between 2010 and 2016 was 0.173 percent slower (direct effect) compared to non-metro counties. This is perhaps consistent with the Solow model since on average, income levels in metro areas are higher than non-metro areas. The total effect, which includes spillover effects is even lower at 0.522 percent. Further into recovery (Model 3; 2016-2018) when average local income growth is higher, Metro counties grew at even slower pace of 0.944 percent compared to non-Metro counties (total effect). More interestingly, there is a relatively large negative spillover effect— by 0.906 percent. Metro areas have the effect of draining human and capital resources from surrounding areas. Our results support the idea that proximity to major urban centers yields larger agglomeration diseconomies than economies, or that being in or near a metro area is associated with lower growth than being in or near a non-metro area. A state-level spatial income growth analysis in the U.S. by (Hall et al., 2019) also found a negative direct effect on Metro areas but a positive spillover effect. It would seem that for a manufacturing-heavy region, in the period further into recovery from a significant economic downturn (Model 3, 2016-2018), ties to Metro areas have large negative spillover effects, further strengthening the negative total impact. On the other hand, (Rupasingha et al., 2002) find ties to urban areas fuel local income growth across the U.S.

Consistent with the empirical literature on convergence, the direct and spillover effects of the initial level of real per capita income (PCPI) is negative and highly significant over the three time periods. (Solow, 1956) refers to this as the "catching-up" process where poorer economies grow faster relative to richer economies. Similarly, a high initial poverty rate is generally detrimental to growth. The adverse direct impact of poverty on growth is consistent with the findings of (Rupasingha et al., 2002) with respect to income inequality. However, in a period when the average growth is higher (Model 3; 2016-2018), poverty has a significant and positive spillover effect—a one percentage point increase in the baseline poverty rate in surrounding counties increases growth on average in a county by 0.073 percent. The positive spillover effect of poverty may be indicative of productive labor movement to surrounding areas in search of better opportunities. This view is perhaps consistent with the results for population growth as well, where a significant and positive spillover effects are observed during the period following the recession (Model 2; 2010-2016), indicating an increase in average population growth rates of surrounding counties is associated with a higher growth rate in a county. During the period further into recovery (Model 3; 2016-2018), the direct effect of population growth is significant and negative, consistent with Solow (1956) view of lower availability of capital per worker slowing growth.

We also find evidence that higher levels of initial local unemployment have significant and positive spillover and total effects on local growth between 2010 and 2018 (Model 1), and more importantly, larger positive spillover and total effects in the period following the Great Recession (Model 2; 2010-2016). These results may be more a reflection of capacity to grow as opposed to high unemployment being a barrier to growth.[12] Lastly, we find significant state level variations in local growth in the Great Lakes region, more specifically slower growth (in terms of total impacts) in IN, MI, OH and WI compared to IL between 2016 and 2018 (Model 3). This is consistent with the descriptive findings presented earlier wherein Illinois showed a more recent growth spurt. We find significant negative spillover effects across all four states compared to Illinois for the latter time period (2016-2018).

5 Conclusions and Policy Implications

The purpose of this study is to empirically examine local economic growth measured by per capita personal income growth, in essence capturing economic well-being, across the Great Lakes region in the decade following the Great Recession, accounting for both spatial effects and two periods of economic growth (i.e., following a recession and further into recovery). Spatial autocorrelation analysis, both visually through maps and statistically through Moran's I, confirm the presence of spatial dependence. Counties with higher growth rates positively impact the surrounding counties, whereas counties surrounded by low-growth counties would experience a negative impact on their own growth. We observe significant clustering of low-low growth counties in Illinois and high-high growth counties in Indiana, Michigan and Ohio.

The Spatial Durbin Model (SDM) results provide us important insights on spatial dependence and spillover effects. First, we find evidence that location does matter in local per capita personal income growth and therefore, the use of OLS in modelling local growth may provide misleading results. Second, we find empirical evidence that shows different levels of human capital are relevant predictors of per capita personal income growth and, more notably, the direction and significance of the impact depend on the period of economic growth. In the period following the Great Recession (2010-2016), there is an indication that a higher proportion of Associates holders impedes growth while a higher proportion of College graduates supports growth. However, further into the expansion (2016-2018), a higher proportion of someone who has "some college" (i.e., is not a college graduate) deters growth, while a high proportion of Graduate degree holders fuels growth. In the period close to full employment (Model 3, between 2016 and 2018), more specialized human capital seems to be the main driver of growth. Similarly, innovation facilitates income growth initially, but loses its significance further into the expansion. Overall, our results suggest that high levels of human capital and a supportive environment that fosters entrepreneurship drive income growth in a period close to full employment. Although the human capital, innovation, and business environment index variables utilized in Model 2 (2010-2016) have limitations, the results generally suggest relatively low levels of human capital, as well as innovation, drive growth in the initial period after a recession.[13] Moreover, the

[12]A high reservation wage would imply there is "capacity to grow" of unutilized workers waiting for high enough wages. A barrier to growth could be due to a structural reason, for example, manufacturing workers are not easily able to switch to more in-demand white collar jobs.

[13]Utilized 2016 rather than 2010 data given data availability

overall value of different levels of human capital is apparent even in a region that is predominantly based in manufacturing.

Third, our findings of spatial dependence and spillover effects have important policy implications. The significant direct effects with respect to human capital, innovation, and business environment indicate the value of policies at the local level with respect to such variables in fueling economic growth. Moreover, the significant spillover effects imply the benefits (and costs) of local policies accrue elsewhere in the regional economy. Therefore, there is something to be gained from region-specific economic development policies with respect to those that aim to increase human capital and initiatives that support innovation and creative destruction. Given the spatial dependence, policy initiatives supporting growth within a locality (county) also promote growth across the region contributing to cross-regional development. And thus, regional policymakers may wish to encourage coordination of certain local policies across independent, adjacent jurisdictions given the spillover effects. Moreover, the impacts of such policies not only depend on the location of the counties, but also where in the overall path of income growth the local economy finds itself. Overall, both local and state policymakers have roles to play in promoting local growth so that these economies can grow with rest of the state, the region, and the country. We provide specific information that may help in prioritizing the allocation of limited resources to fuel economic growth and development.

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