UNDERSTANDING RURAL POVERTY CLUSTERS: THE INTERSECTION OF AGRICULTURE, ECONOMIC STRUCTURE AND LOCALITY UNDER POSTINDUSTRIALISM

A DISSERTATION
PRESENTED TO
THE FACULTY OF THE GRADUATE SCHOOL
UNIVERSITY OF MISSOURI – COLUMBIA

IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE

DOCTOR OF PHILOSOPHY

BY

DAVID J. PETERS

DR. DARYL HOBBS
DISSERTATION CHAIR

MAY 2006

UNDERSTANDING RURAL POVERTY CLUSTERS:
THE INTERSECTION OF AGRICULTURE, ECONOMIC STRUCTURE AND LOCALITY UNDER POSTINDUSTRIALISM

THE UNDERSIGNED, APPOINTED BY THE DEAN OF THE GRADUATE SCHOOL, HAVE EXAMINED THE DISSERTATION ENTITLED

UNDERSTANDING RURAL POVERTY CLUSTERS:
THE INTERSECTION OF AGRICULTURE, ECONOMIC STRUCTURE AND LOCALITY UNDER POSTINDUSTRIALISM

PRESENTED BY

DAVID J. PETERS

A CANDIDATE FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

AND HEREBY CERTIFY THAT IN THEIR OPINION IT IS WORTHY OF ACCEPTANCE.

DR. DARYL HOBBS, CHAIR

DR. THOMAS JOHNSON, OUTSIDE MEMBER

DR. JERE GILLES, MEMBER

DR. PEGGY PLACIER, MEMBER

DR. RONALD POWERS, MEMBER

ACKNOWLEDGEMENTS

I would like to extend a heart-felt thank you to Daryl Hobbs, who made the social scientist I am today possible. He has given me straightforward and insightful counsel throughout my graduate and professional career. His teaching has given me a firm grounding in the discipline. His research advisement has given me an ethic of intellectual craftsmanship. His extension work has demonstrated how important it is to transform data into information and knowledge.

In addition, I wish to thank the following faculty who have assisted me in my professional development. To Jere Gilles for imparting his knowledge of rural development and the sociology of agriculture. To Tom Johnson for imparting his knowledge of rural economics. To Peggy Placier and Ron Powers for their counsel during the dissertation process. Lastly, I also wish to thank the faculty in the Department of Rural Sociology for the excellent graduate education I have received.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

UNDERSTANDING RURAL POVERTY CLUSTERS:
THE INTERSECTION OF AGRICULTURE, ECONOMIC STRUCTURE AND LOCALITY UNDER POSTINDUSTRIALISM

David J. Peters

Dr. Daryl Hobbs, Dissertation Chair

ABSTRACT

Analysis seeks to understand rural poverty within the context of agricultural and postindustrial economic structure. Detailed socioeconomic data are analyzed for 4,610 non-metropolitan census tracts in the north central United States. Statistical cluster analysis is used to group tracts according to their similarity along four poverty measures. Multinomial logistic regression is used to predict cluster membership by taking into account agriculture, industry and occupation structure. Results found that both agriculture self-employment and wage-employment reduced near poverty. Core/basic industry employment tended to reduce near poverty, except for information that increased poverty. Semi-core industries tended to increase poverty while also decreasing near poverty. Periphery/non-basic industries tended to reduce near poverty, except the leisure industry which increased poverty. In terms of occupation, the professional-managerial class was associated with low poverty clusters, except cultural workers that increased poverty. Working class occupations were associated with average poverty clusters. Lower services class occupations were associated with poverty and near poverty cluster membership.

CHAPTER ONE

INTRODUCTION AND JUSTIFICATION

When speaking of poverty in the United States, the usual archetype conjured up in the public mind is a place that is urban and mostly African-American (Gilens 1999). This image has also pervaded much of the academic research, which has focused on the urban underclass created from a culture of poverty and economic decline in urban America (Jones 1992; Wilson 1987). Few Americans realize that poverty, while persisting in places similar to the archetype above, also exists in rural America. This alternative archetype is a place outside of central cities, mostly white, and consisting of mostly intact families or the elderly. Although urban poverty has been studied for the better part of two decades (Gilens 1999; Jones 1992; Katz 1989), rural poverty has only recently begun to be studied in great detail (Albrecht, Albrecht and Albrecht 2000; Duncan 1999; McLaughlin 2002). This research has shown that rural poverty is not only severe, but is enduring and growing.

During the 1990s, America experienced unprecedented economic growth and a large decline in the national poverty rate. Real gross domestic product in the 1990s grew at twice the average rate of the previous two decades, growing by four percent annually. Correspondingly, as the economy grew at a fast rate poverty also declined by a fast rate, dropping by nearly 10 percentage points during the 1990s, from 17 percent in 1993 to 11 percent in 2000 (U.S. ERS-USDA 2004). The new century ushered in a brief recession, thereby halting the nation's economic expansion and leading to an increase in poverty. According to the U.S. Census, the poverty rate has continued to increase even as the nation has begun to recover from the recession, with recent estimates placing the poverty rate at just over 12 percent in 2002 (Proctor and Dalaker 2003).

Further, during this economic expansion the gaps between high income and low to middle income families became historically wide (Jones and Weinberg 2000). Bernstein, Boushey, McNichol and Zahradnik (2002) found that in 45 states the gap between the income of the richest 20 percent of families and the incomes of the poorest 20 percent of families is wider than it was two decades ago. In 39 states the incomes of the richest 20 percent of families grew faster than the incomes of the poorest 20 percent of families. Middle income families also lost ground over the past two decades. In 44 states the gap between the average income of middle income families and the average income of the richest 20 percent of families widened.

The rate of poverty is not only an important social indicator of the well being of America's poor, but it is also a useful tool in shaping public policies and targeting program benefits to those most in need (Nord 1997). However, poverty rates are not equally distributed across the nation, and policies to reduce poverty must consider the differences between nonmetropolitan (rural) and metropolitan (urban) poverty. According to the U.S. Department of Agriculture (U.S. ERS-

USDA 2004), although both rural and urban areas have shown the same trends in poverty over time, the rural rate has exceeded the urban rate every year since the 1960s. This rural-urban gap shrank to its narrowest point during the 1990s, yet even then rural poverty rates were still three percentage points higher than urban rates.

The following section discusses the characteristics of rural poverty, and draws heavily from the U.S. Department of Agriculture's (U.S. ERS-USDA 2004) *Rural Poverty at a Glance*. Nearly 7.5 million rural people were poor in 2002. This translated into a rural poverty rate of 14.2 percent, which was nearly three percentage points higher than the urban poverty rate of 11.6 percent. Rural poverty is strongly correlated with race, ethnicity, age, and family structure. Poverty rates were higher for minorities than for non-Hispanic Whites. More than one out of every four rural Hispanics, African-Americans, and Native Americans live in poverty. Compared to non-Hispanic Whites, the rural poverty rate was nearly three times as high for rural minorities in 2002. For example, the poverty rate for rural non-Hispanic African-Americans was 33 percent, for Native Americans it was 35 percent , and it was 27 percent for Hispanics – all much higher than the 11 percent poverty rate for rural non-Hispanic Whites.

Another strong correlate of poverty is family structure. In rural America, over 75 percent of all rural families were headed by a married couple, and these families had the lowest rate of poverty at seven percent. By contrast, about 15 percent of rural families were headed by a single female, and an astounding 37 percent of these families live in poverty. The poverty rate for people living in female-headed families is 10 percentage points greater in rural areas than in urban areas. In terms of child poverty, in rural American roughly 2.6 million children lived in poverty in 2002. This means that one out of every five rural children was poor. This poverty effect is exacerbated by race and ethnicity, with almost half (46 percent) of all rural non-Hispanic African-American children being poor and 43 percent of rural Native American children being poor.

The rural South has the highest and most persistent poverty rates in the nation. The U.S. Department of Agriculture identifies persistently poor areas that have had 20 percent or more of their populations living in poverty for over the last 30 years. According to this measure of persistent poverty, 386 of the nation's over 3,000 counties were persistently poor, with rural counties making up the large majority (340 of 386) of persistent poverty counties. In terms of population, only four percent of the nation's population lived in persistently poor counties, yet nearly 14 percent of the nation's rural population lived in such counties. Among rural persistent poverty counties, 280 are in the South, 60 are in the West and Midwest, while none are in the Northeast.

Rural areas are very diverse in terms of population size and proximity to urban areas, and rural poverty seems to vary by this rural-urban continuum. Looking at the two ends of this continuum in terms of persistent poverty, 17 percent of all completely rural counties were persistently poor, compared to only four percent of all metropolitan counties. Given these differences and the fact that metropolitan areas had low poverty, it is surprising that 17 percent of metropolitan-adjacent rural counties were persistently poor. For smaller urban areas or micropolitan counties, roughly 13 were persistently poor; and 17 percent of all micropolitan-adjacent rural counties were persistently poor.

Many researchers have identified several factors that have contributed to the presence and growth of poverty and inequality. Much of this research has identified wage inequality and the primary cause of overall poverty (Bluestone and Harrison 2000; Borjas and Ramey 1994; McCall 2001; Morris and Western 1999; Nielsen and Alderson 1997). Wages at the bottom and middle of the wage scale have been stagnant or declined during the last two decades. At the same time, however, the wages of highest paid workers has increased significantly. Based off this premise, other researchers have identified the causes of poverty and wage inequality. These include globalization and restructuring of the economy (Chevon and Stokes 2000; Lobao 1990; Lobao, Rulli and Brown 1999; Murphy and Welch 1993), immigration and migration (Duncan 1999; Fulton, Fuguitt and Gibson 1997), and the weakening of labor laws and unions (Brown and Lee 1999; Osterman 1999).

This dissertation seeks to understand poverty clusters in rural America in the context of the postindustrial economy. It is hypothesized that different types of agricultural and economic structures have a differential impact on the level of poverty in rural areas. In terms of agricultural structure, it is posited that the character of labor relations impacts poverty. In terms of economic structure, it is posited that the type of dominant industries and occupations impacts poverty. By understanding the interaction between poverty and economic structure, rural citizens and governments can be better informed on how the local economy impacts their socioeconomic well being. This information can then be used to inform collective action within the community and public policy within various units of government.

Rationale

Why study rural poverty? Perhaps the strongest justification is the way that poverty is concentrated in rural America. As discussed above, persistently poor counties are disproportionately found in rural areas, especially in the rural South. Among all 386 persistently poor counties, 340 are classified as nonmetropolitan (U.S. ERS-USDA 2004). Of these, 280 are located in the South, 60 are located in the West and Midwest, while none are located in the Northeast. Even within persistently poor nonmetropolitan counties there are differences, with 114 being rural but adjacent to metropolitan areas, 88 being micropolitan areas, 85 being rural but adjacent to micropolitan areas, and 53 being completely rural.

A second reason for studying poverty is to keep the poor on the policy and research agenda in order to target interventions. A credible measure of poverty can be a powerful instrument for focusing the attention of policy makers on the living conditions of the poor. Put more bluntly, it is easy to ignore the poor if they are statistically invisible. The study of poverty is thus necessary if it is to appear on the political and economic agenda. Further, one cannot help the poor without at least knowing who they are. This is the purpose of poverty analysis, which sets out the major facts on poverty and then examines the pattern of poverty to see how it varies by geography, community characteristics, and household demographics. Probably the most important operational use of poverty analysis is to support efforts to target development resources towards poorer areas.

For example, continued poverty and inequality could undercut the basis of reforms made to the welfare system in recent years (Ellwood 2000; Findes and Jensen 1998). Current policy is based on the assumption that a job is the first step to self-sufficiency and to moving out of poverty. When former welfare recipients can only find jobs that do not pay enough to lift a family out of poverty, and the real incomes of the poorest families grow only slowly if at all over time, the underpinnings and future success of policies that encourage work are called into question.

Lastly, social scientists need to study rural poverty to better understand why poverty is deeper and more persistent in rural areas than in urban areas, and why it is more difficult and expensive to implement policies to reduce poverty in rural areas than it is in urban areas. The Rural Policy Research Institute has identified four current trends that articulate clearly the need for understanding rural poverty. First, that persistent poverty appears to be concentrating in rural counties. Second, high barriers to economic self-sufficiency in rural areas continue to yield worse outcomes for rural workers and families. Third, rural communities still do not have the capacity to provide work and family supports that lead to success in the labor market. Finally, policies to improve the well being of low-income families are becoming less effective in rural relative to urban areas.

Previous research has made it clear that poverty has been increasing in the United States. It is generally agreed that changing economic, household, and demographic structures have contributed to the increase in poverty and inequality (Glickman 2000; Lobao and Saenz 2002). This change has been placed in the shift from an industrial to a postindustrial economy, which has been outlined extensively by Bonnanno and Constance (1996), Lash and Urry (1994), and McMichael (1996). Industrial capitalism, also termed Fordism, was dominant throughout the twentieth century until the 1970s. This economy operated around the mass production of homogenous products using inflexible technologies, like the assembly line. This necessitated the adoption of standardized work routines, which increased productivity through economies of scale and the deskilling of labor. In turn, this created a market for the homogenous products of the mass production industry, which resulted in the homogenous consumption patterns of industrial/Fordist workers.

These theorists have argued that the factors contributing to the decline in industrial capitalism or Fordism has given rise to a new economic system. Under this new order termed postindustrial capitalism or post-Fordism, there is a declining interest in the products of mass production and a growing interest in specialized products, particularly those denoting status or quality. These specialized products require shorter production runs using smaller, more productive and technologically dependent systems. To maintain this fast changing and technology dependent production system, workers need more diverse skills and better training. As workers become more differentiated, they come to want more differentiated products, lifestyles and cultural outlets. Further, what is produced under postindustrialism is not just material objects, but also includes signs that have either cognitive content such as data or information, or aesthetic content such as style or popular media (Lash and Urry 1994, 1987).

Change in economic structure, brought on by the transition to postindustrialism, impacts rural communities more acutely because their economies are less diverse than urban ones. Dominated by one or two industrial sectors, any changes in capital, technology, or markets will have a stronger effect on employment and income in rural economies than they would in more diverse urban ones (McLaughlin 2002). Further, any changes in the dominant industries will create a larger ripple or multiplier effect in the rural economy, mainly through household consumption. In short, expansion or contraction of a dominant industry in a less diverse rural economy creates a more pronounced change in income distributions than in more diverse urban economies.

Two major strands of literature, the sociology of agriculture and segmented economy theory, have identified how changes in structure impacts poverty and general socioeconomic well-being. The agricultural structure literature, often termed sociology of agriculture, specifically links the organization of agriculture to the economic and social conditions within a community. This literature argues that communities with absentee-owned industrial farms are less developed both economically and socially than similar communities composed mainly of family farms. The economic structure literature, often termed segmented economy theory, also maintains that different industrial structures result in different socioeconomic outcomes. Communities more dependent on core or basic industries (export-oriented industries dependent on external factors) are more developed both economically and socially than those dependent on periphery or non-basic industries (local-oriented industries dependent on local factors). However, much of the segmented economy literature is based on industrial or Fordist notions of core/basic and periphery/non-basic industries.

There is a need to merge these two traditions of research in the context of postindustrial or post-Fordist economic structure. The agriculture structure literature has largely treated the non-farm economy as a monolithic whole, failing to recognize the different externalities produced by different economic sectors under postindustrialism. At the same time, the segmented economy literature has produced limited understanding of how postindustrial economic structure affects rural communities, and has virtually ignored the farm economy. This analysis merges these two traditions of research and addresses the methodological shortcomings of each approach in the context of a postindustrial economy and postmodern society.

Although previous researchers have already merged these two traditions of research, they have done so in the context of an industrial or Fordist economic structure (Gilles and Dalecki 1988; Green 1985; Lobao 1990; Lobao, Schulman and Swanson 1993). Their research leaves several important questions unanswered regarding the interaction between agricultural and industrial structure. Is the agriculture-industry structure hypothesis still relevant in a postindustrial economy increasingly dependent on services and transfers, and where the agricultural base is rapidly declining? Is the hypothesis a historically specific construct of the industrial or Fordist era that no longer holds true in the postindustrial era? Is using occupational structure a better measure of the postindustrial economy than industrial structure? Does the agriculture-industry structure hypothesis hold true when tested using postindustrial definitions of the economy that focuses more on information, communications and advanced producer services? Does the agriculture-industry structure hypothesis hold true when using occupational structure instead of industrial structure? Does the hypothesis also hold true at a more localized unit of analysis?

Objectives and Significance

The purpose of this analysis is to understand poverty in rural America in the context of agricultural and postindustrial economic structure. It is posited that different types of agricultural and economic structures have a differential impact on the level of poverty in rural areas. To investigate this question, detailed socioeconomic data are analyzed for all nonmetropolitan census tracts in the north central region of the United States. Specifically, this analysis has four main objectives.

The first objective is to identify rural poverty clusters in the North Central region using statistically appropriate methods. Poverty clusters, as they are termed in this analysis, are identified in socioeconomic space, not geographic space. Thus, tracts are grouped according to their similarity on poverty levels and not on any geographic or spatial dimensions. Although there are most likely spatial patterns in the clusters, spatial characteristics are not explicitly incorporated into the analysis. This analysis employs statistical cluster analysis to group census tracts into clusters according to their similarity in poverty rates and change from a decade ago. Cluster analysis is one of the most appropriate methods to create a typology or classification, where the procedure attempts to mathematically reorganize data into homogenous groups that can be statistically validated. Previous research identifying poverty clusters has used relatively simple techniques that group counties based on arbitrary thresholds (Cook and Mizer 1994).

The second objective is to determine how agricultural structure affects membership in a rural poverty cluster. Here the structure of agriculture is defined in terms of labor and ownership relationships. It is posited that greater concentrations of self-employed workers in agriculture reduces poverty. Conversely, it is posited that greater concentrations of workers employed as wage laborers in industrial agriculture increases poverty. These hypotheses are drawn from the sociology of agriculture literature, and tests whether communities characterized by family farm agriculture are more developed socioeconomically than those characterized by industrial agriculture.

The third objective is to determine how postindustrial economic structure affects membership in a rural poverty cluster. It is posited that greater concentrations of workers employed in postindustrial core/basic industries and semi-core/semi-basic industries reduces poverty. Conversely, it is posited that greater concentrations of workers employed in postindustrial periphery/non-basic industries increases poverty. These hypotheses are drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by postindustrial core industries are more developed socioeconomically than those characterized by postindustrial periphery industries.

The fourth objective is to determine how occupational structure affects membership in a rural poverty cluster; and whether the results differ from that of industrial structure. It is assumed that occupational structure will reflect class structure. It is posited that greater concentrations of workers employed in postindustrial professional-managerial occupations reduces poverty. Conversely, it is posited that greater concentrations of workers employed in lower services occupations increase poverty. These hypotheses are also drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by the new postindustrial upper class, which mainly includes professional-managerial occupations, are more developed socioeconomically than those characterized by the new postindustrial lower class, which mainly includes lower-skill services occupations.

By addressing these objectives, this analysis fills existing gaps in the poverty, sociology of agriculture, and segmented economy literatures. In general, the analysis takes four unique approaches to understanding rural poverty and how it is impacted by local agricultural and economic structures under postindustrialism. First, this analysis identifies clusters of rural poverty using statistically appropriate methods. The most commonly used typology of poverty is from the U.S. Department of Agriculture's Economic Research Service, which defines persistent poverty counties as those with a poverty rate of 20 percent or more each year in 1970, 1980, 1990 and 2000 (Cook and Mizer 1994). Although this definition is consistent with the U.S. Census Bureau's practice of identifying poverty areas, it is limited in terms of the methods used. Instead of relying on a single threshold to determine poverty, this analysis will use a statistical procedure termed cluster analysis to group census tracts into homogenous clusters according to their similarity in poverty rates and change from a decade ago. Therefore, there is a need to identify high poverty areas using more rigorous methods.

Second, this analysis examines the relationship between poverty and agricultural structure and economic structure at lower levels of aggregation, specifically at the sub-county census tract level. Appropriately, much of the previous research done to date has used counties as the unit of analysis. However, very little research has looked at whether county-level results hold true when looking at lower levels of aggregation, such as census tracts. Therefore, there is a critical need to reevaluate previous research that tests relationships across lower levels of aggregation.

