

Economic Growth in the United States: A County-level Analysis

**December 2009
PPHA 50800 Practicum
The Harris School of Public Policy Studies
The University of Chicago**

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EXECUTIVE SUMMARY

The objective of this paper is to explore the factors driving differences in county-level economic growth across the United States. We use a recent OECD publication—"The Sources of Economic Growth in OECD Regions: A Parametric Analysis" (December 2008)—as a guide for our analysis of U.S. counties.

The paper first provides an overview of the relevant theories of economic growth, including neoclassical growth theories, endogenous growth theories, and the new economic geography. The paper then estimates a cross-sectional econometric model for 3,079 U.S. counties in 1998, using a number of the same key variables found in the OECD paper. The variables that are used are grounded in the three economic growth theories.

From the OLS cross section regression we find evidence that:

- Counties are converging
- A more educated population is positively correlated with economic growth
- A higher density of major roads is positively correlated with economic growth
- Employment specialization is positively correlated with economic growth

From the spatial regression we find evidence that:

- A county's growth rate is correlated with the growth rates of neighboring counties

In addition, we do not find that the innovation index obtained from the Indiana Business Research Center is statistically significant in our model, meaning that it does not help explain county-level economic growth. However, individual parts of the innovation index were significant. Last, we find that the employment rate is inconsistent across specifications.

INTRODUCTION

To begin to understand the factors that determine regional economic growth, we look to the relevant theoretical literature. This includes a discussion of neoclassical growth theories, endogenous growth theories and the new economic geography. These theories provide us with the basis for choosing variables to include in our econometric and spatial analyses. We include variables for initial income, infrastructure and employment based on neoclassical growth theories. We include variables for education and innovation based on endogenous growth theories. Last, we include variables for employment specialization and distance to markets based on the new economic geography. We regress each of these variables on annualized per capita personal income growth to understand which variables affect growth.

We obtained data on 3,079 counties from 1998 to 2007 from the Bureau of Economic Analysis, the U.S. Census, the Indiana Business Research Center, the Census of Employment and Wages, and the Environmental Systems Research Institute (ESRI).

GROWTH THEORIES

Neoclassical Growth Theory

Neoclassical growth theories considered economic growth to mean the accumulation of capital. However, because capital is subject to diminishing returns and depreciation, the models did not predict long-run growth without technological progress or labor force growth (Ramsey 1928, Solow 1956). Because of modeling difficulties, technological progress was included in the model as an exogenously determined constant rate (Solow 1956, Swan 1956). Without it, growth would stagnate.

Neoclassical growth theories also implied conditional convergence, meaning that if a country starts from a lower level of per capita output, it was expected to attain a higher growth rate (Barro 1997). This was a problem at the time because it was rarely seen empirically. Other problems with the neoclassical theories arose as well. The theories were incapable of explaining long-run growth without technological improvements. Also, determining technological growth exogenously has its own pitfalls: technological growth is not exogenous, as it depends on the human capital and physical infrastructure already in the economy. Later theories and models improved on these issues.

Endogenous Growth Theory

Endogenous growth theories were developed in the 1980s as a response to the weaknesses of the neoclassical growth theories. The endogenous growth models view economic growth as a process tied to a location's innovation, knowledge, and human capital levels, in addition to the accumulation of physical capital. Investing in human capital is thought to lead to the development of new technologies, which leads to more efficient production, leading to economic growth. Unlike the neoclassical growth theories, technology, therefore, is endogenous to the growth models. Endogenous growth theorists model long-run economic growth by assuming

→ Add a P w/ "roadmap" of paper - "We first discuss theories of economic growth, and then..."

either constant returns to scale or increasing returns to scale, but not diminishing returns to scale because human capital results in knowledge spillovers and external benefits. Knowledge is considered a non-rival good.

There exists a divide in the endogenous growth theories between viewing growth as driven by the stock of human capital versus the accumulation of human capital. Nelson and Phelps (Nelson and Phelps, 1996) see the stock of human capital as the key variable in causing economic growth. Lucas (Lucas, 1998) sees the accumulation of human capital as the key variable in economic growth. By viewing the stock of human capital as the key determinant of growth, regions can theoretically increase their amount of human capital during one period. If one region starts with a low human capital stock, and then accumulates a large amount of human capital during a year, that region will be able to innovate and catch up to the regions that started off with high stocks of human capital. A region only needs to increase their human capital stock once to experience long-term economic growth. By viewing the accumulation of human capital as the key determinant of growth, growth can only occur over a long period of time.

Later endogenous growth theories introduce research and development and imperfect competition into the models (Romer 1987, 1990) and Aghion and Howitt (Aghion and Howitt 1992). Private investment in R&D is seen as a key determinant of technological progress, which is itself encouraged through property rights and copyright laws. Unlike the neo-classical growth models, the endogenous growth theories do not predict any convergence of regions.

The key contribution of the endogenous growth theories is that technology is endogenous to the growth models. Physical capital accumulation, human capital and technology are all part of endogenous growth models.

New Economic Geography

Economic geography is the location of factors of production in space. What we want to know is why and when does economic activity concentrate in certain regions with others experiencing less development. NEG theory holds that in order to realize increasing returns to scale while minimizing transport costs, manufacturing industries (all industries other than those engaged in agriculture) tend to locate in regions with larger demand. However, the location of demand itself depends on the distribution of manufacturing. This process leads to the formation of a developed core, or urban region, and an undeveloped (or less developed) periphery. Also, this geographical concentration of manufacturing, or agglomeration, is not certain to occur. Emergence of a core-periphery pattern (agglomeration) depends on transportation costs, economies of scale, and the share of manufacturing in regional income.

The general NEG model has two industrial sectors, agriculture and manufacturing. Agricultural production features both constant returns to scale and use of land, an immobile factor of production. The geographical distribution of this production is thus largely determined by the distribution of arable land – a factor exogenous to production itself. On the other hand, increasing returns to scale and modest land use characterize manufacturing. Because the proportion of a region's economy in manufacturing affects the ability to take advantage of economies of scale, production of each manufactured good will take place only at a limited

number of sites. Ceteris paribus, the preferred sites will be those with relatively large nearby demand. Producing near one's main market minimizes transportation costs¹; thus other locations will be served from these central sites. As transportation costs decrease and economies of scale are present, a region with a relatively large non-rural population (or larger initial production) will be an attractive place to produce because of the large local market and because of the availability of goods and services produced there. This will allow the larger initial region to grow while the smaller initial region does not - or does so to a lesser degree and at a slower rate. Thus, despite early similarity, regions can become quite different.

Unlike neo-classical and endogenous growth theories (discussed earlier), which are only concerned with what happens at the margins, NEG considers scale. In fact, scale is central in NEG theory. NEG relates to this particular research project because NEG explains concentration and dispersion of economic activity, or differentials in economic activity, through agglomeration. NEG proposes that external increasing returns to scale incentivize agglomeration. Agglomeration captures, via scale effects, how small initial differences cause large growth differentials over time. This is precisely what we want to know.

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please add references &/or footnotes
as needed.

¹ Transport costs are a key element of the model (along with population and proportion of the economy in manufacturing); technology (specifically transportation technology) lowers transport costs. Low transport costs encourage manufacturing to aggregate. High transport costs do not favor clustered manufacturing. There exists a tipping point between high and low transport costs; this is an effect of the relationship between wages and transportation costs. Low transport costs and external economies of scale increase the income of the core (urban) region relative to its periphery. Agglomeration raises wages in the core region relative to the periphery. If costs fall far enough (wages increase enough), the wage differential will induce firms to relocate back to peripheral regions.

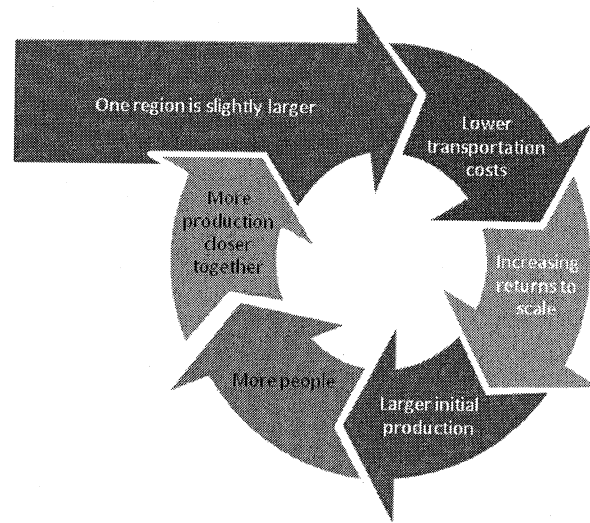


Figure 1 New Economic Geography theory of agglomeration

DATA AND SELECTION OF VARIABLES

We obtained data from a variety of sources. However, not every source contained every data point. We dropped Alaska and Hawaii, as well as Broomfield County in Colorado, Clifton Forge County in Virginia, and County 901 in Wisconsin ((what was this?)) from our model because of missing data.