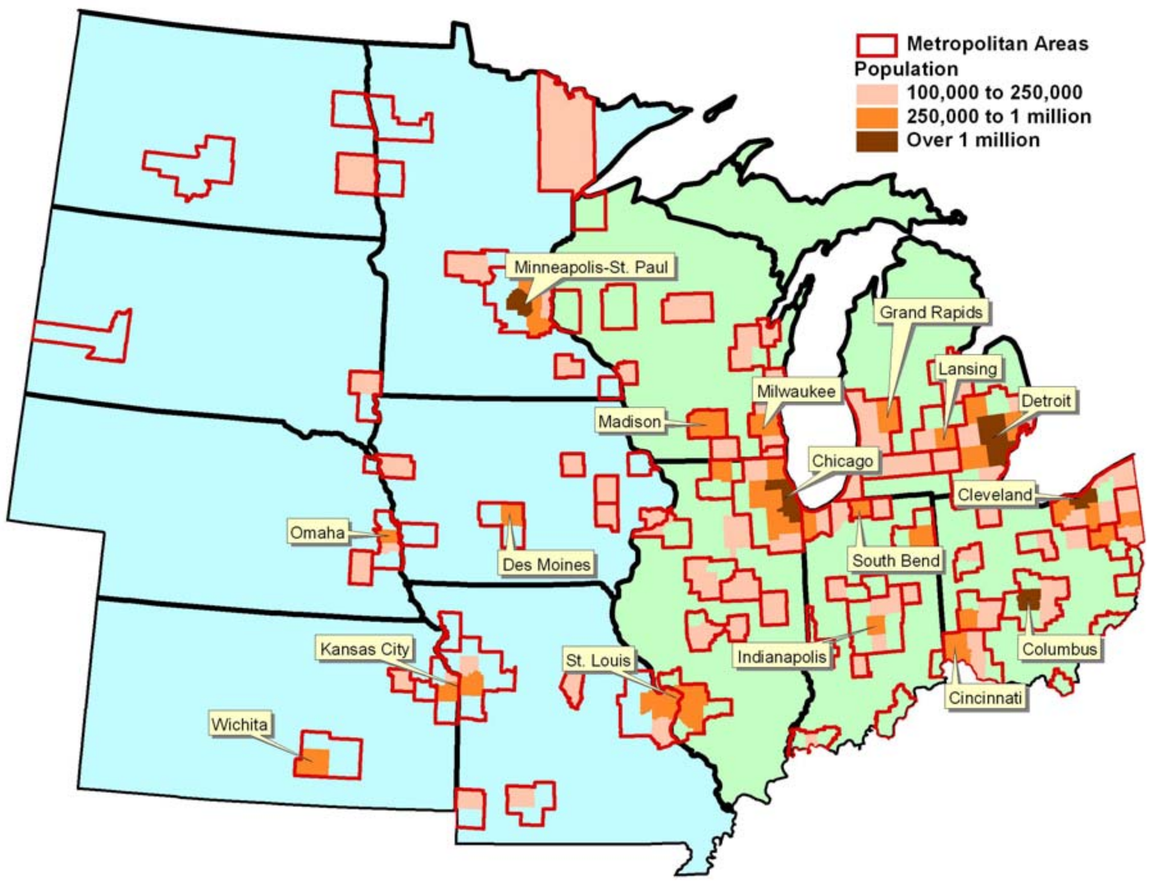
Third, this analysis defines economic structure using industrial classifications that better reflect the current postindustrial economy. Much of the previous research done to date has used industrial classifications that reflect the old industrial economy. The new industry classifications, developed in the late 1990s, are much more reflective of the postindustrial economy in that it places greater emphasis on the information and service producing segments of the economy. By contrast, the old industry classifications were first developed in the 1950s and are outdated since it places greater emphasis on manufacturing and the goods producing aspects of the economy. Therefore, there is a critical need to reevaluate previous research in light of this new and more accurate definition of the economy.

Fourth, this analysis also defines economic structure using occupational classifications that reflect what workers do, not just the type of industry in which they work. Much of the previous research done to date has not looked at occupational structure as the primary organizational principle of the economy. Under postindustrialism, new production systems require workers to possess more diverse skills and better training in order to handle more demanding and sophisticated technologies. This makes it necessary for workers to have more responsibility and autonomy than they did under an industrial economy. This differentiation of labor is occurring in all industries, even in traditional manufacturing sectors. Further, occupations will be used as proxy measures for socioeconomic class, to test whether the new postindustrial class structure impacts poverty. Therefore, there is a critical need to reevaluate previous research that incorporates an occupational-based definition of the economy, which better reflects the postindustrial economy.

Overview of the North Central Region

The north central region is a diverse section of the United States, ranging from densely populated urban centers to sparsely populated rural areas. The region consists of 12 states that encompass over 680,000 square miles and over 60 million people, roughly 20 percent of both the nation’s land area and population. The U.S. Census Bureau often bifurcates this region into the East North Central and West North Central regions. This breakout is instructive given the differences between the two regions. The East North Central region contains the five eastern states of Illinois, Indiana, Michigan, Ohio, and Wisconsin; while the West North Central region contains the seven western states of Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota. Information for this narrative is taken from the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (U.S. BLS 2002).

FIGURE 1
North Central Region – East and West Divisions



The eastern portion of the region is heavily urbanized, containing core metropolitan areas like Chicago, Detroit, Cleveland, and Indianapolis. In fact, the eastern states in this region have the highest population densities per square mile, starting with Ohio (277 people per square mile), Illinois (223 people per square mile), Michigan (223 people per square mile), and Indiana (170 people per square mile). In 2000, the total population of the eastern region stood at 33.9 million people. Between 1990 and 2000, the eastern region had fairly strong population growth, ranging from over nine percent in Indiana and Wisconsin to under five percent in Ohio. The eastern states also had a more ethnically diverse population, with only 86.3 percent of the population being non-Hispanic whites.

In 2000, the labor force participation rate stood at 69.0 percent, with an unemployment rate of nearly four percent. Median household income for the eastern region averaged around $45,000 per year, with an annual poverty rate in 2000 of around 10.0 percent. In terms of industry structure, employment in the eastern region was dominated by manufacturing, trade, and professional services. Manufacturing employed 25.3 percent of all workers in 2000, principally in durable goods producing transportation equipment and machinery. Trade accounted for 24.5 percent of total employment, however nearly all of these jobs were in retail trade. Lastly, professional services employed around 20 percent of the workforce, with about half of these jobs in the health care industry. Next looking at what workers do rather than where they work, the top employing occupations in the eastern region were: operators, fabricators, and laborers at 16.3 percent; professionals at 15.0 percent; executives and managers at 13.8 percent; administrative support and clerical workers at 13.7 percent; and service occupations at 13.2 percent.

By contrast, the western portion of the region is mostly rural, containing only three core urban areas including Minneapolis-St. Paul, St. Louis, and

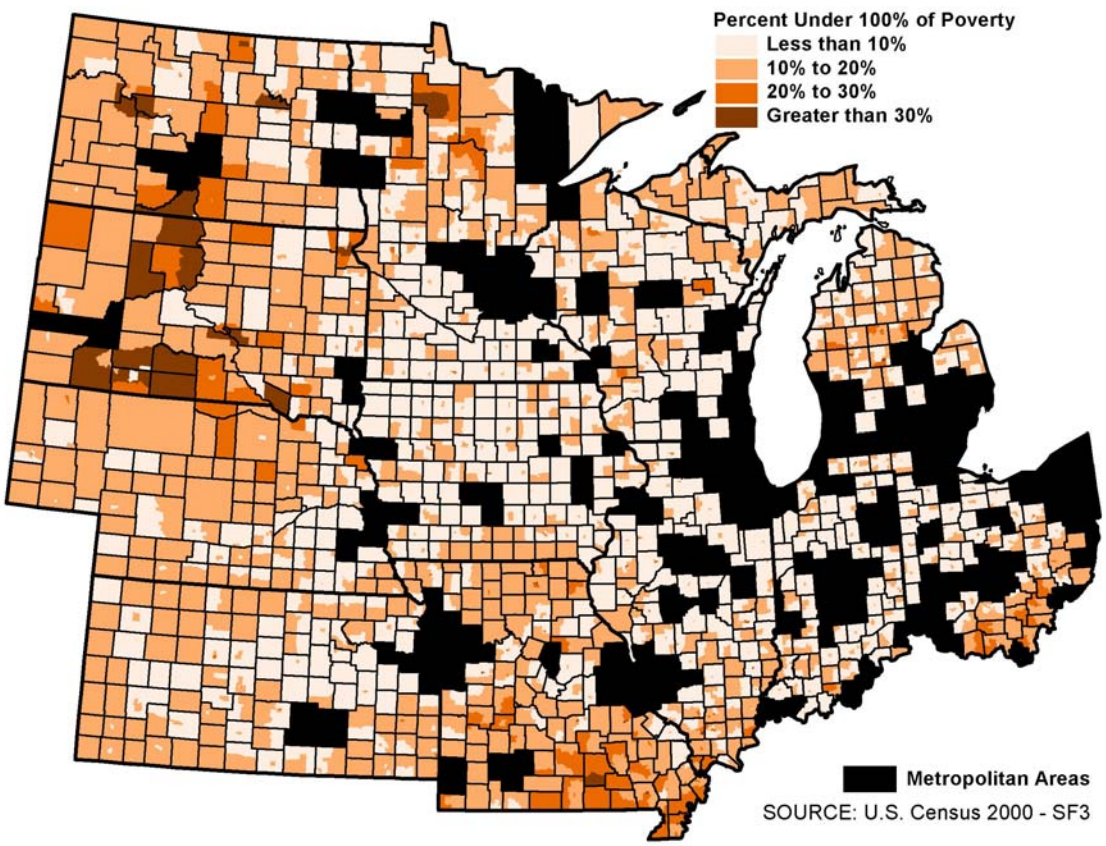
Kansas City. The western states in this region have some of the lowest population densities per square mile, starting with North Dakota (9 people per square mile), South Dakota (10 people per square mile), Nebraska (22 people per square mile), Kansas (33 people per square mile), and Iowa (52 people per square mile). In fact, the highest density occurs in Missouri, with only 81 people per square mile. In 2000, the total population of the western region stood at 14.3 million people, roughly half that of the eastern region. Between 1990 and 2000, the western region had mixed population growth, ranging from fast growth states like Minnesota (12.4 percent) and Missouri (9.3 percent), to slow growth ones like North Dakota (0.5 percent) and Iowa (5.4 percent). The western states also had a less ethnically diverse population, with 92 percent of the population being non-Hispanic whites.

In 2000, the labor force participation rate stood at 72.1 percent, with an unemployment rate of a little over three percent. Median household income for the western region averaged around $37,000 per year, with an annual poverty rate in 2000 of around nine percent. However, within the western region there was greater disparity in incomes, with Minnesota having the highest median income ($47,111) and lowest poverty rate (7.9 percent); and with North and South Dakota having the lowest median incomes (about $35,000) and highest poverty rates (about 12.0 percent). In terms of industry structure, employment in the western region was dominated by trade, professional services, and manufacturing. Trade accounted for 25.5 percent of total employment, however nearly all of these jobs were in retail trade. Professional services employed a little over 20 percent of the workforce, with about half of these jobs in the health care industry. Lastly, manufacturing employed 19.4 percent of all workers, roughly split equally between durable goods (machinery and transportation equipment) and non-durable goods (food products and printing/publishing). Looking at the occupational side, the top employing jobs in the western region were: professionals at 15.2 percent; executives and managers at 14.3 percent; administrative support and clerical workers at 14.0 percent; operators, fabricators, and laborers at 13.3 percent; and service occupations at 12.7 percent. Finally, as one would expect the western region had 4.4 percent of the workforce employed in farming and forestry occupations, compared to only 1.9 percent in the eastern region.

Although the overview given above is useful in getting a broad understanding of the north central region, it does not capture the diversity of socioeconomic conditions at the local level. When using only aggregate statistics, the detail and context of the data are lost. By looking at the distribution of that information at the local level, pockets of poverty and prosperity can be identified that leads to a full understanding of the data and the conditions in local areas.

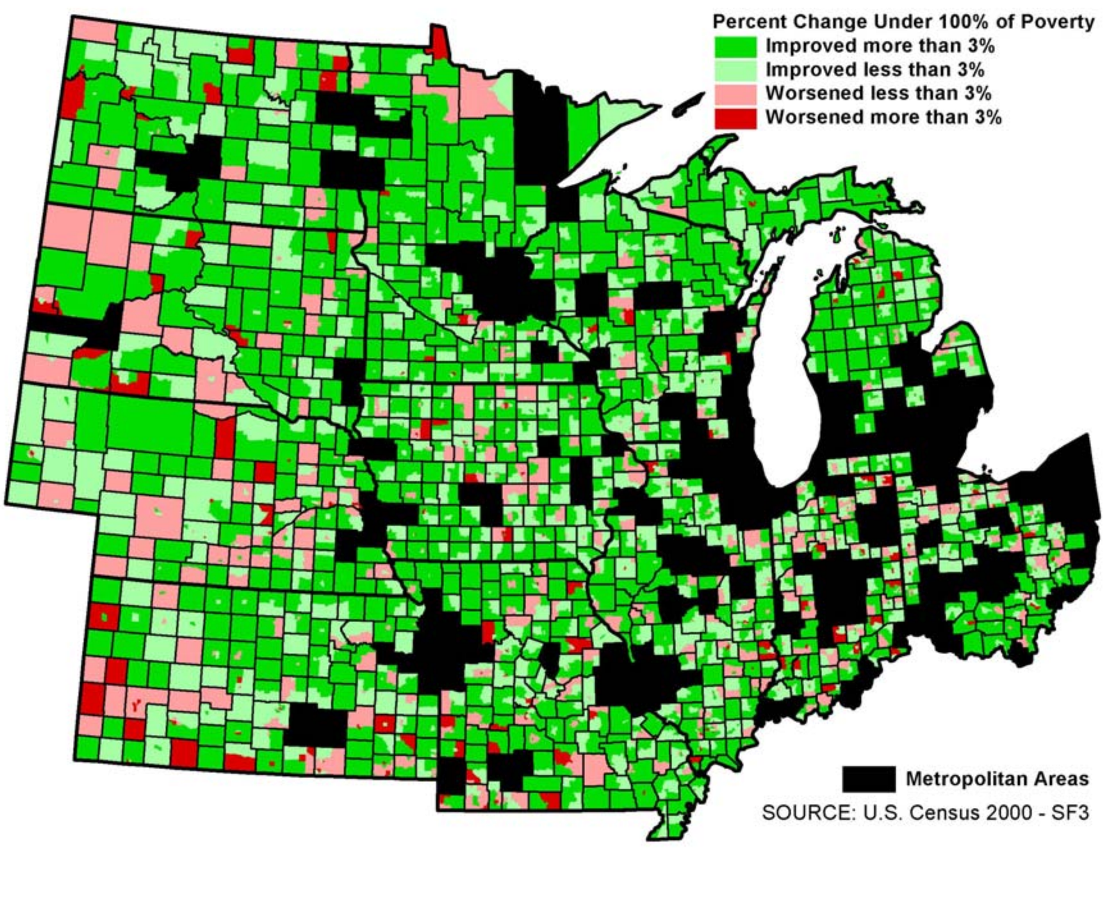
Poverty, measured as the percent of households under 100 percent of poverty in 2000, was unequally distributed in the north central region. The highest poverty concentrations were located on Native American reservations in the Dakotas and northern Minnesota. High poverty areas were also found in the national forest and public land areas of the Ozarks in southern Missouri and the Appalachian foothills of southern Ohio; and in the Bootheel of southeast Missouri. Conversely, poverty was lowest in southern Minnesota, Iowa, Wisconsin, northern Illinois, Indiana, and northern Ohio.

FIGURE 2
Percent Under 100% of Poverty in 2000



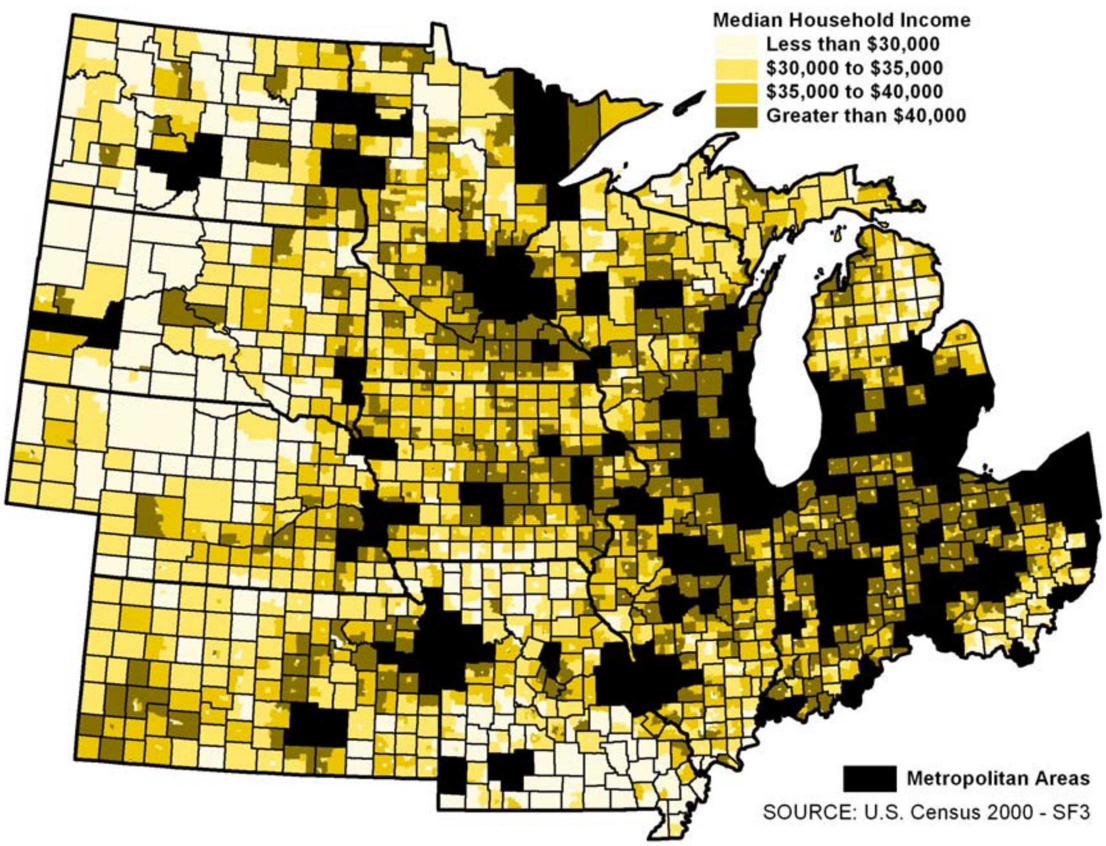
During the last decade, poverty worsened in areas generally west of the Mississippi River. Poverty rates become worse on Native American reservations in the Dakotas and northern Minnesota, in remote rural areas of Kansas and Nebraska, and in the recreation and tourism areas of southwestern Missouri. Otherwise, poverty rates improved throughout most of the region during the decade of the 1990s. Areas with the greatest improvements were found in Minnesota, Wisconsin, and Michigan; and to a lesser extent in Illinois, Ohio, and Iowa.

FIGURE 3
Percent Change Under 100% of Poverty 1990-2000



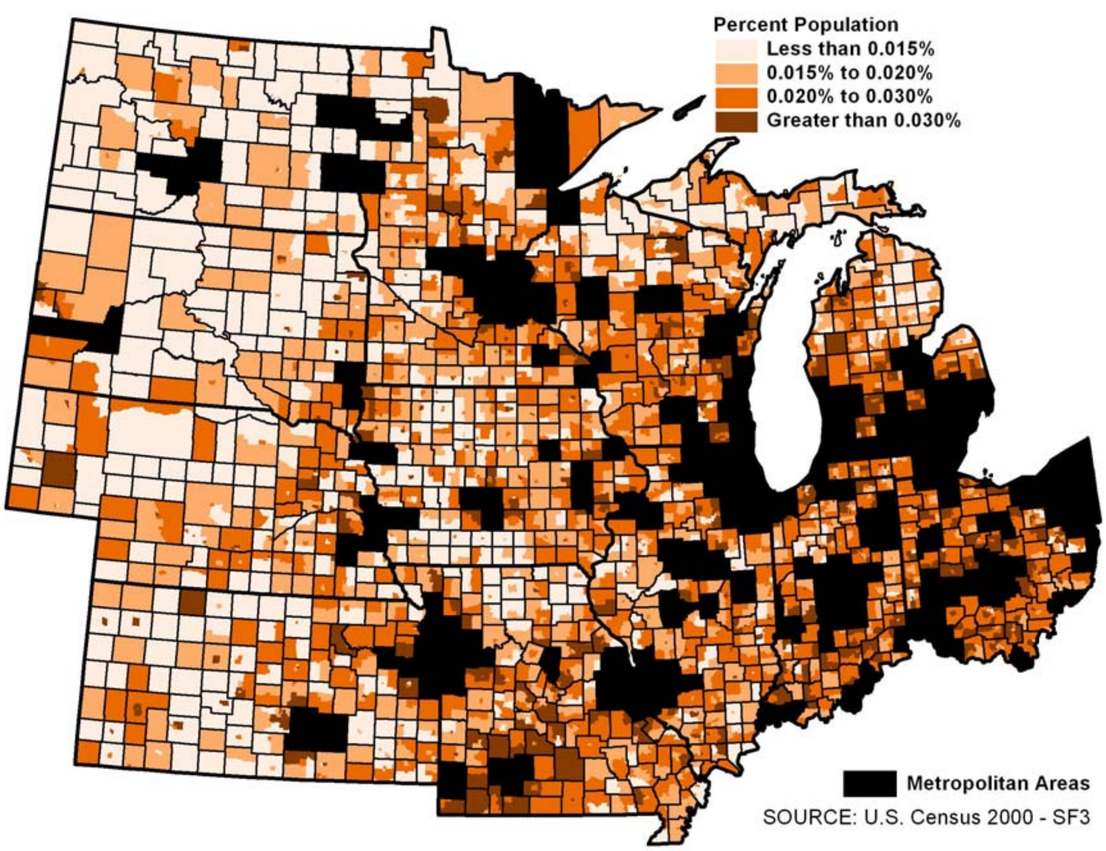
Median household income in 2000 was highest in areas adjacent to metropolitan areas and in the eastern states – especially in southeastern Wisconsin, northeastern Illinois, northern Indiana, southern Michigan, and northern Ohio. Surprisingly, income was also high in areas of northern Minnesota and Michigan, and in southwestern Kansas. By contrast, areas with the lowest median incomes were located in the rural areas of the Dakotas, Nebraska, and northern Missouri; and also in the national forest and public land areas of southern Missouri and Ohio.

FIGURE 4
Median Household Income in 2000



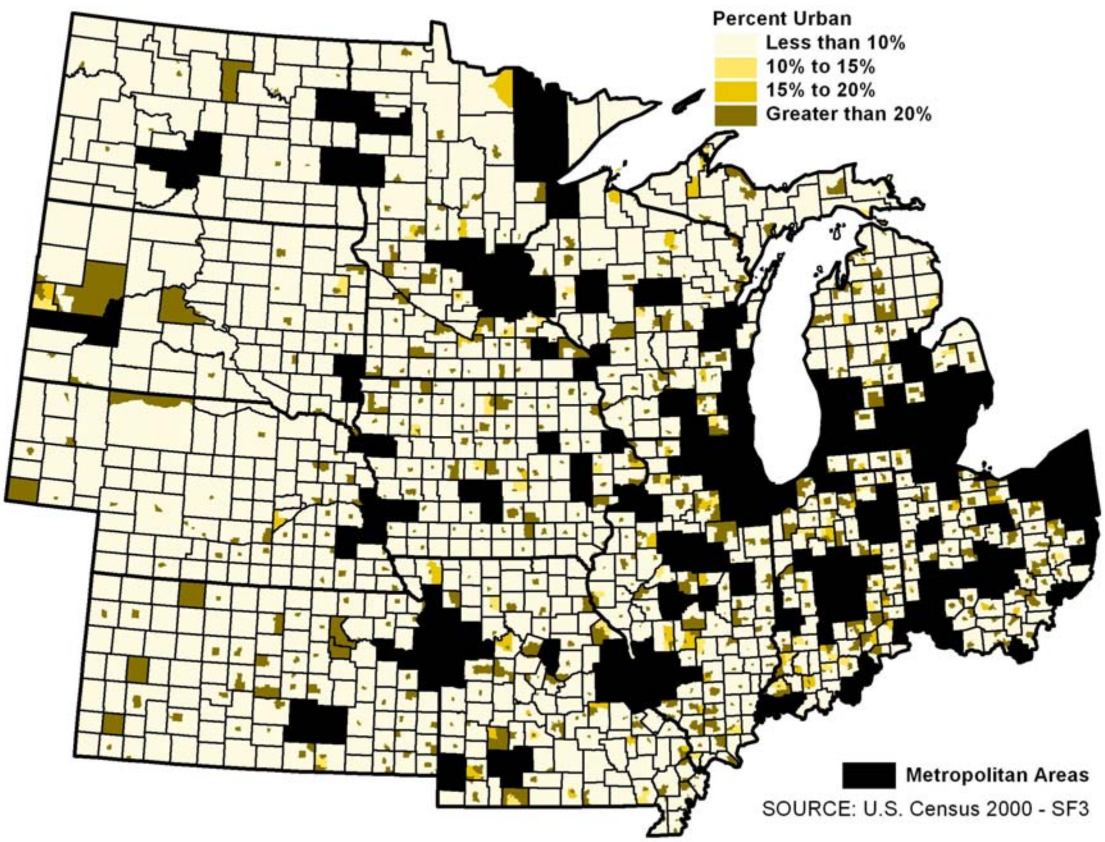
In 2000, the nonmetropolitan population was unevenly distributed across the north central region. Areas with the largest share of the total nonmetropolitan population were generally located in eastern states and areas adjacent to metropolitan areas. Specifically, high population areas were located in Ohio, Michigan, Indiana, northern Illinois, and southern Wisconsin. Large populations were also found in high amenity and retirement areas of southwestern Missouri, and in parts of central Minnesota and Wisconsin. Conversely, low population areas were located in the Great Plains states, western Iowa, northern Missouri, and in the northern areas of Wisconsin and Michigan.

FIGURE 5
Percent of Nonmetropolitan Population in 2000



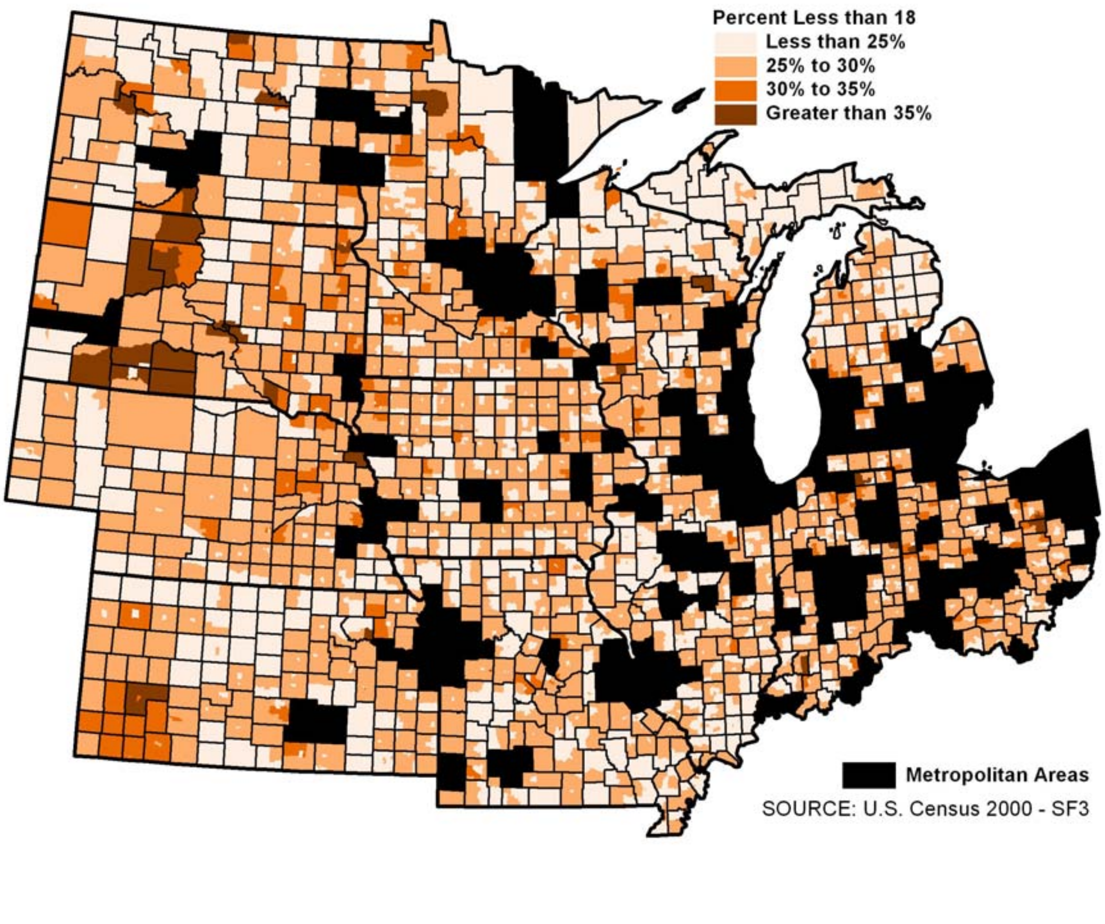
Urban populations were generally dispersed throughout the north central region, but tended to concentrate in tracts adjacent to metropolitan areas and in the eastern states. This information is useful in identifying rural towns in the study area.

FIGURE 6
Percent Urban Population in 2000



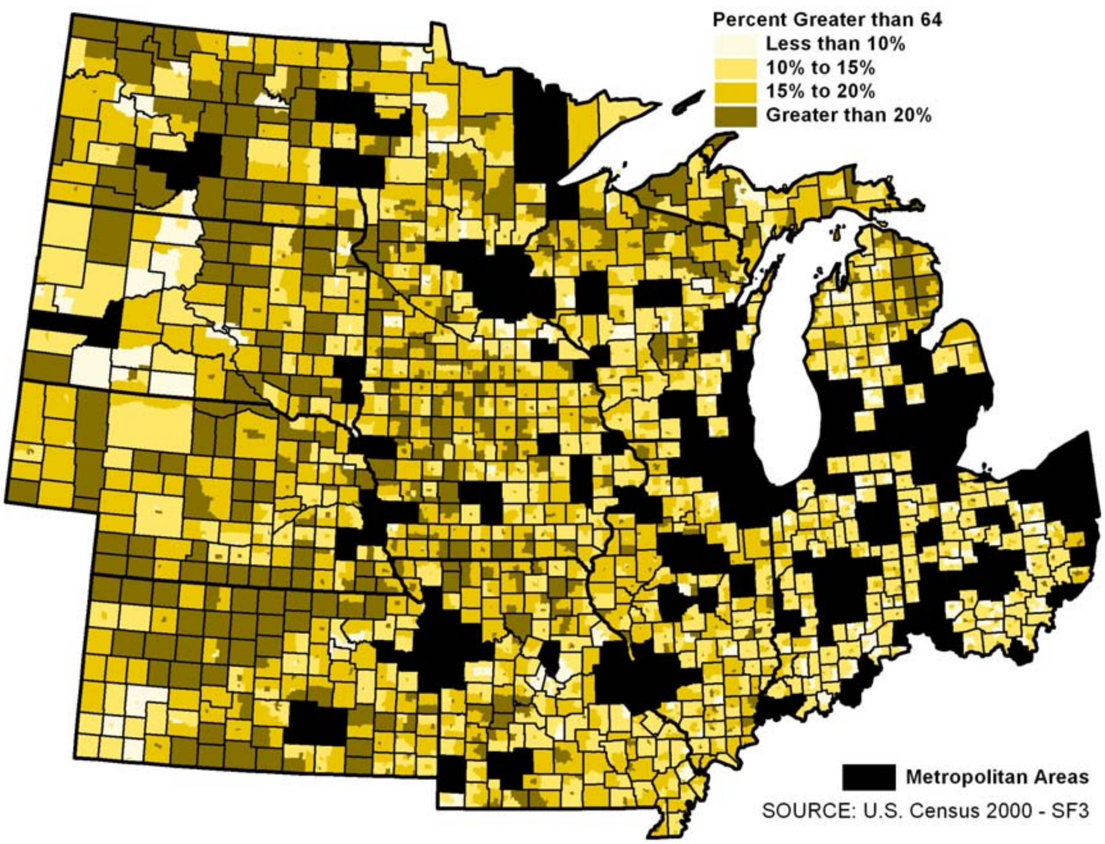
Although the percentage of the population under 18 years of age was fairly uniform across the region, generally standing around 25 to 35 percent of the population, some differences exist. The greatest concentrations of young people were found on Native American reservations in the Dakotas and in northern Minnesota and Wisconsin. Other concentrations were found in southwestern Kansas, eastern South Dakota and Nebraska, and in areas adjacent to metropolitan areas.

FIGURE 7
Percent Under 18 Years of Age in 2000



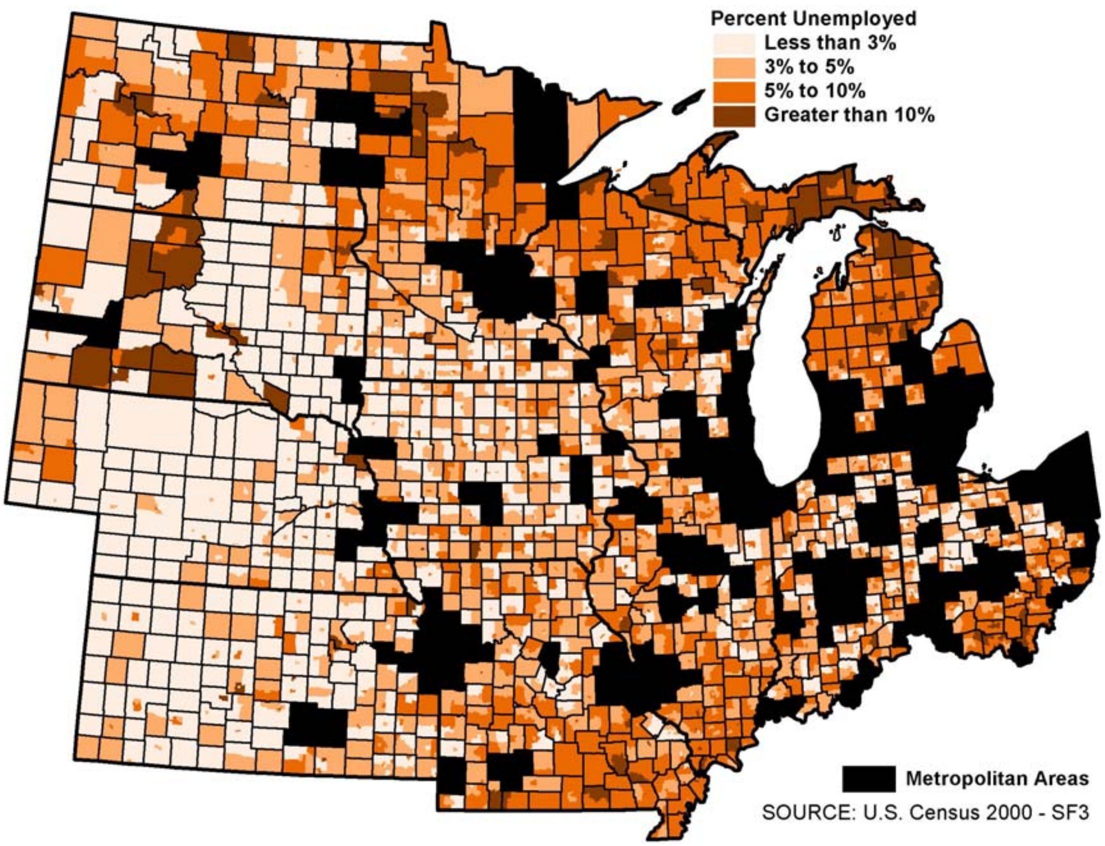
On the other hand, the greatest concentrations of people over 64 years of age were found in more remote and less populated areas of the north central region characterized by public forests and farming. Specifically, these include public forest areas in northern Minnesota, Wisconsin, and Michigan; and in remote farming areas of the central Dakotas, Nebraska, and Kansas.

FIGURE 8
Percent Over 64 Years of Age in 2000



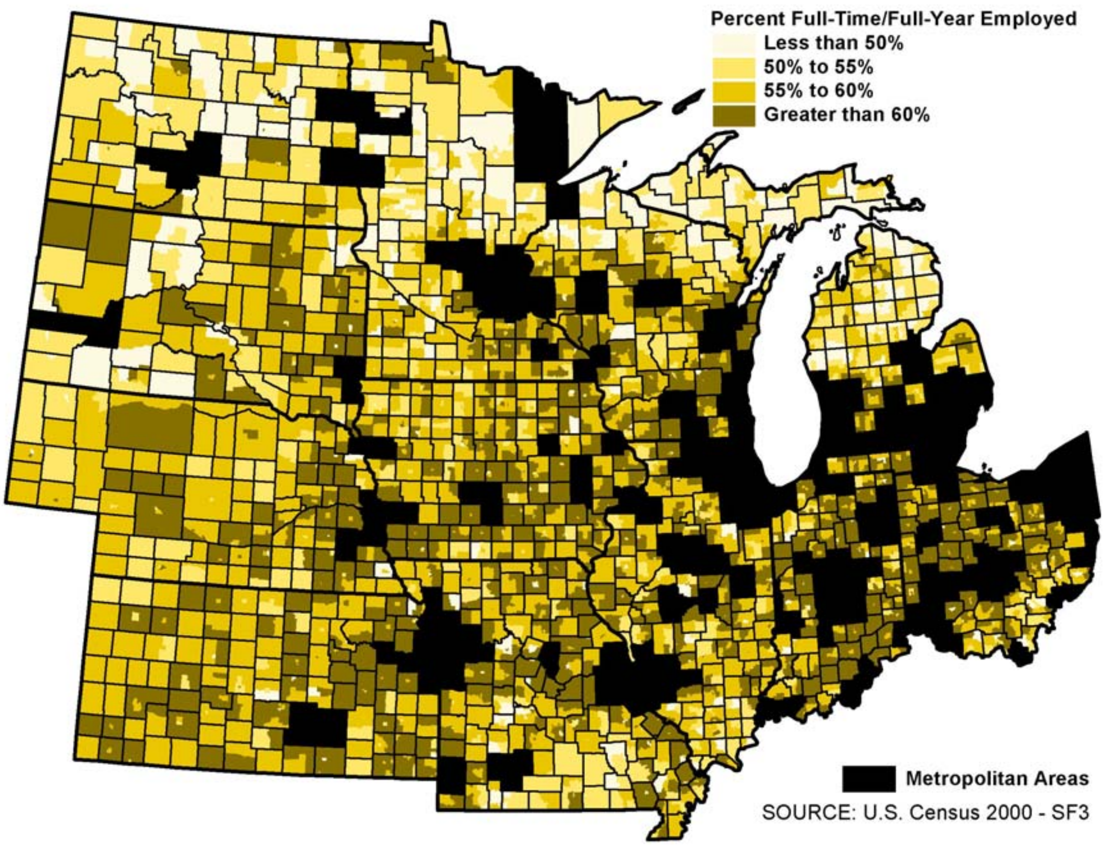
Unemployment was also highly localized in the north central region. Pockets of high unemployment were primarily concentrated on Native American reservations and on national forests and public lands. Unemployment in the Dakotas and northern Minnesota occurred exclusively on reservations, while unemployment in Wisconsin and Michigan was mainly due to large tracts of national forests and reservations. Further south, pockets of unemployment were found in the recreation areas of southwestern Missouri, and in the public land areas of southeastern Missouri and southern Ohio. By contrast, unemployment was lowest in the Great Plains states outside of reservations.

FIGURE 9
Percent Unemployed in 2000



The percent of the working population employed in full-time and full-year jobs mirrored the spatial pattern found in unemployment rates. In general, workers in the north central region were employed in full-time and full-year work, especially in metropolitan adjacent areas and in the eastern states. Lower rates were found on Native American reservations in the Dakotas, and in public forest areas in northern Minnesota, Wisconsin, and Michigan.

FIGURE 10
Percent Full-Time and Full-Year Employment in 2000



CHAPTER TWO

ECONOMIC SOCIOLOGY

This analysis is grounded in an easily recognized field within the discipline of sociology known as economic sociology. However, this field of inquiry is often not well understood by scholars outside of sociology; and even among sociologists the term economic sociology is oxymoronic. Therefore, the purpose of this chapter is to define the field of economic sociology as distinct from traditional economics, and to present the classical traditions of economic sociology found in the works of Marx, Durkheim, and Weber.

Definition and Concepts

Economic sociology is the application of frames of reference, variables, and explanatory models of sociology to the complex of activities concerned with the production, distribution, exchange and consumption of goods and services. This sociological perspective of the economy includes social interaction, group dynamics, social structures and institutions, social control through norms and values, social networks, and cultural contexts. Perhaps the best manner to describe economic sociology is to compare it to mainstream economics, of which a synopsis is presented in Table 1. The following discussion relies heavily on the work of Smelser and Swedberg (1994).

In terms of the *Concept of the Actor*, the analytic starting point of the economic perspective is the individual, whereas in the sociological perspective it is the group, institution, and society. In the sociological perspective, the individual is discussed as a socially-constructed entity, in other words as an actor-in-interaction or an actor-in-society (Schumpeter 1926). Methodological individualism is not necessarily incompatible with a sociological perspective, but individual actors are of interest to sociologists only in understanding social action (Weber 1922).

TABLE 1
Comparison of Economic Sociology with Mainstream Economics

	Economic Sociology	***Mainstream Economics***
Concept of the Actor	Actor is influenced by other actors and is part of groups and society.	Actor is uninfluenced by other actors – methodological individualism.
Economic Action	Many types of economic actions are used, including rationality - rationality as a variable.	All economic actions are assumed to be rational – rationality as an assumption.
Constraints on Action	Economic actions are constrained by scarcity of resources, by social structures, and by meaning structures.	Economic actions are constrained by tastes and by the scarcity of resources.
Economy in Relation to Society	Economy is seen as an integral part of society, where society is always the basic reference.	The market and the economy are the basic references, society is a given.
Goal of Analysis	Description and explanation, rarely prediction.	Prediction and explanation, rarely description.
Methods Used	Plethora of methods used. Data are often produced by the analyst (“dirty hands”).	Formal methods / mathematical models used. No data are used (“clean models”).
Intellectual Tradition	Emphasis on classical theory which is constantly reinterpreted.	Emphasis on current theory, where the classics belong to the past.