Variable	Source	Year(s)
Annualized Per Capita Personal Income Growth	Bureau of Economic Analysis	1998-2007
Log of Initial Income	Bureau of Economic Analysis	1998
Infrastructure	ESRI Data and Maps 9.3	2008
Education Rates	U.S. Census	2000
Innovation index	Indiana Business Research Center	2008
Employment Rate	U.S. Census	2000
Specialization	Census of Employment and Wages	1998
Distance to markets	ESRI Data and Maps 9.3	2008
	Bureau of Economic Analysis	1998

Table 1 Sources of data for variables

SUMMARY STATISTICS

Annualized Per Capita Personal Income Growth

annual
We obtained ~~per~~ capita personal income from the Bureau of Economic Analysis. Personal income is defined as income received by all persons from all sources, including wages, rental income, personal dividends, interest, and current transfers, minus government social insurance. Personal income taxes are not taken out. The BEA used the Census Bureau's annual midyear population estimates to divide personal income by the population that year.

for the 1998-2007 period.

not needed

~~Annualized per capita personal income growth, our dependent variable, was found by subtracting the log of income from the initial year from the log of income in the final year, and dividing by 10, the number of years. All dollars were converted to 1998 dollars.~~

Variable	Highest	Lowest	Mean
Annualized Per Capita Personal Income Growth	7.03% in Sublette, WY	-3.55% in Crowley, CO	1.03%

Table 2 Per capita personal income growth

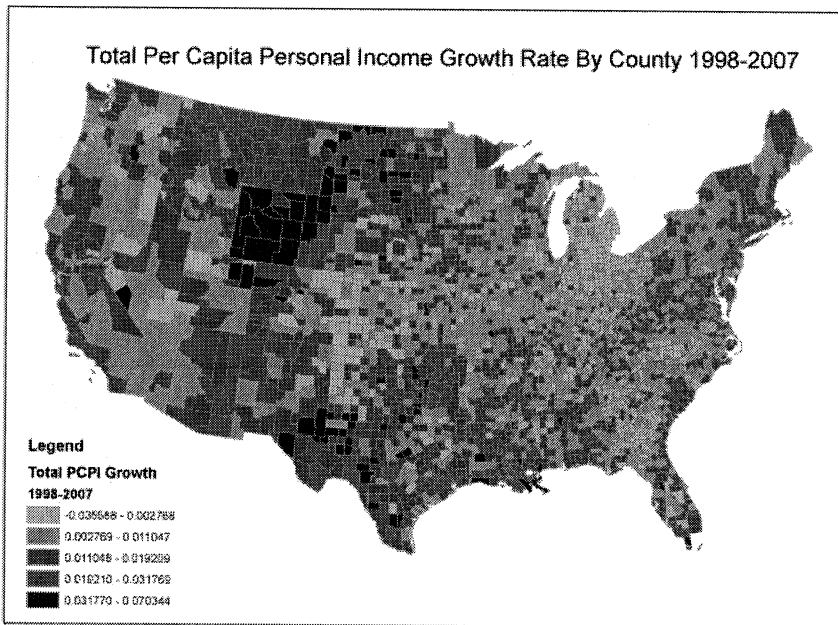


Figure 2 Per capita personal income growth

Log of Initial Income

Because neoclassical growth theories predict convergence, we used the log of initial 1998 income as a baseline in our models. We expect to see a negative sign on initial income if counties are converging—this would mean that higher initial income is negatively correlated with growth, and lower-income counties have greater growth.

Variable	Highest	Lowest	Mean
Income in Initial Year (1998)	\$76,450 in New York, NY	\$7,756 in Loup, NE	\$20,647

Table 3 Initial income summary statistics

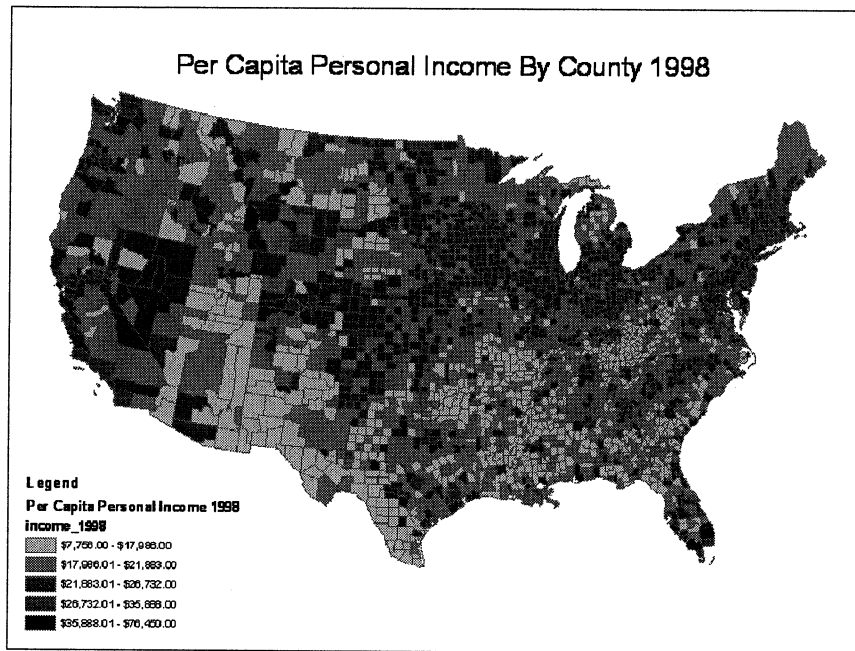


Figure 4 Per capita personal income in 1998

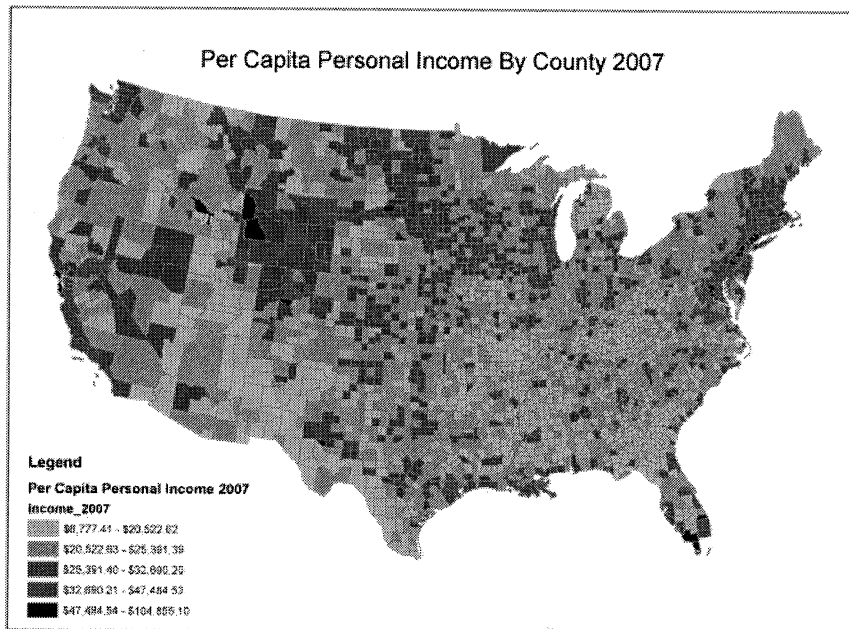


Figure 3 Per capita personal income in 2007

Infrastructure

The neoclassical growth theories view physical capital as the main determinant of economic growth. Because there is no public data available on private investment or gross fixed capital formation, we cannot incorporate a direct measure of physical capital. We therefore use infrastructure as a proxy for physical capital. The OECD paper uses total motorway density (kilometers of highway per region divided by the population per region) as the measure of infrastructure. We use miles of major roads per county divided by the population per county as our measure of infrastructure. To better grasp this variable, we multiply it by 1,000 so that we have statistics per 1,000 people. The average county has approximately 380 miles of major roads.