NOTE: From Smelser and Swedberg (1994).

In terms of the *Concept of Economic Action*, the economic perspective assumes that any actor has a given and stable set of preferences and chooses the course of action which maximizes some utility in the case of individuals or profit in the case of firms. This is termed economic rational action. Conversely, in the sociological perspective economic action can be rational, traditional, or irrational. Weber's (1922) formal rationality is much like economic rational action, concerning itself with the efficient use of scare resources. However, his substantive rationality refers to the allocation of scarce resources within the guidelines of other principles like loyalties, communal affection, values, and other similar concepts.

Sociology views rationality as a variable, not as an assumption. Some action is more rational than others and can be explained (not assumed) to occur under specific social and cultural conditions. A good example of this is Weber's (1922) argument that formal rationality is associated with a specific development process that occurred in the Occident. Further, sociology views the meaning of economic action as historically constructed, which differs from the economic view which is from tastes, prices, and quantity. Perhaps the most important distinction between the two perspectives is the concept of power and how it affects economic action. Sociology explicitly incorporates power into economic action that encompasses the market, politics, and class in society. By contrast, economics rarely includes power because economic action is assumed to occur between equals with free flows of information.

In terms of the *Constraints on Action*, the economic perspective views actions constrained by tastes and the scarcity of resources. It assumes that individuals will always try to maximize their utility independent of other persons. In other words, every individual in society acts independent of other persons, and is assumed to be free from social wants, prejudices, preferences, and values. By contrast, the sociological perspective takes these influences into account. It assumes that other individuals either facilitate or constrain individual actions within the market. For example, a long friendship between a buyer and seller may prevent the buyer from deserting the seller, even though the buyer can obtain the good for less from someone else (Dore 1983). Another example of how cultural meanings affect choices so they are not rational is that many people in the United States would not buy dog or cat meat for food, even though it is cheaper and just as nutritious as traditional meats (Sahlins 1976).

In terms of the *Economy in Relation to Society*, the economic perspective's main foci are on economic exchanges, the market, and the economy. The rest of society is assumed to be stable and operate within certain parameters, including lawful and stable governments, legal systems, and transactions. Recently, economics has turned its attention as to why institutions rise and persist. Termed "new institutional economics", this analytic framework attempts to explain the ways in which institutions and institutional change affect the performance of economies over time (Eggertsson 1990; North 1990). This school of thought argues that institutions exist due to the uncertainties involved in human interaction, and that institutions are devised to structure that interaction. However, institutions vary widely in their consequences for economic performance, with some economies developing institutions that produce growth and development and others developing ones that produce stagnation.

By contrast, in sociology economic processes have always been regarded as part of society in constant interaction with other societal forces. In general, Smelser and Swedberg (1994) identify three main foci of economic sociology in this regard. First, it undertakes a sociological analysis of economic processes. Second, it examines the interactions and connections between the economy and the rest of society. Lastly, it takes into account changes in institutional and cultural parameters that constitute the economy's social context.

In terms of the *Goals of the Analysis*, in economics the main focus is on prediction and explanation, and the field is often critical of description as being too theoretical. By contrast, the main focus in sociology is on description and explanation, and the field relies much less on prediction. As a result, sociology is critical of economics for generating models that are too formal and abstract, and which ignore empirical data. Conversely, economics is critical of sociology for their incapacity to make predictions and their penchant for post-facto social interpretations (Merton 1968).

As for *Methods Used*, economics focus on prediction places a high value on mathematical expressions of hypotheses and models. While there are many advantages to this approach, some economists have noted that formal modeling often becomes an end unto itself. Leontif (1971) critiqued economics for its uncritical enthusiasm of mathematical formulations, noting that more than half of the articles published in the journal *American Economic Review* consisted of mathematical models that were not related to any data (Leontif 1982).

When economics does use empirical data it is generated by economic processes, such as market behaviors, stock indices, and official government statistics. Other sources of data are only occasionally used, such as sample surveys in consumption economics and archival data in historical economics. Needless to say, ethnographic data is rarely used. By contrast, sociology relies on a wide array of methods, from secondary data and surveys, to participant observation and case studies, and the qualitative analysis of texts. In short, an observation by Hirsch, Michaels, and Friedman (1990) nicely sums up the differences in methods between economics and sociology: where economics has “clean models” that use no empirical data, and sociology has “dirty hands” where empirical data is often produced by the analyst.

As one might assume, economics and sociology rely on different *Intellectual Traditions* that only overlap slightly. However, the two disciplines regard their traditions differently. Economics is traditionally influenced by a natural sciences model of systematic accumulation of knowledge. The field is less interested in the study and interpretation of economic classics, save for a few foundational theorists like Adam Smith and David Ricardo. This results in a sharp distinction between current economic theory and historical economic theory. By comparison, sociology often blends current and classic theories, where the classics are constantly reinterpreted and taught. In keeping with this sociological tradition, the following discussion highlights several major classical theorists and their contributions to economic sociology.

Karl Marx

Karl Marx developed his core ideas about the economy and social relations in *Grundrisse* (1858), *A Contribution to the Critique of Political Economy* (1859), and Marx's most well known work *Capital* (1867). His analyses assume that the economy is the real foundation of society, upon which the legal and political system is dependent upon. At the same time, the forces of production come into contradiction with the relations of production, with the resulting crisis leading to revolution. In these works, Marx develops the idea that history is propelled by class struggle, and that there exists only two major classes in capitalist society, namely bourgeoisie and proletarians. The contradiction of these two classes would eventually result in crisis where the proletariat would usher in a classless society through revolution.

Marx begins by stating that the subject of discussion is, above all, material production. Marx states that individuals producing in society – the socially determined production of individuals – constitute the starting point of economic analysis; and not the isolated individual as hunter or fisher, who forms the starting point of other economists such as Adam Smith and David Ricardo. Marx stresses that humans have never been isolated, but have always depended on the larger whole. Marx goes on to say that production must be seen at a certain stage of social development. In order to speak of production at all, he argues, one must trace the historical process of development through its various stages or explicitly state that one is dealing with a particular historical period.

Marx states that a product becomes a commodity through a process of exchange. Commodities are converted into exchange value, so they can be used in other transactions. When a product becomes a commodity, and a commodity an exchange value, it possesses a dual form that includes the material product and the exchange value. When the exchange value is separated from the actual commodity itself and becomes a separate commodity, it is termed money. Money is defined as the exchange value of commodities. This exchange value or money has an existence separate from the commodity or product. Marx conceptualizes money as: a standard measurement of exchange for commodities; a means of exchange; a representation of commodities; and a universal commodity alongside special kinds of commodities. In other words, personal power has changed into material power as people must produce exchange value or products (including the division of labor) in order to provide sustenance for themselves.

Related to this, Marx states that the universal nature of production creates alienation of individuals from themselves and others. In an undeveloped system of exchange, personal relationships between individuals are determined by a fixed set of rules and roles, such as feudal lord to vassal or landlord to serf. In the developed exchange system characterized by money relationships, personal relationships and blood ties are broken, as people are now independent to barter within limits. When A pays for services rendered by B, Marx states that this is not the transformation of money into capital. Rather, it is money as a means of circulation in order to obtain use value – consumption is not equivalent to production.

Marx argues that what is seen as surplus value by capitalists is seen as surplus labor by workers, which is labor beyond the requirements necessary for their livelihood. This surplus value is the essence of capital, where surplus value is equated with surplus labor and surplus production. In order for this surplus production to establish and create itself as capital, it divides itself into two forms: objective labor conditions, meaning the raw materials and instruments of production; and subjective labor conditions, meaning the subsistence for labor during the act of production. Contradictions between objective and subjective labor conditions separate property from labor, and leads to the alienation of living labor which is continually produced by the alienated laborers themselves.

Marx posits that capital strives towards the universal development of productive forces, for wealth, for universal commerce, and for a world market. The more developed capital becomes, the more it seeks to dismantle local barriers to commerce, to capture the world as its market, and to minimize the time required for movement from one place to another. Marx stresses that the development of science (both a product and producer of wealth) aids in these goals, and is a key factor in the disintegration of feudal society and the rise of capitalist society.

Marx delineates two types of labor – specific and general. Specific labor is defined as the autonomous production of private individuals, and mediation is carried out by the exchange of goods, exchange value and money. General labor, on the other hand, views individual labor as collective labor from the start. The worker does not buy the particular products they create, but participates in collective production. Marx indicates that once labor is absorbed into the productive process of capital, it undergoes various metamorphoses, the last of which is the machine.

Marx goes on to state that the historical transformation of the production process to machinery is equated with the trend towards an increase in the productivity of labor. This productivity increase is not due to the direct skill of the worker, but is due to the direct application of science to the production process. This reduces labor to a simple element in the production process. Marx caustically states that only in the imagination of economists does machinery come to the aid of the worker. The introduction of machinery, Marx asserts, expropriates the worker and alienates them from their work and from others. Additionally, machines allow capitalists to produce the maximum number of objects with the minimum amount of labor.

Marx has been critiqued for reifying a set of economic categories and elevating them to the status of universal laws. Many of his ideas and analyses have also been criticized as inapplicable to today's postindustrial society, especially where the dichotomous class structure of bourgeoisie and proletarians no longer exists (Bell 1960; Habermas 1975; Marcuse 1964). However, Marx's ideas have heavily influenced sociology through modern schools of thought like critical theory, political economy, humanist Marxism, and structural Marxism.

For example, the major sociological paradigm for analyzing domestic agricultural development remains Marxian political economy. Similar in many ways to neoclassical economics, this school acknowledges that market competition and petrochemical technology are reasons why farms have gotten larger and fewer. The difference between the two lies in who controls and benefits from this system. Political economy sees market competition as socially produced and regulated in ways that benefit large capital interests, and which are detrimental to most farmers, consumers and the environment (Buttel and Newby 1980; Friedland, Busch, Buttel and Rudy 1991).

Emile Durkhiem

Durkheim, on the other hand, disliked economics because it only acknowledged the individual, of its strict utilitarian interpretations, and its tendency to create an economic world that does not exist. He summarizes his critique of political economy as (Smelser and Swedberg 1994:11):

> … an abstract and deductive science which is occupied not so much with observing reality as with constructing a more or less desirable ideal; because the man the economists talk about, this systematic egoist, is little but an artificial man of reason. The man that we know, the real man, is so much more complex: he belongs to a time and a country, he lives somewhere, he has a family, a country, a religious faith and political ideas."

Durkheim's most important contribution to economic sociology is the *Division of Labor in Society* (Durkheim 1893). From the start it should be pointed out that within this work there is a theory of societal evolution. All throughout the first section, Durkheim draws upon a number of inferences from the field of biology with which he compares to the functioning of society. The demarcations of mechanical and organic solidarity are themselves allusions to biological references – in the very term of "organic" solidarity we see his preference for biological referencing.

Through observation, Durkheim concludes that the two general types of societies are primitive hunting-gathering bands and nineteenth century western nation-states, whose social bonds are held together by two different types of solidarity. Societal evolution is in part responsible for the division of labor in society, and Durkheim proceeds to show how the latter society evolved from the former. Durkheim not only uses biology to explain societal evolution, he also draws upon biological inferences in order to explain the integrative and disintegrative features of social life. A major question that Durkheim tries to answer concerns what factors are responsible for social life – a question that several contemporaries of Durkheim were asking, including those coming from the utilitarian tradition.

It is in reference to his utilitarian peers that Durkheim declares that the division of labor, as a form of social organization, was not the fundamental fact of all social life. His reason for refuting the utilitarian viewpoint seems to be that he could not buy into the utilitarian belief that work is divided among independent and already differentiated individuals, who by uniting and associating bring together their different aptitudes. For Durkheim, it would be a miracle if these differences, arising from chance circumstances, could be so accurately harmonized as to form a coherent whole.

If the division of labor is not the fundamental fact of all social life, then it must have some importance for Durkheim because he used the concept to explain the growth of social organization from the mechanical-based to the organic-based society. Mechanical-based societies are simple social systems, usually consisting of tribes or clans. They operate under legal codes that are repressive, members of the society are homogeneous in that they are all able to perform the necessary tasks that will keep them alive, and the collective conscience is so strong that the individual and society are in such close agreement that a particular set of norms and values are supported. By contrast, organic-based societies are characterized by a division of labor in society. This results in a new legal code that is no longer repressive, but rather restitutive. Differentiation and specialization makes the members of organic societies heterogeneous, and that results in greater complexity and interdependence.

In order to explain the growth of social organization within the confines of comparing and contrasting mechanical and organic societies, Durkheim follows Darwin and posits that a greater increase in population causes greater demands on the resource base, which leads to greater competition. Under the pressure of competition, a more elaborate division of labor may occur. Specialization of labor allows for greater societal output, as each differentiated group comes to exploit select aspects of the resource base and exchange their products with those of others. Durkheim posits that there are certain material and physical requirements that a society must have if the division of labor is to take place. These include an increasing population, the formation of cities, and a system of communications and transportation.

Lastly, Durkheim discusses some of the negative forms associated with the division of labor, which include the anomic division of labor, the forced division of labor, and imperfect integration. In opening up the discussion, Durkheim states that if the division of labor does not produce solidarity it is because the relationships between the organs are not regulated, in what he calls a state of anomie. The anomic division of labor refers to the diminishing of the individual by reducing them to the role of the machine – no more than a lifeless cog. The forced division of labor refers to the institution of classes or castes and constitutes a form that is closely regulated. Durkheim advances that one's birth places them in a particular social group that shapes individuals' tastes and aptitudes, and limits their choices. The final abnormal form concerns itself with the imperfect integration of actor and task. Imperfect integration is largely characterized by a regrettable waste of effort by Durkheim, which leads to anomie and an eventual disintegration of the division of labor.

In short, Durkheim argues that economists were wrong is assuming that the division of labor is only a means to create wealth and further efficiency. To Durkheim, it creates cohesion and solidarity in modern society as roles become more differentiated and people stop being bound together by mechanical solidarity and become interdependent upon one another through organic solidarity. Organic society is held together by the rights and duties that develop around these interdependencies that the division of labor produces, and that it is these rights and duties – not economic exchanges or market structures – that hold society together.

Durkheim’s ideas created the functionalist school in modern sociology, which was the hegemonic perspective in the discipline until the 1970s. The most well known theorist of functionalism is Talcott Parsons, whose social systems theory argues that the crucial feature of any society is homeostasis. The key to achieving homeostasis is a central value system that imputes common values on all of society's members to regulate behavior and to make society function efficiently.

Max Weber

Weber is often considered the founder of modern economic sociology. In *Economy and Society* (Weber 1922), Weber lays out a new broad and multidisciplinary economics that includes economic theory, economic history, and economic sociology. He argues that in studying economic phenomena the researcher has to draw on all three perspectives to achieve understanding, and not let one type of perspective dominate the others. The economic sociology at the core of *Economy and Society* focuses on the economy itself and its links between other parts of society. Weber remarks (Smelser and Swedberg 1994):

> The connections between the economy … and the social order [such as law, politics, and religion] are dealt with more fully [in this work] than is usually the case. This is done deliberately so that the autonomy of these spheres via-à-via the economy is made manifest.

Two of Weber's works can be considered founding documents of economic sociology: *The Theory of Social and Economic Organization* (1920) and *Economy and Society* (1922), both of which are based off Weber's unfinished manuscripts. Throughout these works Weber highlights the unique characteristics of modem society and economic organization. Most of the works are devoted to defining concepts that are relevant to his theoretical understanding of the emerging modern society and economy. Weber demonstrates how rationalization is a key aspect of the modernization process. He suggests that this process changes both social and economic organization. A fundamental aspect of this change is the development of bureaucracy. In his presentation, Weber often responds to earlier descriptions of modernization given by Marx. Most often, Weber demonstrates how even socialism does not address what Weber would consider the most fundamental aspects of modern society.

To begin, Weber argues that sociology can make unique contributions to the understanding of modern society and social changes. He suggests that a purely organic or functional approach will not capture the essence of social change. Instead, Weber argues that sociology also needs to look at the subjective meanings individuals ascribe to changes, but he also notes that institutions influence individual actions. Therefore, this interpretive framework also applies to collective action. Unlike psychology, sociology does not separate the psychic from the physical when trying to explain action. The use of ideal types is one method sociologists may use to explain social actions and their meanings. Taking this as his point of departure, Weber then examines social organization.

Weber suggests that there are four basic types of social action: rational orientation to discrete individual ends; rational orientation to absolute values; affectual orientation; and traditional orientation. A characteristic of modern social action is that it is done out of self-interest rather than just following customs. In traditional society, people were not forced to follow custom but did so more or less because they had always done so in the past. Weber indicates that the more rational social action becomes the more likely people's reactions will be similar to one another. This is evident in market behavior in which people buy and sell commodities guided by similar notions of self-interest.

The legitimacy of social action also differs in modern societies from more traditional societies. Whereas the validity of social action in traditional society was based on custom, with modern society there is a gradual transition to legitimacy based on legality. Rather than action based on compliance with tradition, rational action is based on the belief in rules which are formally correct and have been imposed by an accepted procedure. Weber contends that the nature of social relationships has also changed from the traditional to the modern society. There have been changes from communal forms of solidarity to associative forms of solidarity. The communal form of solidarity is more likely to be based on custom or tradition, and the associative form on rational interests. An example of an associative form of social relationship would be the exchange relationship of the market. Also, social position in communal solidarity is more likely to be determined by selection, rather than through competition as in associative solidarity.

Weber's two works on economic sociology also devotes much space to the sociological categories of economic action. Weber points out several key features in the rationalization process of the economy. First, a rational exchange involves a situation in which both parties involved expect to make a profit and arrive at a compromise over price. Striving to make a profit characterizes the modern era in contrast to meeting needs in earlier times, and money is the most rational means of exchange. Second, he argues the development of the factory system is based on the development of rationality. It is primarily based on mechanized sources of power, the division of labor, and the subsequent development of the managerial function based on technical expertise. Weber cites the following conditions to achieve formal rational organization of productive enterprises: market freedom, autonomy in the selection of management, freedom of labor markets, freedom of consumption, mechanically rational technology, legal legitimation, and the separation of the private from the public.

Another form of social relation is the corporate group. Weber characterizes a corporate group as a closed relation, where there are rules or some means of controlling entry into the relationship. Corporate action may take place when a person has the authority to act on behalf of the organization. Although this is not unique to modern society, Weber briefly describes the modern development of the ultimate corporate group – the nation-state. Weber describes the nation-state as a corporate body into which people are born into and which has a territorial basis. A key feature of the modern state is that it has monopolized the legitimate right to use force.

Weber also devotes time discussing the development of bureaucracy. He argues that both capitalist and socialist societies are subject to bureaucracy, since it is the most rational and efficient form of organization. It is based on a form of hierarchy and is evident in the organization of church, state, and business. Although not essential, capitalism it the most rational economic basis for the development of bureaucracy, and Weber argues it is the most crucial element of the modern western state. Weber suggests the exercise of control in bureaucracy is based on knowledge. The primary social consequences of bureaucracy are: leveling of recruitment based on technical competence, a tendency toward plutocracy, and an impersonality or equality of treatment. This often results in mass democracy with less importance attributed to social standing and more towards merit.

However, technical administrative efficiency is more difficult with an elected administration, since these roles are more likely to be based on appointment. In order for bureaucracy to work efficiently it is necessary for rules to be developed. A consequence of these procedures is that the occupation or office itself acquires greater importance, rather than the attributes of a particular office holder. Bureaucracy also laid the foundations for the development of unique party systems and the representation by special interest groups as means of distributing and controlling power.

Weber's ideas, along with those of George H. Mead, founded one of the major theoretical perspectives in sociology called symbolic interactionism (SI). In short, SI emphasizes the subjective meanings of human behavior, social process, and pragmatism. Interactionists focus on the subjective aspects of social life, rather than on objective macro-structural aspects of social systems as functionalists do. For SI, humans are pragmatic actors who continually interpret the actions and meanings of others, who rehearse their behaviors, and where social processes are negotiated between people.

Synthesis

This dissertation draws on all three classical traditions in sociology. First, my analysis follows Weber's call for a broad and multidisciplinary economic sociology. By using concepts from both economics and sociology, this dissertation seeks to understand the causes of poverty by looking at the structure of agriculture, economic restructuring, and locality under postindustrial capitalism. Second, my analysis follows a Marxian political economy perceptive of agriculture, by arguing that it is not the scale of agriculture that impacts socioeconomic well-being, rather it is the structure of agriculture through wage and ownership relationships. Lastly, my analysis looks at how poverty is explained by the changing structure of the economy, so it obviously draws heavily from functionalist and neoclassical concepts.