Variable	Highest	Lowest	Mean
Miles of major road per 1,000 people	935 in Loving County, TX	0.17 in Kings County, NY	31

Table 4 Miles of major road per 1,000 people

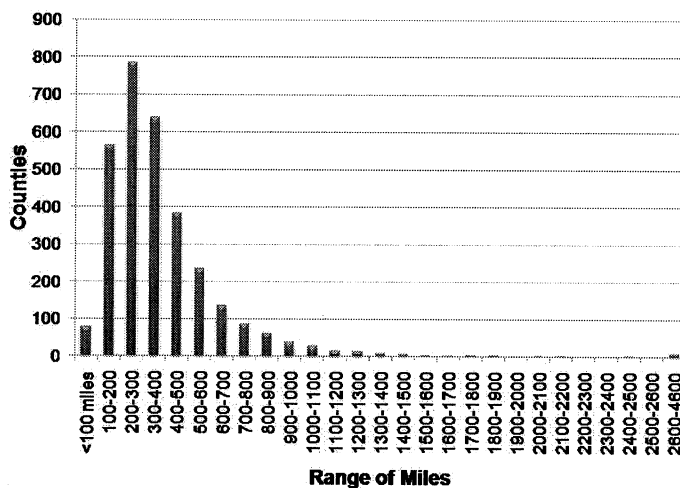


Figure 5 Major road mileage per county

While we do not include airports in the final regression, we included them in preliminary regressions. ~~Though most counties have no airport, airports were found to be statistically significant and highly correlated with economic growth.~~

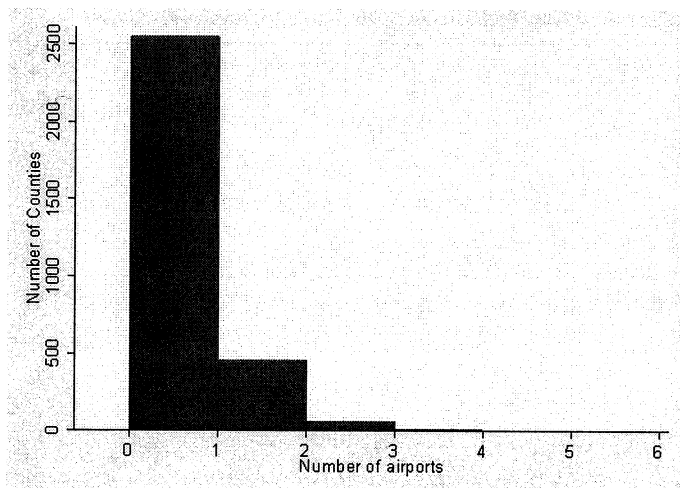


Figure 6 Number of airports by county

↑ You are "giving away" regression results here; this section should define the vars, "show them" (w/ graph or means, etc.), & explain what you expect to see in the regs.

Human Capital

Human capital is considered to be a factor contributing to economic growth in all growth models. A better-trained workforce is more productive and able to command a higher wage. The OECD paper included primary education rates and tertiary, or higher, education rates. We found that a higher share of residents with less than a high school diploma was very highly correlated with a higher share of residents with exactly a high school diploma, and both were negatively correlated with a high share of residents who have pursued higher education. Because these three percentages in any one county add up to 1, we had to drop one of the measures, and we dropped the percent of the county with less than a high school diploma, leaving us with the percent of a county's adult population that has attained a high school diploma and the percent of a county that has pursued schooling beyond a high school diploma.

Variable	Highest	Lowest	Mean
Less than a high school diploma	62.5% in Starr, TX	4.4% in Douglas, CO	21.6%
High school diploma	53.5% in Carroll, OH	12.4% in Arlington, VA	34.7%
More than a high school diploma	82.1% in Los Alamos, NM	17.2% in McDowell, WV	41.4%

Table 5 Education rates summary statistics

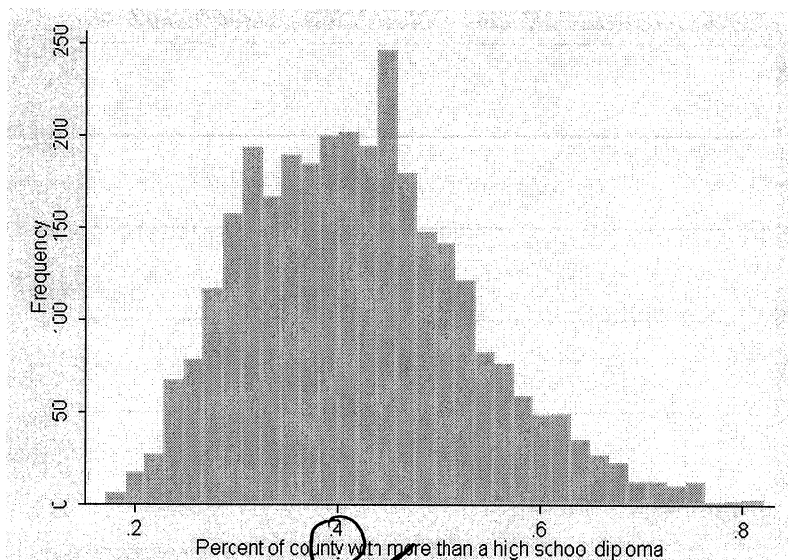


Figure 7 Percent of people with more than a high school diploma

maybe "2% of county population with more than h.s. diploma"

Employment Rate

The OECD paper used youth employment rate as well as total employment rate. The data from the 2000 Census allowed us to make this distinction as well. However, we found that youth employment rate and working employment rate were so well correlated with total employment rate, that total employment rate was adequate for our regression. When we isolated youth employment rate, we found that it consistently had a negative coefficient—a higher share of the youth population being employed is negatively correlated with growth.

again, this is going too far ahead

Variable	Highest	Lowest	Mean
Youth Employment Rate (16 – 20 years old)	100% in Loving, TX	8.8% in Shannon, SD	46.2%
Working-Age Employment Rate (21 – 65 years old)	88.4% in Stanley, SD	35.9% in McDowell, WV	73.1%
Total Employment Rate	86.7% in Stanley, SD	33.6% in McDowell, WV	69.9%

Table 6 Employment rate summary statistics

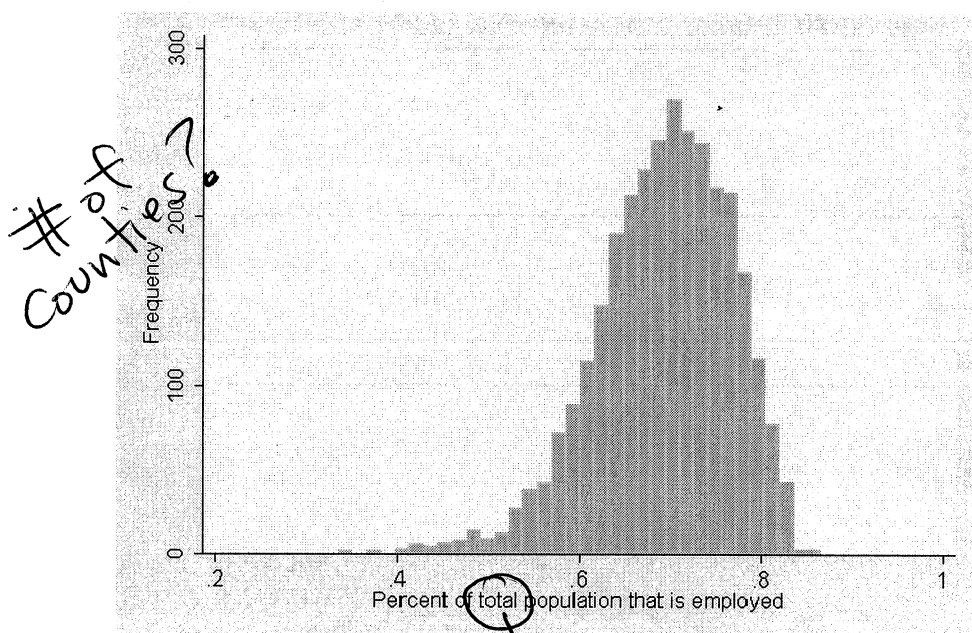


Figure 8 Employment rate

probably this is working age pop,
18-64
or 16-64 or similar?