My analysis takes a labor market approach to understanding poverty, where the characteristics of people and places interact. In terms of people, I look at the individual characteristics of the population in order to explain poverty. In terms of places, I look at the economic structure of the economy in order to explain poverty. In short, my systems approach views economic structure as determining the level of poverty in a community, and individual characteristics as the mechanism that distributes poverty among the population.

More broadly, what can be learned from this discussion of economic sociology? First, it is my view that economic sociology is the most fruitful approach to understanding the economy, especially the economic sociology found in the classic works of Weber. Economic sociology should be a broad-based and multidisciplinary field of inquiry, which should retain its own distinct position within academe, yet still draw from economic theory, economic history, and economic anthropology. For the first time since the nineteenth century mainstream economics has again begun to analyze economic institutions. This has lead to a number of interesting developments within economics, such as institutional economics, as well as a tentative dialogue with sociology (Smelser and Swedberg 1994). It is important that efforts be made by both sociologists and economists to continue and deepen this dialogue, since both disciplines need to fill the void created by nearly a century of neglect of the other's respective disciplines.

Second, a monolithic paradigm – in either its sociological or economic forms – seems an unpromising way of dealing with either economic behavior or economic institutions. The complexity of interactions between the economy and society suggests that greater understanding can be achieved through multidisciplinary approaches. Although monolithic approaches have stimulated engaging debates about the nature of economy and society, this approach must eventually become counterproductive as the debate turns from serious inquiry to territorial battles.

One of the most promising ways in which economics and sociology are relating is through complementary articulation, which is the development of theoretical concepts across disciplines (Smelser and Swedberg 1994). By necessity, any field of inquiry focuses on certain operational variables and concepts, and then freezes other concepts into a set of assumptions about how the world operates. Often, it is these very assumptions that are problematic from the standpoint of other social science disciplines. The best promise for communication and theoretical development between economics and sociology is engagement and dialogue over the roles of operational variables and concepts. After nearly a century of intellectual isolation and neglect between economics and sociology, it is time for the two disciplines to cut across conventional boundaries to begin developing a more comprehensive understanding of today's fast changing economy and society.

CHAPTER THREE

ECONOMIC RESTRUCTURING

Over the past two decades, social scientists have documented changes in the organization of the economy and society, and have termed this hypothesis a transition from Fordism or industrial capitalism to post-Fordism or postindustrial capitalism. This chapter first discusses the characteristics of Fordist and post-Fordist production, which is a necessary prerequisite for understanding economic restructuring. The next section of this chapter argues that production alone cannot fully explain economic restructuring, but that one must understand both production and consumption in terms of cultural change. Under this rubric, the ascendancy of post-Fordist production practices requires workers to be increasing differentiated and self-reflexive. In turn, ever increasing numbers of self-reflexive workers drive a cultural shift towards postmodernism. This cultural shift drives new forms of consumption of postmodern goods, which in turn reinforces and accelerates the shift towards post-Fordist production and postmodern culture.

From Fordism to Post-Fordism

Fordism refers to the period from the end of World War I to the early 1970s, which can be divided into low Fordism that occurred prior to World War II and high Fordism that occurred after World War II (Bonanno and Constance 1996; Lipietz 1992, 1987; Mingione 1991). Low Fordism was characterized by centralized production and vertically integrated firms. This period saw the emergence and consolidation of large companies with economic and geographic concentrations, such as the automobile industry in Detroit.

High Fordism continued this process of geographic and economic concentration. This period was characterized by national economies, domestic mass production and consumption, and regulation by the welfare state (Aglietta 1979; Bonanno and Constance 1996; Gordon, Edwards and Reich 1982; Harrison and Bluestone 1988; Lipietz 1992, 1987). Two key features of high Fordism were rigidity and the capital-labor accord. Fordist rigidity was characterized by mass production and consumption, which required large and expensive fixed capital investments, long production runs of uniform products, and steady streams of raw materials and labor.

Because of this need for steady labor, a corporatist arrangement between labor, business, and government was struck that redistributed wealth to the lower middle classes – termed the capital-labor accord. Under this arrangement, business or capital was guaranteed no labor or raw material shortages in return for paying higher wages, benefits, and taxes. Labor was guaranteed higher wages and welfare-state benefits, like public education and social security, in return for giving up collective bargaining rights and minimizing strikes. Government was guaranteed political and economic hegemony, through global manufacturing dominance, in return for maintaining welfare-state programs and policing the less developed world for the continued extraction of low cost natural resources.

The Fordist regime succeeded for several reasons. First, the capital-labor accord mediated conflicts between labor and business, which resulted in continued economic production with minimal stoppages (Bonanno and Constance 1996; Lipietz 1992; Mingione 1991). The welfare state was an active mediator between capital and labor, and between capital and society. The goals of the welfare state were steady growth and accumulation, regulation and amelioration of the social costs of economic growth, and the redistribution of wealth and increased political participation of previously subordinate classes. This had the effect of pacifying labor through increased wages, job advancement, and social security. In the advanced western societies this occurred primarily in the industrial sector. The welfare-state also played a role in keeping consumption strong through government spending; and by keeping the social costs of Fordism acceptable through public welfare and education. All of this helped maintain accumulation while eliminating capitalist inequalities, without redistributing power and wealth (Aglietta 1979; Gordon et al. 1982).

Second, Keynesian economic policies were enacted that allowed masses of workers to purchase the fruits of their labor (Bonanno and Constance 1996; Lipietz 1992, 1987; Mingione 1991). This was done through managing recessions, legitimating unions, developing economic security policies (such as unemployment insurance, minimum wage laws, and social security), and developing secure credit systems. Using these policies, governments were able overcome cycles of overproduction and underconsumption through mass production and mass consumption. All of this led to increased accumulation of wealth and material abundance that moderated persistent inequality that was a feature of low Fordism. In fact, some thought the increased social and material gains of high Fordism would eliminate capitalism's historic contradictions between the classes of capital and labor.

In short, American Fordism was a system based on continued growth through the capital-labor accord, rigidity in production processes, meritocracy through public education and bureaucracy, and sociopolitical consensus among most citizens regarding the system and path of the economy. Fordism contained capitalism within socially acceptable boundaries. It provided increased, but not inclusive, material quality of life, sociopolitical inclusion, and increased social and economic mobility.

However, starting in the 1960s Fordism began to unravel for several reasons. First, the cost of production in the developed world began to rise as efficiencies in mass production were exhausted, the social wage bill (such as benefits and taxes) grew faster than profits, unions began to rebel against the dehumanizing effects of Taylorism, and anti-trust and environmental regulations increased the costs of production (Aglietta 1979; Gordon et al. 1982; Lash and Urry 1987; Lipietz 1987; Piore and Sabel 1984). Social movements emerged in the developed world that demanded a redistribution of wealth and control over production processes. The success of these social movements increased the social, political, and economic costs of capital as they were overtaxed by the state. This created a contradiction in Fordism, where the system became unable to generate enough resources to meet the demands of capital, labor, and the state – which led to a breakdown of the capital-labor accord.

Second, many former colonies of the less developed world gained independence and began to become economically developed (Lipietz 1992, 1987; McMichael 1996). These newly industrializing counties (NICs) began to penetrate the markets of the developed world by combining Taylorist efficiencies, low labor costs, and scant government regulation into what is termed peripheral Fordism. A surge of post-colonial nationalism and anti-Western movements in the 1960s and 1970s – such as independence movements, Islamism, and OPEC – increased the economic costs of transferring wealth and raw materials from the Third World to the First World.

Lastly, the global stable monetary policy that had been developed after World War II collapsed (Antonio and Bonanno 1996; Bonanno and Constance 1996; Lipietz 1987). Termed the Bretton-Woods Agreement, this system set the U.S. dollar as the standard global currency, which was backed by a gold standard meaning dollars could be exchanged for gold upon demand. This stable monetary system collapsed as the United States withdrew from the Bretton-Woods Agreement and moved the dollar to a variable rate system. This action was the first step in a rapid decentralization of production and deregulation of the finance sector, which allowed large corporations to establish operations in multiple nations using global capital.

These contradictions in Fordism created a situation in which governments faced declining resources and increased social demands resulting in a chronic fiscal and legitimation crisis (Habermas 1975; O'Conner 1973). This crisis accelerated the movement towards a neo-conservative agenda of free market economic policy, which sought to increase economic accumulation and decrease social demands on government in return for fiscal stability (Antonio and Bonanno 1996; Bonanno and Constance 1996; Friedmann and McMichael 1989; Kenney, Lobao, Curry and Coe 1989). Proponents of free market policies viewed the Fordist paradigm as too rigid and instable, and this placed limits on accumulation that decreased profits. Capital began to look for solutions to get flexibility in production that would break the state mediated capital-labor accord. The free market answer to this crisis was to dismantle the Fordist program and introduce flexibility in order to attract and keep investment and jobs. This in turn weakened national governments ability to coordinate the accumulation of capital, its ability to redistribute wealth to the lower middle classes, and its ability to control the social costs of capitalism.

The crises and contradictions described above precipitated a shift away from Fordism to what is termed post-Fordism, which refers to the period generally from the 1970s onwards (Bell 1979, 1976; Bonanno and Constance

1996, Lipietz 1992, 1987). Post-Fordism represents a movement away from the capital-labor accord and mass Fordist production and consumption. Under this regime, production became decentralized in nearly all aspects, especially in terms of geography and scale. Post-Fordism allows firms to escape Fordist rigidities in the developed world and to react to changes in consumer preferences by utilizing flexible accumulation, global sourcing, and informalization of labor.

Flexible accumulation is the organization of production based on multiple labor, production, and market arrangements (Bell 1976; Bonanno and Constance 1996; Harvey 1990). Firms select the best combinations of these factors to fit current economic conditions. Global sourcing is where firms utilize the most convenient and cost effective factors of production, in terms of labor laws, government policies, environmental regulations, and the like (Busch, Lacy, Burkhardt and Lacy 1991; Pugliese 1991). Informalization of labor is the flexible use of labor arrangements, which include the use of temporary jobs with no benefits (Bell 1976; Reich 1991). In short, post-Fordism can be seen as an effort by capital to restore the accumulation lost during the transition away from Fordism.

Bonanno and Constance (1996) identify seven key features of post-Fordism, drawing upon the work of previous theorists (Bell 1979, 1976; Harvey 1990; Lipietz 1992, 1987). As mentioned earlier, the first key feature is a shift towards decentralized production to various locations and subsidiary producers spread across regional and national boundaries. This increased the control of capital over the production process by breaking the power of unions, transferring risk to other regions and subsidiary producers, exploiting cheap labor and raw materials of those regions, and strategically choosing to locate in nations where the regulatory and welfare costs are low.

Second, although production became decentralized, the core knowledge functions of management, finance, and research remained in the developed world. Post-Fordism relies on a strong center in the developed world that controls the fiscal and intellectual capital of the firm. It is this professional-managerial core that directs the subsidiary productions units dispersed across the globe.

A third feature of post-Fordism is the compression of time and space. New technologies have assisted in the control and operation of global production units, which have increased the speed of exchanges across the globe. This has been achieved through electronic information technologies that provide instant communications and credit, and improved methods of transportation like containerization.

Fourth, decentralized post-Fordist production fractures the previous unity of capital and polity, which has limited the ability of the nation-state to mediate between labor and capital as it had done previously. Under Fordism, the state mediated a market-centered democracy that placed limits on capitalist development and protected labor and national institutions from economic rationalization. Beginning in the 1970s, the state was not able to assure growth and keep the economy competitive while at the same time limiting the social costs of capitalism. This crisis precipitated the shift to post-Fordism, where the nation-state can no longer place limits on capitalist development and manage social costs. Capital now uses the nation-state as a means of increasing flexibility by demanding a shift to free market government policies.

Fifth, capitalism has become transnational under post-Fordism rather than multinational. Under Fordism, firms and products were identified by a country of origin, and international operations were merely an extension of multinational corporations (i.e. having an overseas sales office). Under post-Fordism, firms and products cannot be identified with any particular country, since parts and operations are dispersed throughout the globe. This increases flexibility because it allows firms to decrease their economic and sociopolitical responsibilities and loyalties to nation-states.

The last two key features of post-Fordism involve changes in work and culture. The nature and quality of work under post-Fordism has shifted from full-time and lifetime employment towards part-time temporary employment. Lastly, this shift towards post-Fordism has been accompanied by a shift towards postmodern culture. Postmodern culture replaces totalizations with new identities, expressions, and conceptions of time and space. Although the post-Fordism literature makes reference to the role of culture, it does so only in passing. It does not sufficiently deal with issues of how postmodern culture drives both consumption and production in today's economy.

Postindustrial Capitalism and Postmodernism

Lash and Urry (1994, 1987) define economic history through a Marxist perspective of periodization. They identify four key circuits of capital: the objects money (capital), commodities, and the means of production (fixed capital); and the subject labor (workers). Drawing upon the work of Bell (1979, 1976), their economic history is composed of three distinct phases of modern capitalism. The nineteenth century was characterized by liberal capitalism, where circuits of capital operated at the local or region level. Most of the twentieth century was characterized by industrial or organized capitalism where circuits of capital operated at the national level, essentially analogous to Fordism. This period also saw the emergence of bureaucratic firms, vertical integration, national labor unions, and national markets following political boundaries. The latest phase is termed postindustrial or disorganized capitalism where circuits of capital have become international through a global network of trade, finance, and production.

More specifically, industrial or organized capitalism was characterized by the coordination and integration of industrial, financial, and commercial capital that undermined the liberal or free market phase of capitalism that was dominant in the nineteenth century (Bell 1979; Lipietz 1992). Organized capitalism saw increased bureaucratization and institutionalization of society, which sought to rationalize the way the economy operated through modernism, scientific rationality, meritocracy, and technocracy. This phase also saw increased state intervention through regulation, planning, and the welfare state in order to mediate the negative effects of capitalism. Labor, capital, and the state were incorporated into corporatist or neo-corporatist arrangements, which is identical to Bonanno and Constance's (1996) capital-labor accord.

Beginning in the 1970s, several factors occurred that began a shift away from organized capitalism. First, the stable world monetary system collapsed as the United States withdrew from the Bretton-Woods agreement and moved the dollar to a variable rate system. Second, extensive loans made under the Marshall Plan to Europe and Japan after Word War II created a global financial and credit system. Lastly, large capital investments by public and private entities in less developed nations created a system of production in areas with lower costs (Bell 1979, 1976; Lash and Urry 1987).

This precipitated an accumulation crisis that led to the emergence of disorganized capitalism, which sought to restore continued accumulation of the capitalist system. In general, disorganized capitalism is characterized as a global economic system where production is exported to the Third World while services are kept in the First World through firm subcontracting. Lash and Urry (1994) argue that postindustrial-disorganized capitalism leads to smaller and more responsive firms, flexible labor processes replacing Taylorist processes, fractionalization of the workforce, and finally a breakdown of corporatist or neocorporatist arrangements. The following sections discuss in detail the features of disorganized capitalism.

Lash and Urry's (1994, 1987) postindustrial-disorganized capitalism is a thesis of postmodern political economy where there is a rapid circulation of subject and objects – including labor, capital, commodities, fixed capital, information, and symbols. Drawing upon the work of Bell (1979, 1976) and Giddens (1990, 1984), the authors argue that the postindustrial economy primarily produces signs, not material objects. They identify two types of objects that are signs in the postmodern economy. Cognitive signs are postindustrial material goods and informational goods. Aesthetic signs are postmodern goods that have what they term sign-value embedded within the material object, like pop music, films, magazines, and the like. This aesthetication occurs in the production, circulation, and consumption of goods. Therefore, in the production of goods the design component has increased in importance relative to the production components like material and labor costs.

The increased importance of signs coincides with the rise of postmodern culture (Harvey 1990; Lash and Urry 1994). Postmodernism sets people free from control and monitoring by traditional social structures, and they become self-monitoring and self-reflexive (Beck 1992; Giddens 2000). This is rooted in economic structural change that forces people to be freed from the rigid Fordist labor process. Post-Fordism requires a labor force that is increasingly self-reflexive and self-monitoring in the workplace. As people become more self-reflexive they develop a sense of aesthetic reflexivity in the goods and services they consume, and they become more diverse and discerning in what they purchase. These new identities are at once created and maintained through their consumption of particular goods and services.

Since most postindustrial theory reviewed in this section is based on concepts from postmodernism, a short review of postmodern theory is in order. Ritzer (1997, 1994) states that postmodernism is thought of encompassing a new historical epoch, where there are new cultural products and a new type of theorizing about the social world. Postmodernism is critical of modernism and its failures to deliver on its promises in light of the horrors of the twentieth century – it has not brought progress and a bright future. Postmodernism challenges modernist concepts like career, individual responsibility, bureaucracy, liberal democracy, tolerance, humanism, egalitarianism, neutral procedures, impersonal rules, and rationality. In short, postmodernism rejects the notion that there is a single perspective or answer, thus rejecting world views, grand narratives, and totalizations. Postmodernism accords importance to premodern concepts like emotion, feeling, intuition, reflection, speculation, personal experience, violence, magic, and myths. It rejects boundaries between academic disciplines, theory and reality, culture and life, and logical reasoning.

Ritzer (1997) articulates three fundamental positions taken by postmodern social theorists. First is the extreme postmodernist position, which argues that there has been a radical break or rupture in society, with modern society being wholly replaced by postmodern society (exemplars of this position include Baudrillard and Virilio). The second more moderate position argues that although a change has taken place in society, postmodernity grows out of and is continuous with modernity (exemplars of this position include Harvey and Jameson). The last approach argues that rather viewing modernity and postmodernity as epochs, we should view the two as engaged in a long running relationship with one another. This position views postmodernity as an alternative perspective continually pointing out the limitations of modernity.

One of the key features of postindustrial and postmodern capitalism is that reflexivity provides a better account of the modern economy and society than the strict productionist view of post-Fordism (Beck, Giddens and Lash 1994; Bell 1979, 1979; Jameson 1991; Lash and Urry 1994, 1987). Postindustrial theorists argue that reflexivity provides a better explanation than post-Fordism of the service-based economy because it assumes knowledge and information are fundamental to economic growth. Information intensive research and development is just as important, if not more so, than research and development in the material production process. In fact, some research and development has been devolved to workers themselves. Further, reflexivity is not a one-sided productionist view, as is post-Fordism, but includes sociocultural aspects of production and consumption. Lastly, reflexivity assumes that culture has penetrated the economy, where symbolic and aesthetic processes permeate both the production process and consumption. In short, postindustrialists argue that it is more useful to look at economic restructuring as a shift away from materials-based production towards culturally-based production, rather than as only a shift from rigidity to flexibility.

The two key concepts under postindustrial capitalism are reflexive accumulation and reflexive consumption (Beck et al. 1994; Lash and Urry 1994, 1987). These two concepts demonstrate how the economy and symbolic processes are intertwined and act as one system. Reflexive accumulation represents the production of material products embedded with symbols, and the production of symbols by themselves. These symbols represent the creation of knowledge, information, and aesthetic signifiers. In short, the production of knowledge and information is central to the economy, and it involves both information processing and symbol processing. Reflexive consumption refers to individuation, where traditional social structures (such as family, class, and group) no longer determine consumption decisions. There is free choice of lifestyle and consumer choice, where people create identities through consumption. This has led to a proliferation of styles, niches, and distinctions that has in turn drove a shift to small-batch just-in-time production of goods and services to detraditionalized individuals (Bourdieu 1984).

Lash and Urry (1994) explicitly state that this view of production and consumption does not imply that there is a freeing of agency from structure. They argue that postmodern capitalism replaced national social structures based on organizations and institutions with globally-situated information and communication structures, which are not framed by organizations and institutions. Basically, postmodern capitalism does more than simply freeing individuals from social structure, but actually replaces old social structures with new information structures (Harvey 1990). Freed from social structures, people are now able to reflect upon and find meaning in various spheres of social life.

Reflexivity is impossible without the presence of information and communication structures, which allows for the flow of information and the accumulation of information processing capacities (Beck et al. 1994). There are two types of these information structures: cognitive reflexivity which monitors the flow of information and cognitive symbols; and aesthetic reflexivity which monitors the flow of aesthetic symbols like images, sounds, and narratives. Without these information structures, traditional social structures would be replaced by unstructured space, and instead of individuation there would be anomie and social disorganization.

As reflexive production and consumption become more intertwined, this has caused cultural production to supercede material production in the postindustrial economy (Beck et al. 1994; Bell 1979, 1976; Lash and Urry 1994, 1987). Cultural production has not become commodified or more like manufacturing in today's economy, nor was this even the trend as Marxists have argued. Even under Fordism, cultural production existed – albeit small – and was more innovative and design-intensive than other industries. Instead of cultural production becoming more like manufacturing, instead the opposite is occurring where manufacturing is becoming more like cultural production.

The culture industries are both knowledge and design intensive. They are knowledge intensive because the commodities they produce have high information content; and they are design intensive because the commodities they produce have high aesthetic content. The key in these industries is to use knowledge content to produce the commodity, and then aesthetic content to sell it to the public. Needless to say, sign-value is important in all postindustrial products – it has always been so in cultural products, but now it is increasingly so in manufactured products.

In short, information and communication structures have replaced traditional social structures, which are at the same time knowledge and power structures that permit individuation (Beck et al. 1994; Harvey 1990). Isolation and freedom from old social structures creates new lifestyle enclaves, not plural life worlds or neo-tribes (Beck 1992). Culture industries are not becoming more like manufacturing industries, but in fact material commodity production is becoming more like cultural production. The winners in this shift to postindustrial capitalism are the cultural-capitalists engaged in cultural production, and who are located in dense information and communication networks. The losers are the underclass and the new lower class for whom social structures have not been replaced by information and communication structures, and who are geographically isolated from these structures and the industries that produce cultural goods.

Lash and Urry (1994, 1987) expound on how the winners and losers in postindustrial capitalism creates a new class structure. Synthesizing concepts from Giddens (1990, 1984), Bourdieu (1984) and Bell (1979), the authors identify the reasons for increased inequality in the economy. First, the structural shift from a manufacturing-based economy towards a services-based one has resulted in a much greater variation of occupations and incomes in the services industry – from high-paid professionals to low-paid clerical staff – than ever existed in the old manufacturing economy. Second, the outsourcing of services and functions by both industry and government has given rise to a mass of non-standard and temporary workers, who often lose the social and wage benefits they once had when they were permanent workers. In turn, this has led to a decline in union and other collective bargaining powers.

The above trends have created a new professional-managerial-capital class while at the same time creating a new lower class (Beck et al. 1994; Bourdieu 1984; Lash and Urry 1994). The growth of the advanced services industry plays a central role in this new class structure, because it enables reflexive producers to sell symbolic-intensive products and services to reflexive consumers. Advanced services produce specialized products and services that are innovative and have a high symbolic content, which are often protected not by patents but by copyrights. These industries are highly differentiated because classes have become differentiated, which is caused by the decline of traditional social structures and the rise of individuation. These services require a high degree of cultural capital investment (such as information, symbols, skills, and aesthetics) that involves small batch co-production between provider and recipient of multidimensional symbols (such as cognitive, moral, aesthetic, affective, and narrative symbols). Some examples of advanced services industries include information technology, finance, education, health care, business services, cultural industries, and some segments of the hotel and retail sectors (Lash and Urry 1994).

As advanced services grow in importance, it is the professional-managerial class who works in these industries that drives accumulation in postindustrial capitalism, which in turn causes postmodern society to become more individuated and symbol-rich. The professional-managerial class is rooted in labor-intensive assumptions that characterize postindustrial capitalism, as opposed to capital-intensive assumptions that characterized industrial capitalism (Beck et al. 1994; Lash and Urry 1994).

Labor-intensive assumptions are rooted in gentrification, which is characterized by the rehabilitation of old urban homes, employment of personal service workers, and consumption of recreational and leisure services. By contrast, capital-intensive assumptions were rooted in consumption, which was characterized by suburbanization, tract homes, newly-built communities, consumption of household appliances and goods, and the ethic of a self-service society. The consequence of this labor-intensive assumption is the creation of a new lower class of personal service and leisure workers who service the professional-managerial class. This new lower class also creates a new consumer base for downgraded goods and services – a second tier of advanced services production geared to the lower classes.

In summary, Lash and Urry (1994) argue that rise of postindustrial capitalism has led to a new stratification order that is radically different from what existed under industrial capitalism. Under industrialism, the three main classes were a small capitalist class who owned the means of production, a large working class engaged primarily in manufacturing, and a small service class composed of both high and low skill workers. However, the shift to a postindustrial economy shattered the old class structure. The newly emerging postindustrial class structure is composed of four classes: (1) a small capitalist class as existed under previous forms of capitalism; (2) a small working class that has been greatly diminished from previous capitalist periods; (3) a new large professional-managerial class that drives the postmodern economy; and (4) a new lower class that services the professional-managerial and capitalist classes.

It is clear from the preceding discussion that advanced services are an integral part of the postindustrial economy. For advanced services firms, labor is a large part of the service delivery process and workers need to be near consumers. The quality of interactions between service producers and consumers is an important part of the service itself – except where the service can be materialized – and are termed high-contact services. This infuses labor with a set of social compositions that consumers also buy into, such as age, race, education, and culture (Bourdieu 1984). This forces management to control aspects of labor not before controlled – like appearance, speech, personality – in order to improve the quality of the service delivery. In short, consumers buy the service as well as the service provider and the service delivery (Lash and Urry 1994). Therefore, advanced services firms tend to locate where they can find adequate supplies of highly skilled and qualified labor, which includes not only "hard" skills in the form of acquired knowledge, but increasingly "soft" skills that emphasize customer service.

The rise of advanced services under postindustrial capitalism has precipitated a shift in what constitutes the "core" or basic industries of the economy (Bell 1979, 1976; Lash and Urry 1994, 1987; Lipietz 1992). Core or basic industries are those that drive other segments of the economy and are considered the engine that powers the wider economy. These industries are export-oriented and depend largely on factors external to the local economy. Under Fordism, the old core consisted of a set of producer networks centered around material production, like electrical products, steel, chemicals, and machinery. Other functions of the economy were subordinate to and driven by this old core, like transportation, finance, and services. However, with the rise of advanced services under postindustrial capitalism, the new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Industries that drive this new core include information, publishing, telecommunications, advanced producer services, professional services, and to some degree the tourism and leisure sectors.

More pragmatically, Lash and Urry (1994) discuss how the shift to postindustrial capitalism might impact communities. In terms of economic structure, massive declines in manufacturing employment have eroded the old core or export-dependent economic base of many communities (Bell 1976; Lash and Urry 1994; Lipietz 1992). However, advances in telecommunications and transportation mean that, in theory, advanced services can be located anywhere and can replace losses in the old core. Information can be sold over long distances independent of the number of local customers or where they are located. The problem is attracting and keeping a high-quality labor force needed to work in these industries, which often requires communities to have a diversity of sociocultural amenities.

More broadly, many communities are being reconstructed away from being centers of Fordist production. Many of these communities will be unable to become centers of postindustrial production, and their alternatives for development are limited. At best, a community may become a center of consumption; at worst, they may become “ungovernable spaces”. What distinguishes places from each other is the diversity and complexity of the services available and their connections with place images. Communities best able to capitalize on being a center of consumption are those where the social characteristics of the area give it a certain character and imposes a habitus on the area based on class or culture. This includes: a legacy of a built environment with unique styles that can be converted into new postindustrial spaces; a public or social group that develops an aesthetic interest in preserving buildings and the environment; a local government willing to organize and sustain projects that reinforce and are consistent with the community's place image; and no other nearby place images that conflict or compete with the community's image. Further, there needs to be a tradition of entrepreneurship and a shift in consumption where sociocultural services are valued more – such as ethnic foods, cultural tourism, niche shopping, and the environment.

Synthesis

In this dissertation, I take a postindustrial view of the economy and of the economic structure that has resulted from it. Following the works of Bell (1979, 1976) and Lash and Urry (1994, 1987), I agree with the thesis that postindustrial and postmodern reflexivity provides a better account of the modern economy and society than the strict productionist view of post-Fordism. First, postindustrial reflexivity provides a better explanation of the service-based economy because it assumes knowledge and information are fundamental to economic growth – where cultural production has superceded material production. Second, postindustrial reflexivity is not a one-sided productionist view, but includes the sociocultural aspects of production and consumption. Lastly, postindustrial reflexivity assumes that culture has penetrated the economy, where symbolic and aesthetic processes permeate both the production process and consumption.

In turn, these changes in the economy create a new economic and class structure. Postindustrialism precipitated a shift in what constitutes the core or basic industries of the economy, which includes those export-oriented industries that drive other segments of the economy and are considered the engines that power the wider economy. Under industrialism, old core or basic industries consisted of a set of producer networks centered around material production. However, with the rise of advanced services under postindustrialism, the new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers.

People who work in these new core/basic industries represent a new professional-managerial class. The rise of postindustrial capitalism has led to a new stratification order that is radically different from what existed under industrial capitalism. The newly emerging postindustrial class structure is composed of a small capitalist class as existed under previous forms of capitalism; a small working class that has been greatly diminished from previous capitalist periods; a new large professional-managerial class that drives the postmodern economy; and a new lower class that services the professional-managerial and capitalist classes.

In short, postindustrialism is a more useful approach in understanding how the economy is restructuring away from material-based production towards cultural-based production. However, I disagree with the assertion that this economic shift is caused by a radical break or rupture between modernism and postmodernism. My more moderate view acknowledges that although there have been changes in society, postmodernity grows out of and is continuous with modernity. It is my view that capitalism is entering a new postindustrial phase: where capitalism is required to produce ever more novel goods at ever increasing rates of speed, where cultural production is becoming more integrated into material commodity production, and where changes in economic structure are reflected in cultural changes.

However, these changes are not indicative of a new hegemonic form of culture. Drawing upon the work of Jameson (1991), it is my view that society is increasingly operating under a postmodern cultural logic, but that it is not the only cultural logic operating in society. Even though a postmodern cultural logic is dominant, other cultural logics persistent and are resistant to it – there is no cultural uniformity. Just as there were postmodernist elements under culturally dominant modernity, there will continue to exist modernist elements within a culturally dominant postmodernity.

CHAPTER FOUR

UNDERSTANDING POVERTY

Theories on the causes of poverty are at the core of both economics and sociology. In fact, theories on this topic date to the very beginnings of both disciplines. This chapter is divided into two sections. The first section reviews the major sociological theories of poverty, discussing the theoretical foundations and conceptualizations of what causes poverty. The second section reviews current community poverty research in relation to the goal of this analysis, which is to understand rural poverty clusters in terms of agricultural and economic structure under postindustrial capitalism.

Beyond giving a theoretical foundation for this analysis, there are several reasons why understanding rural poverty is important (Gilens 1999; Proctor and Dalaker 2003). Persistent poverty is becoming more concentrated in rural areas. There are high barriers to economic self sufficiency in rural areas that yield worse outcomes for rural people. Many rural communities do not have the capacity to provide enough economic or other opportunities to ameliorate poverty. Lastly, public policies aimed at reducing poverty and welfare dependency are less effective in rural areas.

Poverty Theory

Theory and research over the past five decades has identified many of the causes of poverty, which has coalesced into three main theoretical approaches (Beeghley 1983; Bluestone and Harrison 2000; Duncan 1999; Duncan and Brooks-Gunn 1997; Nord 1997; Tickamyer and Duncan 1996). The individual or person approach argues that the causes of poverty are rooted in the individual characteristics, qualifications, attitudes, and behaviors of a person. On the other hand, the structural or place approach argues that the causes of poverty are rooted in the structure of economic and social opportunities available to a person. Historically, these approaches have been in opposition, each seen as mutually exclusive in terms of theory and method.

However, recent research has argued for merger of these two approaches in theory and method for a fuller understanding of poverty (Albrecht et al. 2000; Cotter 2002; Crandall and Weber 2004; Levernier, Partridge and Rickman 2000; Licther and McLaughlin 1995; McLaughlin 2002; Partridge and Rickman 2005; Swaminathan and Findes 2004). This third way, termed the labor market approach, argues that the causes of poverty are rooted in both individual characteristics of the poor and local socioeconomic structures. The individual and structural approaches to poverty have been sufficiently conceptualized and contrasted within the social sciences, and a review of this work is presented below.

The individual or person poverty approach draws heavily from functionalist theory in sociology and human capital theory in economics (Beeghley 1988; Fitchen 1995; Fulton et al. 1997; Lobao 1990; Murphy and Welch 1993; Nord, Luloff and Jensen 1995). These theories argue that individuals are sorted into economic positions according to their characteristics, qualifications, attitudes, and behaviors. Therefore, the level of poverty within a locality is a function of differential sets of skills and demographic components. This approach argues that areas are poor because they have more people with demographic characteristics associated with poverty. For example, poor areas are often correlated with large minority populations due to discrimination in the labor market, low educational attainment which sorts people into lower skilled and lower paid jobs, and female-headed households resulting in a single source of earnings (Brown and Lee 1999; Duncan and Brooks-Gunn 1997; McCall 2001; Morris and Western 1995).

The individual approach assumes that labor, industry, and government are rational economic actors making free and informed choices that determine a course of action that maximizes some utility, usually economic (Lobao 1990). This approach assumes that rewards made by the economy and society to individuals reflect the economic and social value placed on that person's occupation. This differential in rewards is seen as a necessary condition for the operation of the economy, so that workers with the best attributes enter into occupations that are of importance to the larger society. Economic rewards include earnings, capital, and property. Social rewards include power, prestige, and status. Rewards are seen as necessary for the efficient operation of the economic system; and rewards are seen as just because they reflect the economic and social value of the occupation. In short, individual or person poverty refers to the demographic and social characteristics of individuals or groups in poverty. This approach states that the uneven distribution of poverty is due to the unequal distribution of key characteristics of the population.

On the other hand, structural or place poverty approaches argue that poverty is not caused by some deficiency in human capital. Rather, poverty is caused by lack of opportunity in the macro-level economic and social structure (Beeghley 1988; Lobao 1990; Lobao et al. 1999; Tomaskovic-Devey 1988, 1987). The structural approach draws heavily from Marxist political economy theory, and argues that individuals are sorted into economic positions according to a set of social processes. These structural processes include the local economic structure, natural environment, community institutions, and social conditions. These processes constrain opportunity and choices to certain groups of people based on race, gender, or socioeconomic status. Therefore, the level of poverty within a locality is a function of social processes that create differential access to opportunity.

The structural approach explains socioeconomic differences through constraints on opportunities and choices. These constraints are organized through economic production, specifically the quantity and quality of employment within a given locality. Structural approaches assume poverty is caused by a social order that constrains opportunity and choices, and individual characteristics are used only as a means for sorting workers in different economic positions to reinforce that order. Tomaskovic-Devey (1988) presents an excellent argument of why individual characteristics are not the main cause of inequality and poverty:

> Suppose all Americans became white, college-educated men. As Tomaskovic-Dewey notes, the amount of poverty would not change because the quality and quantity of employment has remained unchanged. This argument also challenged policy prescriptions central to functionalist and human capital perspectives which have stressed job training and schooling as a solution to low wages and poverty. Rather than reduce poverty, such programs merely reshuffle the queue of people waiting for available jobs.

The structural approach argues that people within a locality share a common fate because the place where they live has unique advantages and disadvantages for economic growth and capital investment, which causes a spatial distribution of poverty and socioeconomic well-being (Fitchen 1995; Lobao and Saenz 2002; Tickamyer 2000). Blank (2004) identifies several key features of place that interact with poverty and well-being. First, the economic structure of a locality provides a unique mix of industries and job opportunities that, when linked to regional and national economic structures, affects the mix of choices and opportunities available for people. Second, each locality has unique environmental and locational attributes that distinguish it from other places. Isolation limits accessibility to labor markets with greater economic opportunities through distance and geographic barriers. Climate and natural resource endowments can also impact the type of economic activities in the area. For example, inhospitable climates can inhibit economic growth; or economic structure may be determined by access to good soil, water, forests, and minerals. However, modern transportation and communication networks have reduced the impact of these attributes. Lastly, community institutions matter for the development of an area. These include the degree of social networks both within the community and its linkages to the wider world, the openness of the institutions, the effectiveness of those institutions, and the degree of public-private partnerships.

In short, structural or place poverty refers to the manner in which poverty is distributed unevenly across space. Structural or place explanations of poverty tend to focus on the local economic and social structure. This approach states that the uneven distribution of poverty is due to the unequal distribution of opportunities manifest in the economic and social structure. Place characteristics that may affect poverty include specialization in core/basic or periphery/non-basic industries, economic diversification, institutional discrimination, and unrepresentative power structures. Cotter (2002) summarizes this approach nicely by stating that, "structural thinking about place poverty implies that there must be something wrong with the locality where poverty is concentrated – some factor or factors which produce poverty."

From a policy perspective, the disadvantages of individual or person-based policies are that many poor are not geographically mobile and at the same time live in places where there are few economic opportunities (Bluestone and Harrison 2000; Glickman 2000; Ellwood 2000; Fulton et al. 1997; Nielsen and Alderson 1997; Nord et al. 1995). So policies designed to increase human capital without taking into account issues of transportation are bound to fail, because the higher skilled poor are often unable to migrate or commute to areas with greater economic opportunities. On the other hand, disadvantages with structural or place-based policies are that they often create jobs that go to better skilled commuters and not the poor, and that providing public services in remote places is expensive because local governments are too small to provide economies of scale.

Individual or person-based factors are important in understanding poverty and locality that cannot be ignored. At the same time, structural or place-based factors are also important in understanding poverty and locality. Both approaches need to be considered in any thorough analysis of inequality and poverty. Merging the individual/person-based and structural/place-based approaches permits one to determine the likelihood of a household being poor, based on the differentiation of individuals within the locality and the differentiation of opportunity structures within the locality.

The labor market approach is a body of theory and research that incorporates both the individual and structural approaches within a spatial context (Cotter 2002; Findes and Jensen 1998; Lobao 1990; Lobao and Schulman 1991; Lobao et al. 1999; McLaughlin 2002; Osterman 1999; Weber and Jensen 2004). There are two key facets of the labor market approach. First, rural poverty is due to the distribution of individual characteristics in the population, which is consistent with individual/person-based approaches. Second, rural poverty is also due to the socioeconomic division of labor, which represents structural/place-based approaches. Under this rubric, poverty is higher in areas with an economic structure that provided limited opportunities, usually associated with periphery or non-basic industries; and lower in areas where there better economic opportunities that are concentrated in core or basic industries. This determines the level of poverty within an area, with individual characteristics providing the means by which poverty falls more heavily on certain groups.

The local labor market refers to the geographic area where transactions between buyers and sellers of labor occurs (Lobao 1990). The labor market is structured by the economic organization of firms and by the distribution of skills and education among the population. It is this two-fold structure that determines and constrains the economic opportunities available to individuals. Both theory and research agree that labor markets dominated by core/basic industries of the economy offer better opportunities and rewards than those dominated by peripheral/non-basic industries (Bloomquist, Gringeri, Tomaskovic-Devey and

Truelove 1993; Lobao 1990; Lobao and Schulman 1991; Lobao et al. 1999; Murphy and Welch 1993).

Termed dual or segmented economy theory, this framework states that uneven development of certain industries results in three distinct categories (Edwards 1979; Hodson 1984; Lobao 1990). First, core or basic industries are those that drive other segments of the economy and are considered the engines that power the wider economy. In economics, basic industries are entirely dependent on factors external to the local economy. Since basic industries export most of what they produce, their success or failure has much to do with national and global economic conditions. Second, periphery or non-basic industries are those that are subordinate to and driven by the core. Non-basic industries are entirely dependent on local economic conditions, since most of what these industries produce is sold locally. Third, semi-core or semi-basic industries are dependent on both external and local economic conditions, since what they produce is both exported and sold locally. Under Fordism, the old core consisted of a set of producer networks centered around material production, like electrical products, steel, chemicals, and machinery. Other functions of the economy were subordinate to and driven by this old core, like transportation, finance, and services.

However, with the rise of advanced services under postindustrial capitalism, the new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers (Lash and Urry 1994, 1987). Industries that drive this new core include information, publishing, telecommunications, advanced producer services, professional services, and to some degree the tourism and leisure sectors.

In terms of postindustrial class structure, Lash and Urry (1994, 1987) argue that changes in core and periphery has given rise to a new stratification order that is radically different from what existed under industrial capitalism. Under industrialism, the three main classes were a small capitalist class who owned the means of production, a large working class engaged primarily in manufacturing, and a small service class composed of both high and low skill workers. However, the shift to a postindustrial economy and what constitutes core and periphery has resulted in a newly emerging postindustrial class structure. The two major postindustrial classes include a new large professional-managerial class that drives the postmodern economy; and a new lower class that services the professional-managerial and capitalist classes. However, remnants of the old industrial classes still exist, including a small capitalist class as existed previously; and a small working class that has been greatly diminished from previous capitalist periods.

Wilson (1987) and others (Gilens 1999; Jones 1992) also take the view that structural change has created new social classes different from what existed under industrial capitalism. These theorists argue that the decline of manufacturing and the rise of services, both high-skill and low-skill, precipitated a shift from a job-related lifestyle to a non-job practices lifestyle. Wilson argues that this structural and social change has created an underclass of poor rooted in a culture of poverty. This culture is a reaction or adaptation of the poor to their present position in an individualistic society. Instead of adopting "national" values, the poor underclass adopts the values of peers in local subcultures. In Chicago, Wilson found that the underclass resided in a space isolated from other socioeconomic classes, had been jobless for a long time, were dominated by female-headed households, possessed few skills, had been in poverty for multiple generations, were dependent on welfare, and were engaged in street crime and the informal economy for money.