Employment Specialization²

Employment specialization is a measure of industrial concentration of a region (county). It is included to capture notion of agglomeration (industrial spatial concentration), which is a determinant of economic growth in NEG growth theory.

The two most prominent choices to model industrial specialization are the Herfindahl and Krugman indices. The Herfindahl index is the sum, across industrial sectors j , of the square of sectors' share of employment in region (county) i . $\sum_{j=1}^N s_{ij}^2$. The Herfindahl index ranges from 0 to 1. An index of 0 signifies industrial diversity while an index of 1 signifies industrial homogeneity. This index does the basic job of capturing industrial specialization; however, it is an absolute measure that fails to include any degree of comparison to other regions. This project is very concerned with *relative* economic growth, why county A experienced X amount of economic activity while county B experienced Y amount. The Herfindahl index does not encapsulate this relative information.

The Krugman index is the sum of the absolute value of the difference between the share of industry j in region (county) i 's total employment and the share of the same industry in the employment of all other regions (counties), $-i$. $KI = \sum_j |s_{ij} - s_{-ij}|$. The Krugman index ranges from 0 to 2.0. Zero means region i has an industrial composition identical to its comparison regions. Two means region i has an industrial composition without any similarity (no common industries) to its comparison counties. This index captures industrial specialization, as does the Herfindahl index, but also incorporates the desired regional comparison.³ Because of our specific interest in why regions grow at different rates *relative* to one another, the comparative nature of the Krugman index seems better suited to our needs than the Herfindahl Index.

In our data, the minimum calculated KI was 0.115 for Onondaga County New York. The maximum value was 1.812 for Eureka County Nevada. The mean value was 0.750, with a standard deviation of 0.318 and variance of 0.101.

① What year do the employment come from?
② use a Enote table or similar to list your industry (sector) exactly 20 or so
20 in all

² The micro-data used to calculate employment specialization come from the Census of Employment and Wages, supplied by the Indiana Business Research Center. The level of aggregation used is the county-level with industrial sectors specified by two-digit NAICS codes.

³ Whether relative concentration measures fully capture agglomeration economies, or whether absolute economic region size is best for appreciating the effects of geographical concentration on economic growth is debatable. Objections hold that the level of specialization is systematically underestimated for larger metropolitan areas when relative levels of concentration are used.

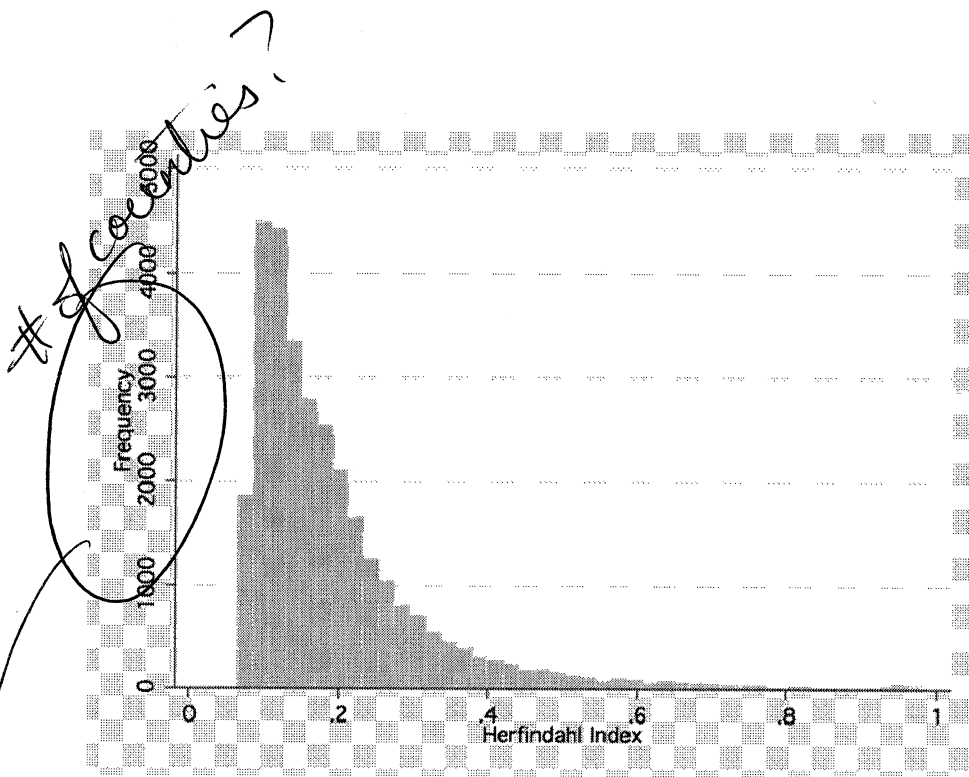


Figure 9 Herfindahl index distribution

I am puzzled here - there are only 3079 countries, so the vertical axis should basically be in hundreds, not thousands

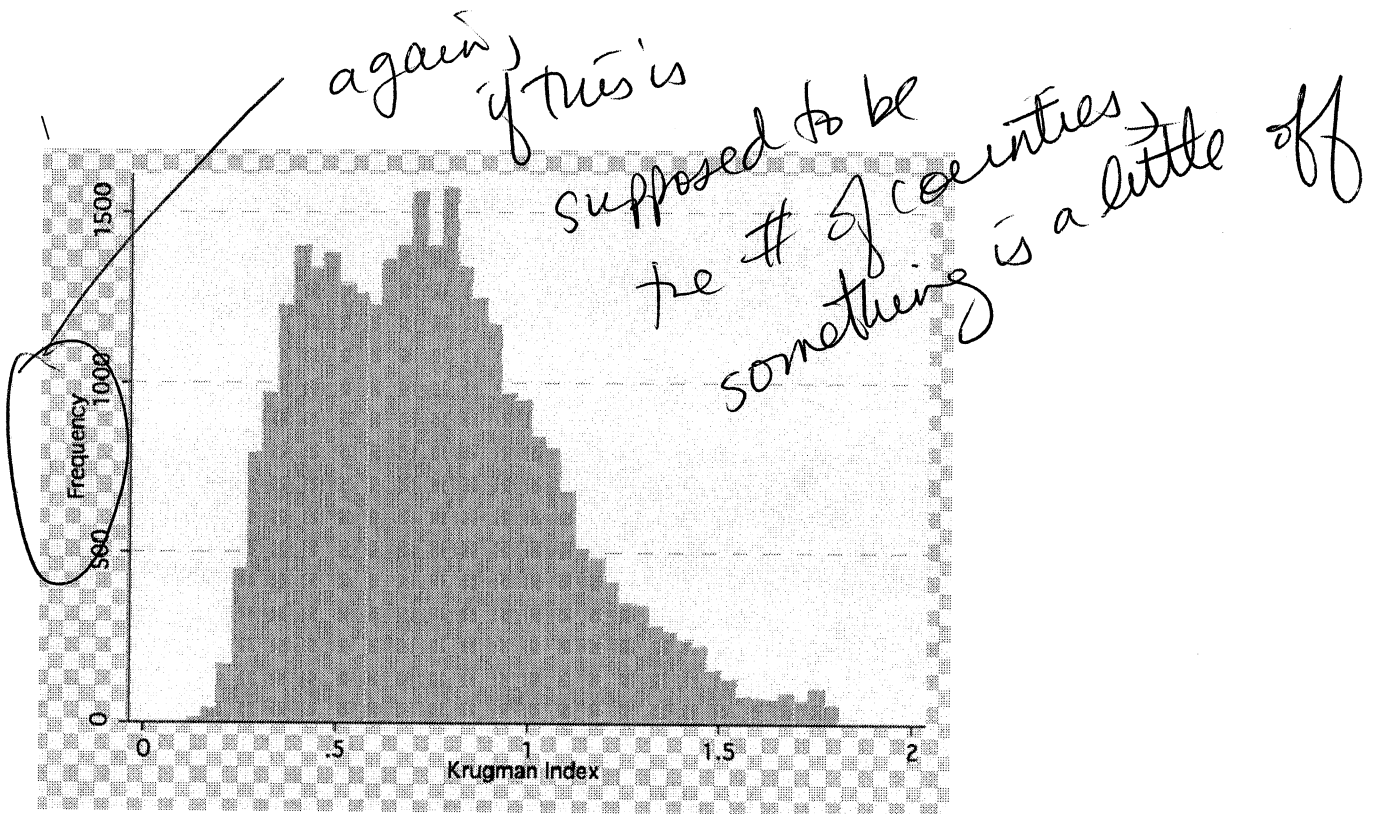


Figure 10 Krugman index distribution

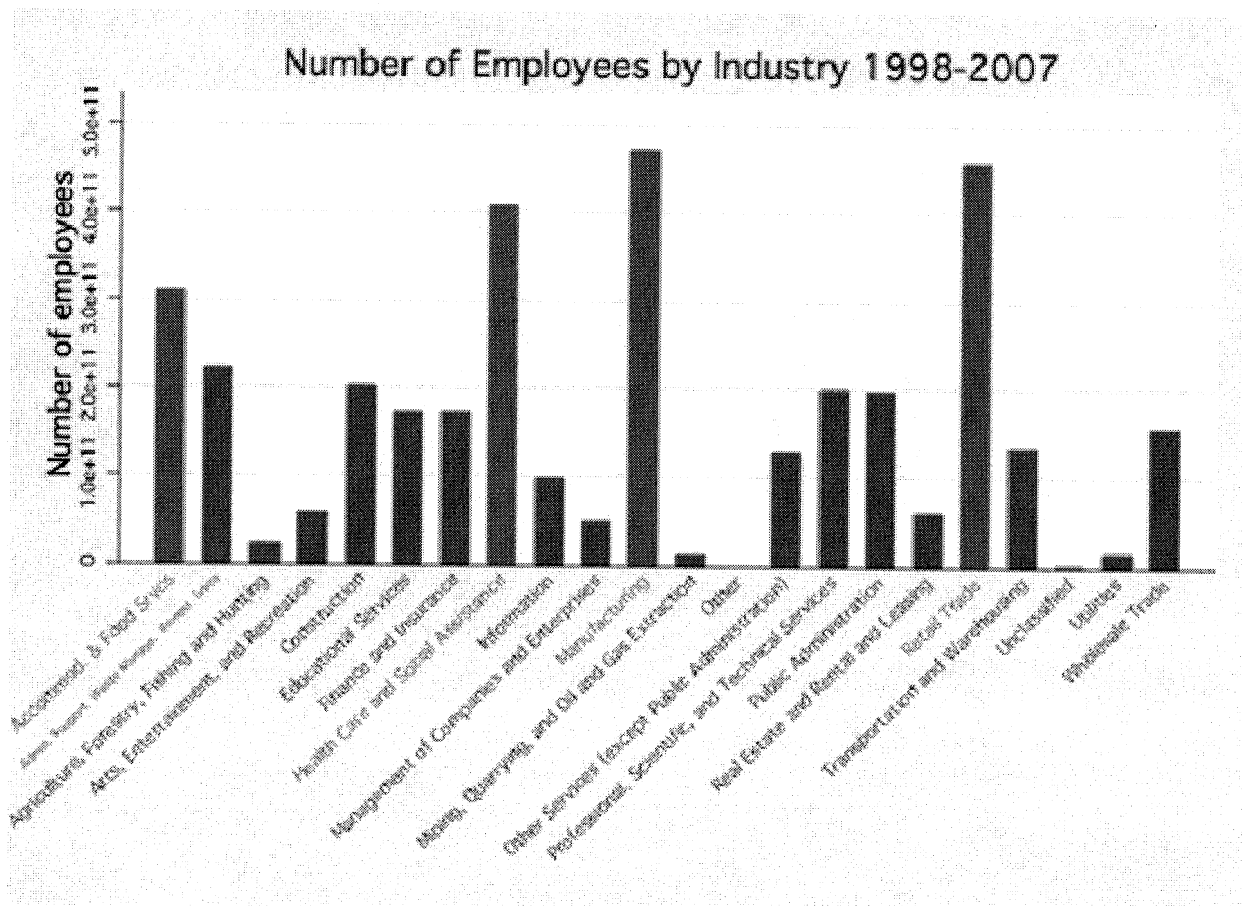


Figure 11 Number of employees by industry, 1998-2007

Distance to Markets

The *distance to markets* variable is an accessibility indicator that takes into account the connectivity of transport networks and the activities that can be reached by this network. Such an indicator is constructed by summing the product of two separate functions – an *activity function* and an *impedance function*. It is expressed mathematically as follows:

$$A_i = \sum_j g(W_j) f(c_{ij})$$

where,

$g(W_j)$ = market size = activity W to be reached in county j

$f(c_{ij}) = c_{ij}$ = generalized cost of reaching county j from county i

The intuition is that the higher this index, the higher the “marginality” of county i – in other words, the more distant will be this county to the markets (keeping market size constant).

More specifically, we calculated the centroid (geographical center) coordinates of each county, and then calculated the distance between one county and all its neighbors. These distances are used here to capture the generalized cost of reaching county j from county i .

Without limitations, we would have preferred to use the inverse distance between county i and county j as oppose to the absolute distance, which represents a generalized cost, in order to capture a distance decay effect taking place as the distance increases to other markets – thus, becoming less accessible. The OECD paper offers other methods to construct an accessibility indicator in its appendices.

Innovation Index

At the request of the EDA, we obtained an innovation index from the Indiana Business Research Center. The OECD paper uses patents as a proxy for technology. However, recent research (CC's paper?) has shown that since patents are not specific to regions, they are a poor proxy for innovation. The innovation index contains many different measures of innovation, including some we had already included in our regression, ^{as well as} and our dependent variable. These variables are highlighted in bold in the outline below. It also includes some variables that are inputs in growth models, such as human capital, and some outputs, such as poverty rates and GDP per worker. Poverty rates and GDP per worker have a very strong relationship with the dependent variable, per capita personal income growth. In general, we don't want our dependent variable to have a close conceptual relationship with our independent variables—then it would be unclear which is causing which. Therefore, using the innovation index in our regression as-is would not be effective, though we did find that some individual parts of it were significant in our regression.

I. Portfolio innovation index

a. Human capital - input


i. Annual average population growth rate for ages 25-44

Preface this outline with something like "According to documentation provided by the IBRC, the innovation index is comprised of the following components:"

- ii. **Percent of population with some college**
 - iii. Percent of population with Bachelor's degree or higher
 - iv. Technology-based knowledge occupation cluster
 - v. Average high-tech employment share
 - b. Economic dynamics - input
 - i. Venture capital investment per \$10,000 GDP
 - ii. Average private R&D per \$1,000 compensation
 - iii. Population-weighted mean of broadband service providers
 - iv. Average establishment churn
 - v. Average small establishments per 10,000 workers
 - vi. Average large establishments per 10,000 workers
 - c. Productivity and employment - output
 - i. Job growth rate over population growth rate
 - ii. Change in share of high-tech employment
 - iii. Change in GDP per worker
 - iv. GDP per worker
 - v. Average patents per 1,000 workers
 - d. Economic well-being – output
 - i. Average poverty rate
 - ii. **Average unemployment rate**
 - iii. Average net migration
 - iv. **Per capita personal income growth**
 - v. **Compensation**
 - 1. **Annual wage and salary earnings per worker**
 - 2. **Proprietors' income per proprietor**

The portfolio innovation index was calculated by weighting each of the above measures. Human capital received a weight of 0.3, economic dynamics received a weight of 0.3, productivity and employment received a weight of 0.3, and economic well being received a weight of 0.1. Other measures collectively called “state context” were given a weight of zero because the data was only available at the state level. This included science and engineering graduates from state institutions per 1,000 members of the population, and R&D spending per capita. The data also included a dummy variable for whether the county is included in a Metropolitan Statistical Area, or an area with more than 1,000,000 people.

The innovation data we received was indexed around a score of 100. Counties with scores of 100 on any variable were exactly like the US average. Counties with less than that are doing worse, and counties with more are doing better.



Variable	Highest	Lowest	Mean
Input: Human Capital (HC) Sub-Index	147.2	50.3	147.2
Input: Economic Dynamics (ED) Sub-Index	119.3	40.8	129.3
Output: Productivity & Employment (PE) Sub-Index	142.2	55.6	138.9
Output: Economic Well-Being (EWB) Sub-Index	119	81.1	96.73

Table 7 Innovation sub-indices summary statistics

CROSS SECTION MODEL

We ran the following regression:

$$\text{Economic Growth} = \beta_0 + \beta_1 \text{Log of Initial Income} + \beta_2 \text{Infrastructure} + \beta_3 \text{Education Rates} + \beta_4 \text{Employment Rate} + \beta_5 \text{Employment Specialization} + \beta_6 \text{Distance to markets} + \beta_7 \text{Innovation index} + \varepsilon$$

The results are given in the table below. T-statistics are given in parentheses below each coefficient. Coefficients that are significant at the 5 percent confidence interval are marked with an asterisk. The dependent variable was annual per capita personal income growth.