The underclass also has a spatial dimension (Katz 1989; Lobao and Saenz 2002; Tickamyer 2000; Wilson 1987). As manufacturing declined and services grew, the professional-managerial class located to areas separate from the new lower service class. This created a normative and economic vacuum, where the new lower class was isolated socioeconomically and culturally. Filled with people too poor or too old to move out, many communities developed a culture of poverty that replaced the mainstream culture needed to advance economically and socially in modern society. An underclass is more apt to form in restructured areas (those shifting from an industrial to postindustrial economy) than in deindustrialized areas (declining industrial economy, no postindustrial economy) or postindustrial areas (always postindustrial, never had an industrial economy); and that the underclass is least prevalent in postindustrial areas.

In summary, the labor market perceptive explains poverty as a combination of person-based and placed-based factors, thus merging the theories of functionalism and structuralism. This analysis takes a labor market perspective in understanding poverty, assuming that poverty is due to the distribution of individual characteristics and the socioeconomic division of labor. Operationally, certain types of economic structures determine the overall level of poverty within a locality, with individual characteristics providing the means of distributing that level of poverty to certain individuals.

Poverty Research

This section provides a review of the literature on rural poverty. The focus is principally on quantitative studies, recognizing full well that when it comes to capturing the richness of context and the constraints of place, ethnographic studies are superior. Qualitative studies are critical for generating new insights and hypotheses that can be examined in subsequent research. Two such qualitative studies are briefly mentioned here. While not the first of its kind, a seminal work in qualitative poverty research is *Poverty in Rural America: A Case Study* by Janet Fitchen (1981). Based on hours of in-depth interviews with families in a struggling agricultural hamlet in rural upstate New York, Fitchen portrays the day-to-day struggles of living on the edge. Fitchen begins with a tight focus on how families make and spend money, but then incorporates broader levels of context. Ultimately, this includes consideration of the relationships of poor families with the institutions of the surrounding county, such as schools, county offices, and the labor market. Fitchen concludes that poor families' relative isolation from these institutions is maintained both by themselves and these institutions, and is complicit in their desperate economic circumstances.

More recently, Duncan (1999) in *World's Apart: Why Poverty Persists in Rural America* suggests that the depth and persistence of rural poverty are rooted in a rigid two-class system of haves and have-nots. Based on years of fieldwork in Appalachia and the Mississippi Delta, Duncan paints vivid and intricate portraits of power and privilege. The “haves” wield their power over jobs and opportunities to maintain their privilege, while at the same time subjugating the “have-nots” who are desperately poor and socially isolated. In both settings, those historically in power have manipulated all facets of the local social structure to maintain their position. Moreover, she finds that the social isolation of those at the bottom has deprived them of the "cultural tool kit" they need to participate in society. For comparison, Duncan also studied a paper mill town in Maine and found no evidence of the same rigid class hierarchy. Rather, because of its unique economic and social history the town was characterized by inclusiveness, trust, widespread community participation, and high social capital. Importantly, this work and that of Fitchen underscores that it is much more than just economic variables that drive place effects. Local power relationships and levels of social isolation also are critical.

The quantitative research on poverty reviewed here focuses on community studies of poverty. Poverty studies of this type seek to explain differences in rates of poverty across communities as a function of community demographic and economic structure variables, including whether the community is rural or urban (Duncan and Brooks-Gunn 1997). This section reviews current community poverty research in relation to the goals of this analysis, which is to understand rural poverty clusters in terms of agricultural and economic structure under postindustrial capitalism.

To begin, Partridge and Rickman (2005) examine why persistent poverty counties continue to exist in the United States, and seek to understand whether these areas are poor because they have weak economies or disadvantaged populations. To them, this raises an important policy question: should poverty-reducing policies be directed towards helping poor people or directed towards helping the places where they live? Using a variety of regression approaches, including a geographically weighted regression analysis, they attempt to explain poverty rates in both persistently poor and non-poor counties.

In predicting poverty rates in persistently poor counties, a number of community and demographic factors were significant. For community factors, the authors found that high poverty rates in 1990, industrial restructuring, and employment in agriculture increased poverty rates. Conversely, employment growth and labor force participation tended to reduce poverty. For individual factors, they found that single-headed households with children increased poverty. On the other hand, high school graduates, associate degree graduates, African-Americans, and Hispanics tended to reduce poverty rates.

For non-persistently poor counties, Partridge and Rickman found some interesting differences and similarities compared to persistently-poor counties. Community factors that increased poverty included higher poverty in 1990, higher poverty in surrounding counties, industrial restructuring, male unemployment, agriculture employment, and employment in goods producing industries. Conversely, lower poverty rates were associated with employment growth, female labor force participation, male full-time employment, and out-migration. In terms of the individual factors, the authors found that single-headed households with children tended to increase poverty rates. On the other hand, higher educational attainment, African-Americans, and Hispanics tended to reduce poverty in non-persistently poor nonmetropolitan counties.

Swaminathan and Findes (2004) explore the interactions between welfare reforms, employment growth, and poverty rates across all counties in the United States between 1990 and 2000. The authors predict employment growth and changes in poverty rates by specifying a spatial model that includes demographic, geographic, economic, and community factors. Looking first at their model explaining changes in poverty rates, counties with improving poverty rates had higher base poverty rates in 1990 and had more high school graduates. On the other hand, counties with worsening poverty had larger non-African-American populations and female-headed households. Economic factors that improved poverty rates included employment in manufacturing, trade, services, and self-employment. However, employment in agriculture worsened poverty. Interestingly, counties with higher levels of social capital experienced improved poverty conditions, while counties with high levels of political competition experienced worsening poverty conditions.

Looking at their employment growth model, Swaminathan and Findes found that lower employment growth was associated with higher base poverty rates, higher numbers of young adults and older adults, non-African-American minority populations, female-headed households, and lower educational attainment. In terms of economic factors, lower employment growth was associated with employment in agriculture and services, while higher employment growth was associated with industrial restructuring. None of the geographic or welfare service factors were significant in predicting employment growth in the spatial model.

Levernier, Partridge and Rickman (2000) assert that persistent poverty in the United States remains a central policy issue. Their study uses county-level data to explore the potential explanations for the observed regional variation on poverty rates across metropolitan and nonmetropolitan counties. The factors the authors consider include those relating to both area economic performance and area demographic composition.

In terms of economic factors, they found that higher levels of nonmetropolitan poverty were associated with industrial restructuring, agriculture employment, transportation and utilities employment, trade employment, and services employment. Conversely, lower poverty rates were associated with high labor force participation. In terms of demographic factors, higher nonmetropolitan poverty rates were associated with female-headed households, larger family sizes, non-African-American minority populations, and migration. On the other hand, lower poverty rates were associated with higher educational attainment, young adults aged 18 to 24, older adults aged 60 and over, and African-Americans.

The authors also looked at how these same factors predict poverty rates in high-poverty counties. In terms of economic factors, higher poverty rates were associated with industrial restructuring and agriculture employment. Lower poverty rates were associated with high labor force participation and employment in finance, insurance, and real estate. In terms of demographic factors, higher poverty rates were associated with female-headed households, larger family sizes, and non-African-American minority populations. Conversely, lower poverty rates were associated with higher educational attainment, adults aged 65 and older, and African-Americans.

Albrecht, Albrecht and Albrecht (2000) argue that poverty is more extensive and severe in nonmetropolitan areas than in metropolitan areas. They maintain that the extensive industrial and economic transformation occurring in rural areas has resulted in patterns contributing to high poverty levels. These transformations, which include an increase in service sector employment, in many ways mirror the economic changes that have occurred in the inner city. The authors use Wilson's (1987) model of the inner city underclass to understand poverty trends in nonmetropolitan areas. To test this hypothesis, the authors analyze 1990 census data using both individual and economic structure variables. The results generally support the underclass model in explaining higher poverty levels in nonmetropolitan areas.

Specifically, Albrecht et al. (2000) found that larger employment concentrations in the agriculture and services industries increased poverty. However, larger employment concentrations in manufacturing decreased poverty. In terms of individual and household controls, the authors found that larger populations of minorities and female-headed households increased poverty. Conversely, more high school graduates and full-time employment decrease poverty. Although the authors claim to look at industry restructuring, they use no industrial change variables.

Lobao and Schulman (1991) bring together two theoretical perspectives to understand the impact of farming patterns and rural restructuring on poverty. Building from agrarian political economy and rural restructuring literatures, they present a comparative regional analysis of how farming patterns and other aspects of economic organization differentially affect poverty in rural areas. Their data is based on 2,349 nonmetropolitan counties between 1970 and 1980, grouped into major agricultural production region. For this review, I will only focus on their analysis of the central agricultural region in the United States.

In terms of industrial structure, the authors found that higher poverty rates were associated with greater employment in periphery industries and government, while lower poverty rates were associated with smaller establishment employment sizes. In terms of agriculture structure, they found that smaller family farms increased poverty, while larger family farms and industrial farms reduced poverty. The authors also found that non-white minorities, unemployment, and farm and rural populations tended to increase poverty rates. Conversely, higher welfare payments, higher educational attainment, urban populations, and metropolitan adjacency tended to reduce poverty rates.

Lobao and Schulman also examined how these same factors influenced changes in poverty rates. In terms of industrial structure, they found that employment in periphery industries and government tended to accelerate poverty growth. For agriculture structure, larger family farms tended to slow poverty growth, while the other farm variables were not significant. They also found that non-white minorities, unemployment, farm and rural populations, and higher base year poverty tended to accelerate poverty growth. Conversely, higher educational attainment and urban populations tended to reduce the growth in poverty.

Lichter and McLaughlin (1995) examine the extent and causes of changing spatial inequality both between and within metropolitan and nonmetropolitan areas, as measured by increasing or decreasing county poverty rates. The results, based on data from the 1980 and 1990 census, suggest several conclusions. First, poverty rates increased more rapidly in nonmetropolitan than metropolitan counties during the 1980s, while historical patterns of metropolitan-nonmetropolitan economic convergence slowed over the same decade. Second, poverty rates tended to decline in nonmetropolitan counties with traditionally high rates of poverty, thus providing counterevidence to arguments suggesting that the gap between traditionally poor and non-poor nonmetropolitan counties has widened.

Specifically, the authors develop a cross-sectional model to explain poverty rates in nonmetropolitan areas taking into account demographic and economic structure variables. In explaining 1990 poverty rates, demographic factors that increased poverty included populations under 18 and over 65 years of age, female-headed households, and low educational attainment. In terms of economic structure, the authors found that employment in extractive industries, government employment, and unemployment increased poverty rates. Conversely, manufacturing employment and female labor force participation reduced poverty. In their 1980 poverty model, the authors found that populations of African-Americans, populations under 18 and over 65 years of age, female-headed households, and less educated persons increased poverty. In terms of economic structure, employment in extractive industries and government increased poverty. On the other hand, employment in manufacturing, services, and female labor force participation reduced poverty rates.

Though not directly related to poverty, McLaughlin (2002) makes linkages between income inequality, poverty, and industrial restructuring in nonmetropolitan areas. She uses census data from 1980 and 1990 to estimate an ordinary least squares model of income inequality change. Household income inequality increased in a smaller share of nonmetropolitan than metropolitan counties from 1980 to 1990. Increases in income inequality were influenced more strongly by economic restructuring in nonmetropolitan than in metropolitan counties. Other factors were generally similar in affecting income inequality in nonmetropolitan and metropolitan counties, such as change in household structure, demographic composition, labor supply, and job quality. The greater importance of economic restructuring in nonmetropolitan counties indicates that less diverse and small size local economies are more vulnerable to the forces of economic restructuring.

The next set of community poverty studies looks more broadly at how economic opportunities affect poverty rates within communities and the poverty status of households. Cotter's (2002) innovative study integrates individual and structural accounts of poverty by examining the relationship between person poverty and place poverty in nonmetropolitan and metropolitan labor markets using a multilevel model framework. Taking a labor market perspective to explain poverty, Cotter develops a hierarchical linear model incorporating compositional and contextual factors that affect a households' likelihood of being in poverty.

Generally, he found that a number of labor market factors proved to be powerful predictors of household poverty beyond household-level predictors, while at the same time the household predictors retained their effects. He also found that nonmetropolitan households had a greater probability of being poor after controlling for compositional factors. This indicates that nonmetropolitan poverty is attributable to the context of rural areas rather than to the composition of rural people. Lastly, employment had a much stronger effect in household poverty in nonmetropolitan areas than in metropolitan areas, especially when taking into account head-of-household employment status.

Specifically, household factors that increased the chances of a household being poor included having more children, being a female-headed householder, being a minority-headed householder, having a work disability, being divorced or separated, and being single. Conversely, household factors that reduced the chances of being poor included being older, having a high school or college degree, and being presently employed. In terms of labor market factors, Cotter found the chances of a household being poor increased if the labor market was in the Southern United States, was nonmetropolitan, and had large numbers of people under 18 years of age. Labor market factors that reduced the chances of a household being poor included larger female-headed household populations, increase female labor force participation, higher education expenditures, larger shares of good jobs, and larger shares of manufacturing employment.

Crandall and Weber's (2004) analysis looks at how local socioeconomic conditions affect the spatial concentration of poverty. Specifically, the authors have four main objectives. They first seek to determine whether county-level job growth and social capital affect tract-level poverty rates. Second, they seek to understand how tract-level poverty rates are affected by initial rates and adjacency to high-poverty tracts. Third, they test to see if the effect of job growth on poverty is mediated by social capital and adjacent poverty. Lastly, they estimate the spatial spillovers of poverty changes in nearby tracts. Their analysis looks at these interactions across several groups of poverty-impacted counties between 1990 and 2000.

For high-poverty counties, demographic factors that hindered poverty reductions included larger populations of other races, single mothers, college graduates, and persons over 64 years of age. Conversely, populations of African-Americans, Native Americans, and Hispanics aided poverty reduction. In terms of structural factors, they found that higher poverty in 1990 and the interaction between urban adjacency and employment growth hindered poverty rate declines. On the other hand, urban adjacency, employment growth, and high levels of social capital aided poverty reductions.

Looking at low-poverty counties for comparison, the authors found some striking differences. In terms of demographic factors, larger shares of all minority populations and single mothers hindered poverty reduction. On the other hand, high school and college graduates, and populations of people under 18 and over

65 years of age aided in poverty declines. In terms of structural factors, they found that urban adjacency and low population densities hindered poverty reduction. Conversely, higher poverty in 1990, employment growth, and the interaction between urban adjacency and job growth aided in reducing poverty in low-poverty counties.

Davis, Connolly and Weber (2003) track the employment outcomes of a cohort of jobless poor in Oregon in order to analyze the relative importance of local labor market conditions on their employment outcomes. Specifically, the authors are interested in determining how local job growth affects the employment success of the jobless poor, and whether local job growth is less effective at improving employment outcomes in rural rather than urban labor markets. They found that local job growth increases the probability of a jobless poor adult getting a job, and shortens the length of joblessness in urban areas. The results imply that job growth has a reduced impact in rural areas because of traditional labor market disadvantages, rather than low population densities.

Synthesis

In this dissertation, my theoretical approach to understanding poverty is based in the labor market perspective. The labor market approach is a body of theory and research that incorporates both the individual and structural approaches within a spatial context. Also, I agree with the two core assumptions of the labor market approach. First, that rural poverty is due to the distribution of individual characteristics in the population, which is consistent with individual/person-based approaches. Second, that rural poverty is also due to the socioeconomic division of labor, which is consistent with structural/place-based approaches. Under this rubric, I posit that poverty is higher in areas with an economic structure concentrated in peripheral/non-basic industries (local-oriented markets), and lower in areas concentrated in core/basic industries (export-oriented markets). This determines the level of poverty within an area, with individual characteristics providing the means by which poverty falls more heavily on certain groups.

The labor market is structured by the economic organization of firms and by the distribution of skills and education among the population, and it is this two-fold structure that determines and constrains the economic opportunities available to individuals. Both theory and research agree that labor markets dominated by core industries of the economy offer better opportunities and rewards than those dominated by peripheral industries. However, with the rise of advanced services under postindustrial capitalism old definitions of core and periphery are no longer accurate. The new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Industries that drive this new core include information, publishing, telecommunications, advanced producer services, and professional services.

Further, I agree with the postindustrial literature that argues the new core and periphery has given rise to a new class of winners and losers. The ascendancy of postindustrial capitalism has led to a new stratification order that is radically different from what existed under industrial capitalism. I posit that the newly emerging postindustrial class structure is composed of four classes: a small capitalist class as existed under previous forms of capitalism; a small working class that has been greatly diminished from previous capitalist periods; a new large professional-managerial class that drives the postmodern economy; and a new lower class that services the professional-managerial and capitalist classes.

CHAPTER FIVE

AGRICULTURE, ECONOMIC STRUCTURE, AND RURAL DEVELOPMENT

Two major strands of literature have identified how changes in structure impacts socioeconomic well-being. The agricultural structure literature, often termed the sociology of agriculture, specifically links the organization of agriculture to socioeconomic conditions within a community. The economic structure literature, often termed segmented economy theory, links the organization of the non-farm economy to socioeconomic well-being by segmenting the economy into core/basic and periphery/non-basic industries. In this chapter, the first section discusses current literature on how agricultural structure affects rural development. The second section discusses current research on how non-farm economic and industrial structure affects rural development. Both of these sections are viewed within the context of the postindustrial economy.

Agriculture Structure and Rural Development

The exodus of Americans from farming is one of the most important economic and social changes within the last century. According to the U.S. Department of Agriculture's Economic Research Service, in 1900 nearly one in three American lived on farms. By 2000, the farm population was less than two percent of the population, with most of this population earning income from non-farm sources. Agricultural transition means the abandonment of farming as a household livelihood strategy. Today's farmers range along a continuum from independent family farms to industrial corporate farms (Lobao and Meyer 2001). Family farms are those where the family unit provides the labor, management and capital needed to run the farm, often supplemented by off-farm work (Salamon 1992). Industrial corporate farms supply their operations using labor, management, and capital from outside entities, such as wage laborers and capital markets (Lobao 1990).

Lobao and Meyer (2001) outline several reasons why farming is important in understanding rural communities. First, the farm sector and agrarian change was the starting point for classic sociologists – like Marx, Durkheim and Weber – who saw agricultural transformation as reinforcing capitalist expansion. Second, farming is an important source of exports and income from many rural communities. Third, by not including the farm sector social scientists miss an important segment of many rural economies. Fourth, farming is at the center of many current social issues (such as genetically modified organisms, land use, and food safety) and environmental issues (such as global trade talks, government subsidies, and trade barriers). Fifth, farming has distinct characteristics that allow social scientists to investigate the informal sector, alternative household strategies, unpaid labor, and why farming doesn't fit neatly into modernist conceptions of the economy. Lastly, farming is subject to such a variety of government programs that probably no other workforce has such extensive policy interventions.

Decades of research have identified agriculture as a key ingredient in rural development (Gilles and Dalecki 1988; Green 1985; Heffernan 1982; Jaffe 1991; Lobao 1990; Lobao et al. 1993; Lyson, Torres and Welsh 2001; Rhodes 1995; Salamon 1992). The sociology of agriculture is divided into two major schools of thought. The political economy school looks at the structural transformation of farming using macro-level theories of national and global trends. The community school focuses on the impacts of agricultural change on communities.

The political economy school takes a sociological perspective on the agricultural economy. Similar in many ways to neoclassical economics, this school acknowledges that market competition and petrochemical technology are reasons why farms have gotten larger and fewer. The difference between the two lies in who is assumed to control and benefit from this system. Political economy sees market competition as socially produced and regulated in ways that benefit large capital interests, which is detrimental to most farmers, consumers and the environment (Buttel and Newby 1980; Friedland et al. 1991). The political economy school also articulates the state's role through programs and policies. These include development and dissemination of technology through land grant universities, low cost food policies, and integration of farming into the global economy through world trade agreements (Lobao and Meyer 2001).

The political economy school has been critiqued on several fronts (Lobao and Meyer 2001). The school ignores human agency and culture, saying little about how farmers' choices, beliefs, and political actions shape agricultural transformation. The school also has a strong production bias, arguing that increased production drove the growth of capitalist farming, rather than consumption factors. Lastly, the macro-level focus downplays the role of subnational units like communities and regions. However, some political economists have attempted to address these issues by focusing on meso-level and micro-level analyses, particularly on the social practices and values of farm households that cause them to either exit or adapt (Brown, Xu and Toth 1988; Garkovich, Bokemeier and Foote 1995; Salomon 1992). These studies have tended towards a human ecology approach, which brings it much closer to the community school of thought, which is discussed next.

As the name implies, the community school looks at the community impacts of agricultural transformation. This school initially concerned itself with the effects of rapid farm decline that occurred prior to the 1970s, and what happened to rural communities as families left farming. Currently, the community school concerns itself with the relative growth of large labor-dependent industrial farms and the concurrent decline of moderate-sized family farms. Lobao and Meyer (2001) identify three generations of community perspective literature.

The first generation of community research, dating from the 1930s and 1940s, examined the relationship between concentration of economic power at the local level and the socioeconomic well-being of local residents. Two key reports, both commissioned by the United States Congress, advanced the hypothesis that communities where the economic base was composed of small locally-owned businesses would have higher levels of socioeconomic well-being and political representation, compared to those communities where the economic base was composed of a few large absentee-owned businesses. These two reports were called *Small Business and Civic Welfare* by C. Wright Mills and Melvin Ulmer; and *Small Business and the Community* by Walter Goldschmidt.