Table 8: OLS Results

Dependent variable: Annualised growth in p.c. ~~personal~~ income

1998-2007

Variable	1	2	3	4	5	6	7	8
Constant	.0447* (5.52)	.032* (3.98)	.121* (12.46)	.027* (2.89)	0.026* (3.18)	.048* (6.05)	.074 (7.48)	.075* (6.62)
Initial Income	-.003* (-4.12)	-.002* (-2.70)	-.011* (-10.39)	-.001 (-0.68)	-0.002* (-2.18)	-.004* (-5.56)	-.007* (-6.52)	-.006* (-4.88)
Highways		.025* (8.11)						.017* (4.57)
High school diploma		-.023* (-6.45)					-.013* (-3.25)	
More than high school		.017* (6.58)					.017* (5.45)	
Employment Rate			-.012* (-3.95)				-.011* (-3.15)	
Krugman index					.002* (3.29)			.001 (1.44)
Distance to markets					8.98e-14* (12.55)		4.46e-14* (5.65)	
Innovation index							.000* (5.12)	-.000 (-0.39)
R-Squared	0.0055	0.0263	0.0746	0.0105	0.0090	0.0539	0.0139	0.1056
F-Value	17.00 (1,307 7)	41.57 (2,3076)	82.59 (3,3075)	16.36 (2,3076)	13.94 (2,3076)	87.63 (2,3076)	21.68 (2,3076)	45.32 (8,3070)

use smaller font - e.g. a pt for tables

Table 8 OLS results

Log of initial income is consistently negative and significant across the specifications, ~~promoting~~ the idea of convergence—the poorer a county is to start, the faster its growth. Having a higher share of the population with only a high school diploma is negatively correlated with growth.

consistent with

Having a larger share of the population with higher education is positively correlated with growth, as would be expected.

Employment rate is negatively correlated with growth, which is counterintuitive. The OECD paper found the same result, and explained it by pointing out that the higher the employment rate, the less capacity there is for new employment opportunities to come in and be successful. Our employment rates are from the 2000 Census, near the beginning of the period we looked at. If everyone is already employed, there is no talent to hire.

Alone, industry specialization as measured by the Krugman index is positive and insignificant, but with all of the covariates it loses its significance. Distance to markets is positive across all specification. This was also found in the OECD paper, and is a counterintuitive finding, since it means that the farther a county is from other markets, or the smaller those markets are, the better off the county is. One plausible explanation is that when there are fewer nearby markets, a county must learn to become more self-sufficient and conduct most of its business itself.

The innovation index was not found to have a large or significant correlation with growth. However, because some of the parts of the innovation index are very closely tied to the dependent variable, it probably was not appropriate to include the entire innovation index in our regression.

Try something like:

~~On the basis of the results below, we suggest that future work experiment w/ including selected components of the index, to increase our understanding of which individual innovation measures affect growth.~~

State Fixed Effects

The above regressions were run without using state fixed effects. State fixed effects hold constant any factors that affect specific states. There are several reasons why we would think that certain states are privileged when it comes to economic growth, such as state-owned banks, tax breaks for businesses, or senators with good committee appointments or chairmanships. Results from this regression are given below.

Dep Var = usual...

Variable	Coefficient
Constant	.0447* (5.52)
Initial Income	-.006* (-5.16)
Highways	0 (0.02)
High school diploma	0.003 (0.82)
More than high school	0.023* (7.72)
Employment Rate	-0.01* (-2.28)
Krugman index	0.001* (2.03)
Distance to markets	1.89e-13* (7.69)
State fixed effects	Yes
R-Squared	0.3591
F-Value	30.80 (55, 3023)

(which could affect the quantity or quality of public infrastructure)

Table 9 Regression with state fixed effects

When we used state fixed effects, the coefficient on highways went almost to zero and became insignificant. The effect of having a higher share of the population with exactly a high school diploma became positive and very small, but was also insignificant. Distance to markets remained positive, which is an encouraging finding. Because county size varies by state, this means that

the effect of simply being in a state with larger counties is held fixed, and the coefficient on distance to markets really is positive.

The effect of living in any one state was typically insignificant, except for a few notable exceptions. Living in California, Nevada, Utah, or Washington had a significant and negative correlation with income growth. Living in Wyoming or the District of Columbia had a significant and very positive correlation with income growth. Being in North Dakota or Oklahoma also had a significant but smaller correlation with income growth.

Drop this - usually we think
of doing FE when we don't
have a specific story for
individual states

Education Spillovers

In addition to distance to economic markets, we created a variable that measures distance to clusters of highly educated workers. Because the new models of economic growth consider education to be non-rival, counties located near large markets of highly educated workers should have more growth. We created a distance to education markets variable the same way we created a distance to markets variable—by multiplying the distance to each county from each other county by the percent of the population with more than a high school diploma. The dependent variable is per capita personal income growth.

Variable	Coefficient
Constant	.070* (6.17)
Initial Income	-.005* (-4.02)
Highways	.015* (4.02)
High school diploma	-.015* (-3.60)
More than high school	.014* (4.33)
Employment Rate	-.015* (-4.00)
Krugman index	.0007 (1.07)
Distance to markets	2.82e-13* (4.06)
Distance to Education Markets	-1.23e-11* (-3.44)
R-Squared	0.1090
F-Value	46.95 (8, 3070)

Table 10 Regression with distance to education markets

The coefficient on distance to education markets is negative, meaning that the closer markets are, or the more educated nearby people are, the more a county's per capita personal income grows.

Innovation Index Components

Though the innovation index as a whole was insignificant and close to zero in our regression, we wanted to further explore its components to see if any individually might be significant.

First, we wanted to exactly replicate the regression run for the OECD paper, using patents as a proxy for technological innovation. Our findings are in the table below. We can see that patents have a slightly negative correlation with income growth, though close to zero. Youth employment rate has a negative correlation with growth. Initial income, highways, percent of the county with higher education, and distance to markets remain unchanged in this specification.

Variable	Coefficient
Constant	.052* (4.49)
Initial Income	-.006* (-4.43)
Highways	.015* (3.86)
Less than high school	.012* (2.84)
More than high school	.030* (9.59)
Youth employment rate	-.012* (-4.25)
Total employment rate	.003 (0.52)
Average patents per 1,000 workers	-.000* (-4.31)
Krugman index	.000 (0.05)
Distance to markets	4.31e-14* (5.49)
R-Squared	0.1162
F-Value	44.85 (9, 3069)

Table 11 Regression using patents as proxy for innovation

We also ran a regression using all of the input-related data points that went into the innovation index, but only if they didn't duplicate variables we had already researched and included. After running the regression, only a few of the variables remained significant, and all of the innovation index-related variables had extremely small coefficients, meaning that a change in any one of these variables has a limited relationship with per capita personal income growth. ~~The one exception was the Metropolitan Statistical Area dummy—it had a significant coefficient of 0.001.~~

These results suggest that most of the variation in the dependent variable is being explained by the original covariates we used—infrastructure, human capital, distance to markets, and specialization. In this model, factors related to innovation and technology have a less clear relationship with income growth.

same thing as
state FE —
if you don't
have an economic
story to tell, leave
these alone

SPATIAL SPECIFICATIONS

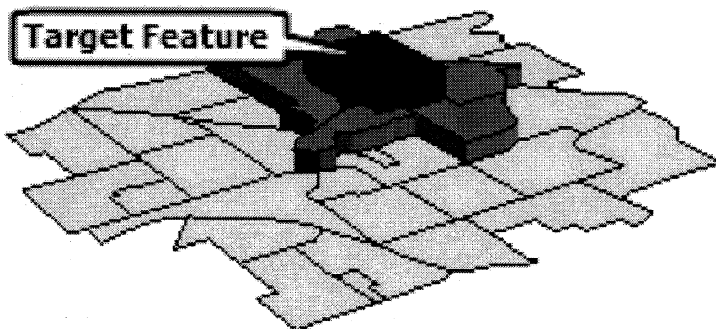
The reason for a spatial specification is to formulate a parsimonious model that reflects the spatial structure in our data. This spatial structure is captured in a spatial weight matrix, which is then used in a spatial model to provide unbiased and consistent estimates in presence of spatial dependence. This section will break down our spatial econometric analysis in the following manner: identifying a spatial weights matrix; proving the presence of spatial autocorrelation; and estimating a spatial lag model for Midwestern pilot counties.

Modeling Spatial Relationships

As advised in the OCED paper, we conducted a sensitivity analysis before choosing a weight matrix that reflects the interconnectedness of our data. We explored with various matrices including: inverse distance, inverse distance squared, contiguous neighbors and k-nearest neighbors. Furthermore, we played with the idea of setting a distance threshold (or band width) around counties. For instance, we chose a range from 80 to 110 kilometers.¹ It is important to note that not all of these weight matrices were ~~creatable~~ ^{considered} for a 3079 sample size.

Given the nature of our investigation, we imposed a spatial structure on the data by constructing a spatial weight matrix based on first-order contiguity (for non-geo-referenced data), reflecting the relative position of one county to another county – specifically, two counties are neighbors if they share a common border or edge. Therefore, we assigned a value of one to a neighboring county that is contiguous (dark blue) and a value of zero to all other counties (light blue). This concept is visually represented in the Figure 12.

Figure 12 Contiguous counties

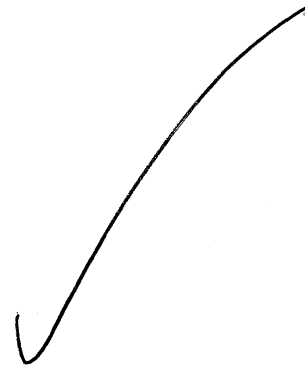
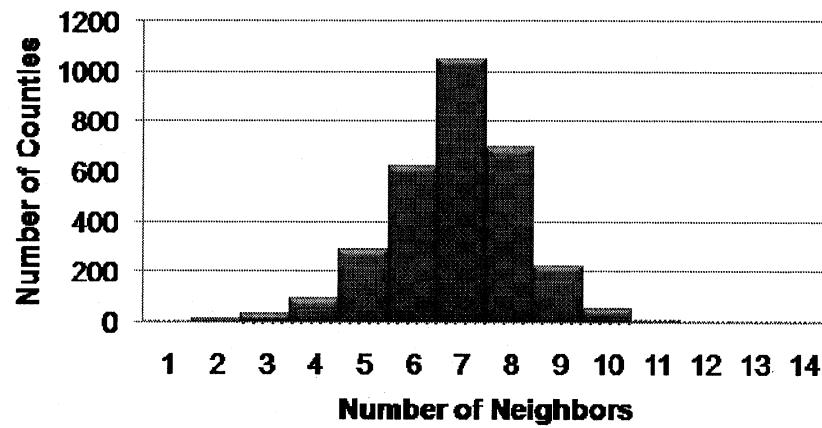


~~Furthermore, we found that the average number of county neighbors that a county has assumes a normal distribution. This is illustrated in the frequency distribution in Figure 13. Thus, a county has an average of five to six neighboring counties.~~

no distribution of the depicted
(no need to take a stand on "statistically normal" distribution)

29

Figure 13 Number of County Neighbors



Spatial Autocorrelation

We have good reason to suspect that our data not independent and identically distributed (that is, there is no spatial dependence) given that we have areal (administrative) data. We know this because our unit of analysis is United States counties in our application. Perhaps this could be a source of measurement error in data collection or a larger aspect of the socio-demographic, economic or regional activity reflected in the spatial dimension.

Now that we have defined a weight matrix, we will now prove that there is spatial autocorrelation in our data by using a spatial econometric technique called Moran's I . This index is analogous to the correlation coefficient, and its value ranges from 1 (strong positive spatial autocorrelation) to -1 (strong negative spatial autocorrelation). Moran's I is defined by,

$$I(d) = \frac{\sum_i \sum_{j \neq i}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_i \sum_{j \neq i}^n w_{ij}}$$

where,

$$S^2 = \frac{1}{n} \sum_i^n (x_i - \bar{x})^2$$

w_{ij} = contiguity-based weight matrix

Given our neighborhood structure, our Moran's I statistic on the dependent variable results in a value of 0.439. Based on this result, we can reject the null hypothesis that there is zero spatial autocorrelation present in growth rates at the 5% level of significance.

This degree of spatial autocorrelation on growth rates is depicted in a Moran scatterplot shown in Figure 14. It is divided into the following four quadrants:

- The upper right quadrant represents spatial clustering of high growth rates around high growth rates locations.
- The lower left quadrant represents spatial clustering of low growth rates around low growth rates locations.
- The lower right quadrant represents spatial clustering of low growth rates around high growth rates locations.
- The upper left quadrant represents spatial clustering of high growth rates around low growth rates locations

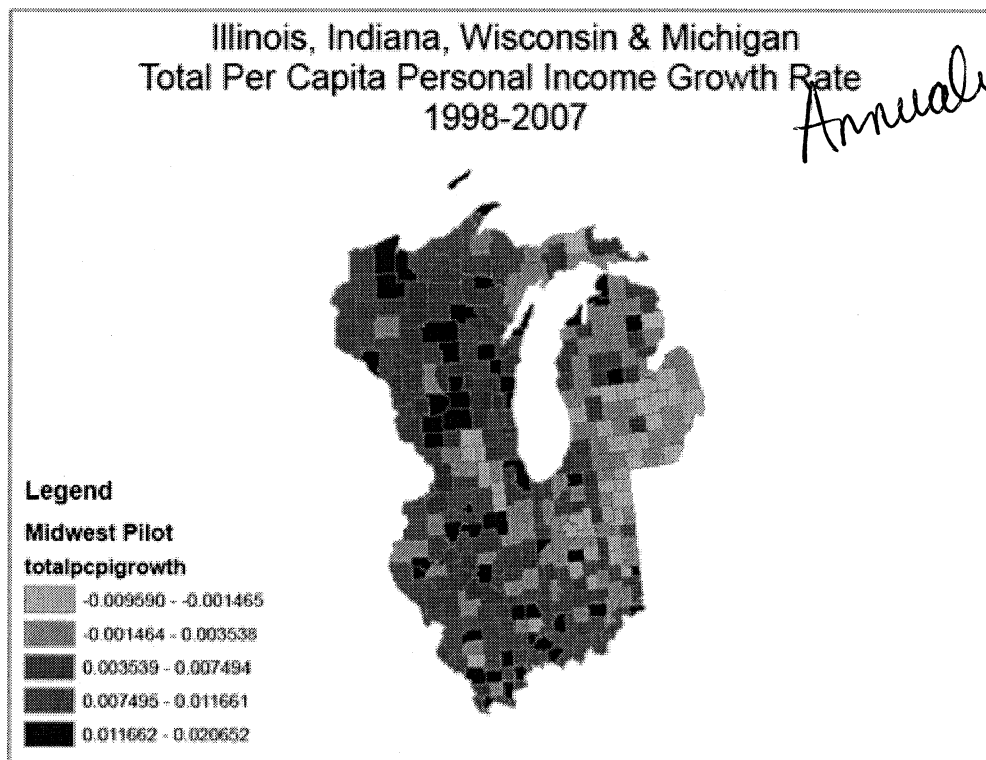


Figure 15 Per capita personal income growth in Midwestern pilot counties

Let us now confirm positive spatial autocorrelation in Midwestern pilot counties. Our Moran's I statistic on the dependent variable results in a value of 0.334 – less than the positive spatial autocorrelation found on growth rates across the United States. However, based on this result, we can still reject the null hypothesis that there is zero spatial autocorrelation present in growth rates at the 5% level of significance.

Again, this degree of spatial autocorrelation on growth rates is depicted in a Moran scatterplot shown in Figure 16 (It is more clearly ~~shown~~ this time give the smaller sample size.). It is divided into the following four quadrants:

- The upper right quadrant represents spatial clustering of high growth rates around high growth rates locations.
- The lower left quadrant represents spatial clustering of low growth rates around low growth rates locations.
- The lower right quadrant represents spatial clustering of low growth rates around high growth rates locations.
- The upper left quadrant represents spatial clustering of high growth rates around low growth rates locations.

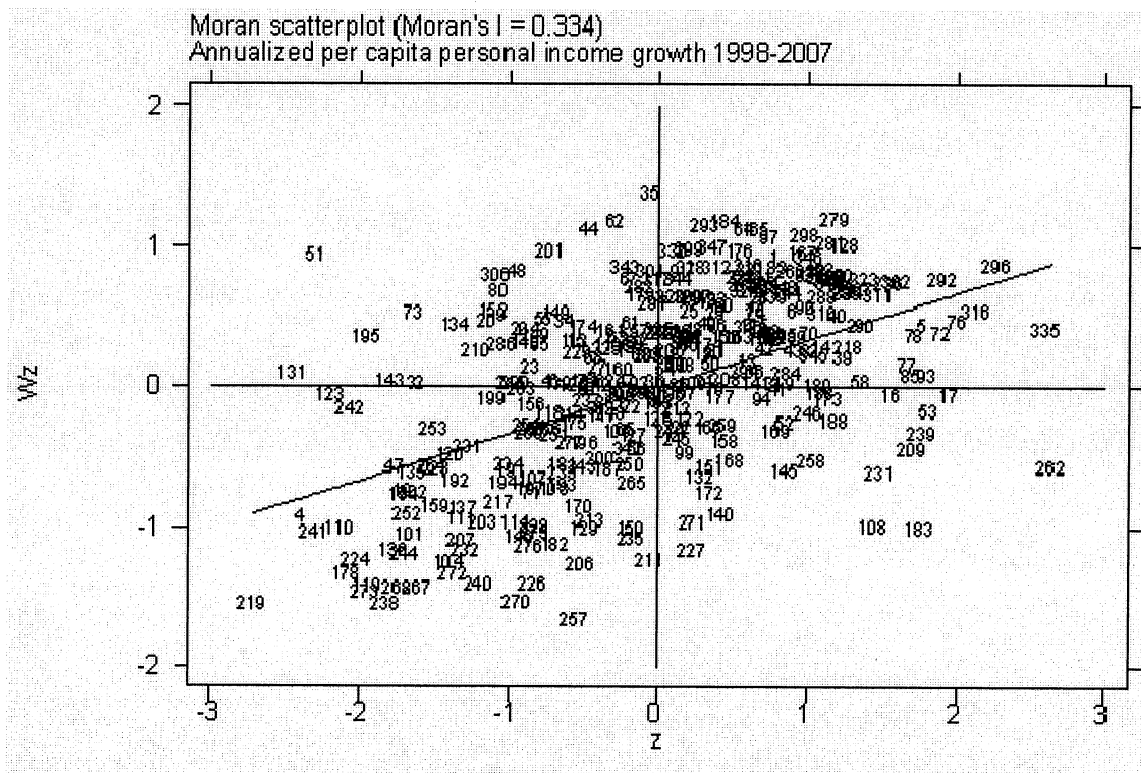


Figure 16 Moran's I scatterplot for Midwestern pilot counties

The spatial econometric regression for Midwestern pilot counties uses the cross-sectional specifications from earlier. The first regressor is the lagged dependent variable – that is, their respective value in neighboring counties. The spatial lag model used here is a mixed regressive-spatial autoregressive (SAR) model.

We have specified three SAR models: first, our dependent variable is regressed on the lagged dependent variable and the initial dependent variable; second, our dependent variable is regressed on the lagged dependent variable, the initial dependent variable, infrastructure, education and innovation (similar to the OECD spatial lag model); and third, our dependent variable is regressed on all independent variables.

Table 12 Spatial Regression Results

Dependent variable: ann. growth in p.c.
p.c.
etc.

	1	2	3
Lagged dependent variable	.517*	.477*	.448*

	(9.23)	(8.09)	(7.47)
Constant	.030	.045*	.074*
	(1.88)	(2.05)	(3.07)
Initial Income	-.002	-.005	-.009*
	(-1.69)	(-1.91)	(-3.11)
Highways		.084*	.080*
		(3.25)	(2.91)
High school diploma		-.005	-.015
		(-0.58)	(-1.56)
More than high school		.004	.002
		(0.61)	(0.23)
Employment rate			.021*
			(3.23)
Krugman index			.001
			(0.62)
Innovation index		.000	.000
		(1.47)	(1.41)
Variance Ratio (R-Squared)	0.132	0.183	0.213
Squared Correlation	0.257	0.274	0.288
Sample Size	349	349	349

The results show that the lagged dependent variable is significant and positive across the three models which means that there is significant positive spatial correlation of the dependent variable in these Midwestern pilot counties.

It is also important to note that infrastructure is positive and significant in models two and three confirming our previous results in the cross-section specifications.

The explanatory power is greatest when all independent variables are included in the spatial regression given a relatively high variance ratio.

MAIN FINDINGS

From the OLS cross section regression we find evidence that:

- Convergence of counties is occurring
- A more educated population is positively correlated with economic growth

- weakly but positively?*
- A higher density of major roads is positively correlated with economic growth
 - Employment specialization is positively correlated with economic growth
 - Distance to markets is positively correlated with economic growth

From the spatial regression we find evidence that:

- A county's growth rate is correlated with the growth rates of neighboring counties

In addition, we do not find that the innovation index obtained from the Indiana Business Research Center is statistically significant in our model, meaning that it does not help explain county-level economic growth. Individual components of the innovation index were also either not statistically significant or close to zero. Last, we find that the employment rate is inconsistent across specifications.

As displayed in Table 9, five of our findings were consistent with the OECD paper's findings for OECD regions: infrastructure was found to have a positive and significant relationship with per capita personal income growth; higher education was found to be positive and significant; employment rate was found to be negative and significant; employment specialization was found to be positive, although not statistically significant across all specifications; and distance to markets was found to be positive and significant. Both studies found the initial level of per capita personal income growth to be negative, although our study found it to also be statistically significant. Innovation, with number of patents per 10,000 people as a proxy, was found to be positive and significant in the OECD paper, while innovation, with the innovation index from the Indiana Business Research Center, was found to be negative and insignificant in our study. However, even when we isolated patents per 10,000 workers (a variable included within the innovation index), the coefficient was still negative and not statistically significant.

	Harris findings	OECD findings
Initial level of per capita personal income growth	Negative*	Negative
Infrastructure	Positive*	Positive*
Higher Education	Positive*	Positive*
Employment rate	Negative*	Negative*
Specialization	Positive	Positive
Distance to markets	Positive*	Positive*
Innovation	Negative	Positive*

Table 13 Comparison of papers' findings

When we included state fixed effects, we found that most of our results held. We found that including distance to education markets yielded higher growth for counties that are close to large pools of highly educated workers.

FUTURE RESEARCH

We have eight main recommendations to guide future research on the factors guiding economic growth in U.S. counties. First, future researchers should extend the analysis to more years and conduct a panel regression. Due to time constraints we were only able to evaluate a cross-section of the 10 years in question, 1998 to 2007. Second, we would have preferred to use the economic center of each county as the reference point for creating the distance to market variable, as opposed to the centroid, or geographical center, of each county. We were unable to locate this data with geographic coordinates attached. Third, it would be useful to calculate the actual road distance and time it takes to travel between county economic centers. In our construction of the distance to markets, we used straight-line distances between county centroids. Real road distance and travel time is a better indicator of distance to markets.

Fourth, we encourage future researchers to go beyond analyzing solely counties. It would be interesting to conduct regressions using Metropolitan Statistical Areas and Bureau of Economic Analysis economic areas. Fifth, future researchers should work more with the innovation index provided by the Indiana Business Research Center. While we conducted regressions using the composite index and various individual parts of the Index, none of which resulted in positive or statistically significant coefficients, there is more than can be explored. Putting the entire innovation index into a regression may not be the best way to use it, and other kinds of models should be explored.

Sixth, we think that further investigation into the effects of education and research spillovers would provide insight into economic growth. We captured the effects of being near other counties with high per capita personal income growth and a highly educated workforce, but other kinds of spillovers can be integrated into the model. Seventh, we would consider alternative definitions of neighboring. We used the concept of contiguity, although defining neighbors through inverse distance of k-nearest neighbor may lead to different results.

Last, future researchers should experiment with more and alternative measures of physical infrastructure. While we used major road density, as the OECD paper did, and experimented with airport density, it would be useful to incorporate railroad density, port access, among other types of infrastructure.

What about the issue of
"boundary" counties near
Mexico & Canada?
Might consider some type of
adjustment for them.

APPENDIX I

APPENDIX II

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ⁱ "...knowledge spillovers, in general, do not spread beyond a 80 to 110 kms radius from the MSA where they are generated (Varga 2000; Acs 2002)..." p. 22 (Crescenzi et al.)