Specifically, Goldschmidt (1978) looked at the consequences of farm inequality by studying two California towns named Arvin and Dinuba. Arvin was a community dominated by large industrial farms, while Dinuba was dominated by family farms. Goldschmidt found poorer conditions in Arvin, such as a smaller middle class, lower family incomes, poorer public services, and less civic participation. He argued that the scale of farming affected farm and local stratification patterns, and thus in turn affected other community outcomes.

The second generation of community research, done in the 1970s and 1980s, involved updating Goldschmidt's work in the context of postwar farm concentration. Quantitative in nature, these studies examined the links between farm scale versus structure and indicators of local socioeconomic well-being. Although there are several methodological shortcomings of Goldschmidt's work (Hayes and Olmstead 1984), his hypothesis has been well tested by other researchers. In general, the literature shows a consistent trend that dependency on farm wage laborers exerts a negative influence on socioeconomic well being. Such studies have found that industrial farming leads to declines in local population (Heady and Sonka 1974), lower incomes and lower standards of living (Gilles and Dalecki 1988), lower numbers and quality of community services (Poole 1981), lower community integration and greater psychological stress (Heffernan 1972; Heffernan and Lasely 1978; Martinson, Wilkening and Rodefeld 1976), and a less diverse economic base and higher unemployment (Marousek 1979).

Lobao (1990) reviewed 18 such “Goldschmidt” studies done between 1985 and 1992. She found that nine supported Goldschmidt’s hypothesis, seven offered mix support, and two offered no support. Some major critiques of this body of work were that the studies used cross-section rather than panel data, they were regionally-specific rather than national, and many omitted important non-farm control variables. Perhaps as important, this literature did not resolve the debate whether it was farm scale (i.e. size of farm operation) or farm structure (i.e. farm labor relations) that mattered in affecting socioeconomic well-being.

The third generation of community studies, done since the 1990s, attempted to address the critiques of second generation research and to add new theoretical dimensions. This literature combined Goldschmidt’s hypothesis with theories of spatial inequality, economic structure, state and policy factors, civic society, and social capital. According to Lobao and Meyer (2001), the current literature is more mixed on the impact of industrial faming. For example, several studies have documented that industrial farming had a detrimental impact on community well-being Irwin (MacConnell 1988; Tolbert and Lyson 1999; Tolbert, Lyson and Irwin 1998). However, contradictory evidence from other studies has found that industrial farming had no significant impact (Buttel, Lancelle and Lee 1988; Lyson et al. 2001; Van Es, Chicoine and Flotow 1988). These studies suggest that regional differences exist and that state policy and regulation, civic activism, and labor market conditions may ameliorate the negative impacts of industrial farms. However, it is still unclear whether it is farm scale or farm structure that causes differences in community well-being.

Lobao's (1990) seminal study explores how postwar economic restructuring, particularly in the farm sector, contributes to socioeconomic inequality at the local level. Using 1970 and 1980 census data, Lobao uses regression analyses to test how the structure of the economy, agriculture, and community demographics influences socioeconomic outcomes. These outcomes include median family income, poverty, income inequality, and various child well-being indicators. Lobao's analysis provides limited support for the Goldschmidt hypothesis that industrialized farming reduces socioeconomic conditions across rural counties in the United States.

She found that the impact of industrialized farming is neither automatic nor strong. However, industrialized farming also appears incapable of generating high and equitable levels of economic well-being over time, mainly due to the industry's extensive use of low-wage, seasonal, and unskilled hired labor. In some areas, Lobao found that industrial farming counties had more unequal income distributions, but not higher poverty or lower family incomes. Spatially, industrialized farming led to better socioeconomic conditions in central U.S. counties, and lower outcomes in southeastern U.S. counties. Also, industrial farming areas were favorably endowed with worker power characteristics, such as unionization, low unemployment, and degree of rurality. In short, she found that the economic context of industrialized farming is characterized by internal disparities between rich and poor, and cumulative underdevelopment in the long term.

A consistent finding of Lobao' study was that a production system of family operated commercially-oriented farms – what she terms larger family farms – results in better socioeconomic conditions for localities, including higher and more evenly distributed incomes, lower unemployment, and lower infant mortality. Lobao concludes that these positive effects are due to the fact that these farms operate units that are large enough to support their households without much operator off-farm work, but that they are not so large as to require the use of hired labor.

Lobao's findings also shows that smaller family farming units interact with the non-farm sector much more closely and complexly than do the other two farming patterns already discussed. She found that in counties where smaller family farming predominates, the industrial base is larger and particularly dependent on peripheral manufacturing and educational attainment. These areas appear to be better linked to urban consumption and labor markets, and that their higher health status and educational attainments may be a consequence of their metropolitan and structural linkages.

Heffernan (2000) argues that in the case of agriculture, transnational corporations (TNCs) have created an hourglass economic structure, where a few TNCs have positioned themselves at the processing phase between thousands of agricultural producers and millions of food consumers. Being in control of this bottleneck, TNCs exert a disproportionate influence on the price, quality and type of agricultural commodities bought from producers and sold to consumers. In essence, a large portion of the food system is increasingly being controlled by a few TNCs, which operate beyond the control and regulation of the nation-state. Why this matters, Heffernan argues, is that TNCs cannot therefore be held accountable by the nation-state for the negative externalities TNCs may produce. Heffernan goes on to state that TNCs usually care little about how their operations negatively impact labor, the environment, food security, minorities and rural communities.

The key point is that most third generation studies note some significant impact of farm structure that persists over different degrees of rurality, farm dependence, and time. Even in postindustrial society farming appears to affect communities, though not to the degree of other industries like manufacturing or services. Lobao and Meyer (2001) note some issues that third generation research needs to address. To begin with, systematic comparisons across time and space are limited, and longitudinal quantitative and comparison case studies beyond 1990 are needed. Little research has been done to date examining how institutional factors impact and mediate farm change. More attention also needs to be given to outlining the causal paths by which farm change filters down to communities. More broadly, current research needs to address and inform sociological theory rather than merely producing more results.

Economic Structure and Rural Development

For well over 100 years, social scientists have been interested in how the industrial structure of a locality affects its ability to develop. As agriculture has become a less important part of the rural economy, researchers have shifted their focus from agricultural structure to the structure of key industries and characteristics of the labor force (Albrecht 1998; Barnes and Blevins 1993; Bender, Green, Hady, Kuehn, Nelson, Perkinson and Ross 1985; Lobao and Schulman 1991). These studies have found that economic structure and socioeconomic well being vary by region. Factors such as climate, natural resource endowment, and economic history have substantial impacts on the relationship between economic structure and quality of life.

To begin, the dual or segmented economy literature maintains that different industrial structures result in different socioeconomic outcomes (Bartik and Eberts 1999; Edwards 1979; Hodson 1984). Specifically, a distinction is made between core and periphery industries, which in economics are termed basic and non-basic, respectively. These concepts are grounded in economic base theory in economics, which posits that the local economy is strongest when it develops economic sectors that are not closely tied to the local economy (Ullman, Dacey and Brodsky 1971). By developing basic firms that rely primarily on external markets, it is argued that the local economy can better insulate itself from economic downturns as export-oriented firms will remain strong even as the local economy experiences problems. By contrast, a local economy mostly dependent on local markets will have great difficulty rebounding from economic slumps.

Economic base theory assumes that all economic activities can be identified as basic or non-basic, and firms that sell to both external and local markets must be apportioned in some fashion. Basic or core industries are made up of export-oriented firms that are mostly dependent on external factors. Core industries are characterized as large scale and highly productive exporting economic sectors that employ highly skilled labor at above average wages. Conversely, non-basic or periphery industries are composed of firms that depend largely on local economic conditions. Periphery industries are characterized as smaller scale and less productive, which employ lower skilled labor at below average wages. Since they depend entirely on the local economy, the fortunes of these industries is ties to the growth and decline of the community since they do not bring new money into the economy. It is therefore argued that communities more dependent on core industries, such as manufacturing and professional services, are more developed both economically and socially than those dependent on periphery industries, such as retail trade and personal services (O'Connor 1973).

Lash and Urry (1994, 1987) argue that the postmodern economy under postindustrial capitalism primarily produces signs, not material objects. As reflexive production and consumption become more intertwined, this has caused cultural production to supercede material production in the postmodern economy (Beck et al. 1994; Bell 1979, 1976; Lash and Urry 1994, 1987). Cultural production has not become commodified or more like manufacturing in today's economy, but instead cultural production is becoming more like manufacturing. The cultural industries are both knowledge and design intensive. They are knowledge intensive because the commodities they produce have high information content; and they are design intensive because the commodities they produce have high aesthetic content. The key in these industries is to use knowledge content to produce the commodity, but use aesthetic content to sell it to the public. Sign-value is important in all products – it has always been so in the cultural products, but now it is increasingly so in manufactured products.

The rise of culture industries under postindustrial capitalism has precipitated a shift in what constitutes the core or basic segments of the economy (Bell 1976, 1976; Lash and Urry 1994, 1987; Lipietz 1992). Core or basic industries are those export-oriented sectors that drive the wider economy.

Under Fordism, the old core consisted of a set of producer networks centered around material production, like electrical products, steel, chemicals, and machinery. Other functions of the economy were subordinate to and driven by this old core, like transportation, finance, and services. However, with the rise of advanced services under postindustrial capitalism, the new core or basic industries consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Export-oriented Industries that drive this new core include information, publishing, telecommunications, advanced producer services, and professional services.

Related to these “new economy” industries, Goe (2002) looked at the growth in nonmetropolitan producer services between 1980 and 1990, and how this growth resulted in the development of nonmetropolitan growth nodes in producer services industries. A nonmetropolitan producer services growth node refers to a nonmetropolitan area that contains a greater than average concentration of employment in producer services relative to other areas, with the concentrations increasing over time. Goe’s analysis identifies 317 rural producer services growth nodes between 1980 and 1990. He found that development of producer services growth nodes was associated with access to workers with administrative support and clerical skills, access to highly educated workers, higher earnings per employed worker, access to recreational amenities, and proximity to metropolitan areas.

Besser (2003) takes issue with the conventional notions that advanced producer services are unlikely to locate to rural areas due to the economic and cultural benefits offered by central cities; and that producer services firms in rural areas are qualitatively different from the urban counterparts. To investigate these questions, Besser analyzes perceptions about the environment, management strategies, and community citizenship of 259 producer services business owners in rural and urban Iowa. Rural producer services firms were less likely than urban ones to view the local economic climate, costs of rent, costs of labor, and the quality of labor as threatening to their operations. Further, rural firms were more likely than urban ones to cooperate with other businesses, to work at strengthening the community, and to improve the community's image as a business as a competitiveness strategy. Also, rural firms were more committed and supportive of the community, and provided more community leadership than their urban counterparts.

Several studies have demonstrated that the mix of industries and economic sectors in a community can affect the rate and nature of development (Adamchak, Bloomquist, Bausman and Qureshi 1999; Bloomquist 1988; Feser 1998; Kusmin 1994; Kusmin, Redman and Sears 1996). The overall economic development success of a region will likely reflect the success of industries that have already concentrated there. Particular industries may be more likely to locate in areas where firms in related industries are already present, thus ensuring easier access to appropriately trained labor and other inputs. Thus, growth in a particular industry will reflect the current distribution of that and similar industries. Further, several of these studies have theorized that certain places constitute a central node in an economic exchange network (Bloomquist et al. 1993; Yanagida, Johnson, Young and Lundeen 1991). Industries locate in certain nonmetropolitan cities and larger towns where they can take advantage of economies of scale in both the composition of the labor force (such as occupational availability and skills) and related input industries (such as suppliers and transportation and communications networks).

Lobao's (1990) seminal study explores how postwar economic restructuring, particularly in the farm sector, contributes to socioeconomic inequality at the local level. Using 1970 and 1980 census data, Lobao uses regression analyses to test how the structure of the economy, agriculture and community demographics influences socioeconomic outcomes. These outcomes include median family income, poverty, income inequality, and various child well-being indicators. Lobao's analysis provides strong support and extends the research on industrial structure and segmentation.

She found that localities with greater core employment exhibited higher income levels, lower poverty rates, and had less income inequality. The reverse was true for localities dominated by peripheral employment, where socioeconomic conditions were worse than in core employment areas. One interesting finding she notes is that state or government employment had a negative impact on socioeconomic well-being, much like that of peripheral industries. Though supportive of recent research, this finding runs contrary to the old Fordist segmented economy theory, which assumed more favorable outcomes were attributable to the government sector.

Numerous studies were conducted in the 1980s and early 1990s on the structural and resource endowment factors affecting both metropolitan and nonmetropolitan employment. Most studies used state-level data, with only a few using county or sub-state level data (Kusmin 1994). Further, few of these studies have paid specific attention to nonmetropolitan economic growth in high technology industries (Bergman 1998; Wojan 2000). However, there is a substantial body of research that has identified key predictors of nonmetropolitan employment.

In the case of highways and interstates, Smith, Deaton and Kelch (1978) found a significant relationship between access to an interstate or other major highway within a county and the likelihood of attracting manufacturing plants. Carlino and Mills (1987) also found that interstate highway density (highway mileage per square mile) was a highly significant predictor of both population and employment growth at the county level.

According to McGranahan (1999) and others (Beale and Johnson 1998; Cromartie and Nord 1996), employment change in rural counties over the past 25 years has been highly related to natural amenities. Counties with low natural amenities had relatively little employment growth, while high natural amenity counties had an average of three times as many new jobs in 1996 as in 1969.

The authors state that the accessibility of counties to recreational visitors is probably more critical for determining where employers locate rather than where people move. Further, Galston and Baehler (1995) note that natural characteristics have emerged as a new source of rural comparative advantage, especially in terms of retirees, tourists and certain businesses. However, McGranahan (1999) points out that much of the current work relating natural amenities to growth is largely indirect, based on the growth of recreation industries and retirement destination counties.

Many studies reviewed by Kusmin (1994) have used population as a possible predictor of economic growth. A study by McNamara, Kriesel and Deaton (1988) used such an explanatory variable, which had a significant positive effect on employment growth. On the other hand, several other researchers have found no relationship, and even a negative relationship, between town population and the likelihood of attracting manufacturing plants (John, Batie and Norris 1988; Kuehn, Braschler and Shonkwiler 1979). Kusmin (1994) notes that many studies have included population without presenting any justification for doing so, and that it is often used as a demographic control.

In addition, many studies have attempted to assess the impacts of educational attainment on economic growth and social development. Most studies have measured this as either median years of school completed, or the percent of adults who have completed high school (Kusmin 1994). Bartik (1985) finds that median educational attainment has no significant influence on 1972-

1978 manufacturing plant location decisions, once regional control variables were included in the model. Bartik states that without regional controls, the relationship was significant and negative – indicating that manufacturers preferred locations that had a less educated workforce. However, Wasylenko and McGuire (1985) found that median educational attainment had a significant and positive association with employment growth between 1973 and 1980 for manufacturing, transportation and wholesale trade. However, this relationship was not found in overall employment growth. In summary, the studies reviewed by Kusmin (1994) provide limited and contradictory evidence for the effects of educational attainment on economic growth. Several recent studies have attempted to separate college-level from lesser degrees of educational attainment (Carlino and Voight 1992). These studies seem to indicate that educational attainment may not have a linear function.

Some researchers (Kusmin 1994) have argued that higher per capita and family incomes may be more attractive to businesses because of greater market demand in a community. Higher per capita income levels may be associated with greater growth of businesses that market products locally if these areas also have greater demand for such products and if that demand is unfulfilled. Carlino and Mills (1987) found that higher 1970 family income levels were strongly associated with higher 1980 population and employment.

Several authors have suggested that proximity to institutions of higher education may have some effect on growth. Smith et al. (1978) found that the presence of a college in rural Kentucky and Tennessee communities had a significant positive effect on the likelihood of attracting a manufacturing plant between 1970 and 1973. On the other hand, McNamara et al. (1988) found a nonsignificant negative relationship between distance to the nearest four-year accredited colleges in a county and the probability of attracting new manufacturing plants. There have been few studies since 1994 assessing the influence of higher educational institutions on other employment sectors – notably services – or overall employment (Kusmin 1994). It is argued that although this variable may be ineffective at predicting manufacturing employment, some evidence suggests that it may be significant in predicting overall employment and particularly services employment (Drabenstott and Smith 1996; Kusmin et al. 1996).

Another group of rural social scientists has focused on the relationship between state and local initiatives on rural development. This body of research differs in that it concentrates on the variables over which people have some control. Most of the studies have examined the effectiveness of industrial recruitment efforts compared to local development initiatives. There have been previous regression analyses that attempt to account for economic growth by taking into account levels of taxation, infrastructure and human capital. The results of these types of studies have been mixed. It was found that economic growth does occur in areas with low levels of taxation (Bartik 1985), yet tax burden is better at explaining inter-state differences in development rather than inter-county differences. In fact, Carlino and Mills (1987) found that taxation had little influence on employment when they controlled for location. The impact of taxation appears to vary by region, time and industry. Access to markets and long term investments in infrastructure are larger determinants of local economic development than local tax policies (Fox and Murray 1990).

Overall, the implications for level of taxation are unclear. Several studies have indicated that a negative relationship exists between business taxation and economic growth/business location, while other studies have found that business taxation yields insignificant or ambiguous results (Kusmin et al. 1996). Research by Bartik (1985) suggests that business taxation has a negative effect on employment growth and small business start-ups. However, research by Quan and Beck (1987) suggests that educational expenditure and employment growth has a positive relationship – although it varies by region. Further, various other studies provide limited and contradictory evidence on whether other types of government expenditures – such as education, public safety, and highways – have any impact on economic growth (Kusmin 1994). Specifically, Kuehn et al. (1979) attempted to identify factors associated with the attraction of new manufacturing plants in a sample of 115 small Missouri communities. The authors found that property tax rate had a negligible effect on the likelihood of attracting a manufacturing plant.

There is little consensus on the benefits of industrial recruitment in the literature. Research by Smith et al. (1978) and Luloff and Chittenden (1984) have demonstrated the benefits of local efforts to recruit industry through the development of industrial parks, the creation of development agencies and the use of incentives. On the other hand, research by Carlino and Mills (1987) and Humphrey and Wilkinson (1993) have shown this is not necessarily the case. Self-development has been proffered as an alternative to industrial recruitment. Self-development, it is argued, may be more sustainable in a global economy where manufacturing and agricultural firms have become increasingly mobile, and where the service sector is expanding more rapidly.

Initially, self-development research focused on descriptions of successful self-development strategies and efforts, but these were largely anecdotal (Honadle and Reid 1987). Eventually, detailed case studies cataloged shared traits and characteristics common in communities where successful self-development activities had occurred (Flora, Green, Gale, Schmidt and Flora 1992; Green, Flora, Flora and Schmidt 1990). Out of these case studies emerged a theoretical concept termed Entrepreneurial Social Infrastructure (ESI).

ESI was developed by combining the case study results of self-development activities and the literature on social capital. In essence, ESI consists of the social features which enhance a locality's ability to successfully engage in collective action aimed at solving community problems and issues. Flora and Flora (1993) states that the central hypothesis of ESI is that it is higher in communities which have successfully carried out a self-development or industrial recruitment effort; as opposed to communities who have not successfully carried out economic development projects. Through observation of numerous case studies of successful economic development projects, they concluded that certain styles of interactions and manners of approaching and addressing problems collectively contributed significantly to whether a community was successful at economic development. The authors have identified three main conceptual structures of ESI – symbolic diversity, generalized resource mobilization, and diversity of networks.

There is also a body of research which asserts that local control of the economy fosters a stronger commitment to equitable relationships and community well being (Gunderson, Sack, McCartney, Wakely and Eaton 1995). Common types of locally owned business establishments in rural areas include owner-operated farms, grocery, hardware, and clothing stores. Locally owned businesses deduct annual expenses from its total income to determine profits, which is allocated between labor, management and capital. In terms of the economic well being of the community, it makes little difference how profits are allocated among these three costs of production since most of it is spent within the local economy. This contributes to economic development through the creation of spin-off jobs, termed indirect and induced effects. Conversely, non-locally owned businesses tend to transfer profit from the local economy to corporate headquarters or shareholders; and they often obtain intermediate inputs from outside the local economy resulting in fewer spin-off jobs. In addition, there is evidence that communities with locally owned firms tend to result in greater economic performance, community satisfaction and responsiveness to community needs (Beckley and Krogman 2002).

Synthesis

Two major strands of literature, the sociology of agriculture and segmented economy theory, have identified how changes in structure impacts poverty and general socioeconomic well-being. The agricultural structure literature, often termed sociology of agriculture, specifically links the organization of agriculture to the economic and social conditions within a community. This literature argues that communities with absentee-owned industrial farms are less developed both economically and socially than similar communities composed mainly of family farms. The economic structure literature, often termed segmented economy theory, also maintains that different industrial structures result in different socioeconomic outcomes. Communities more dependent on core or basic industries (export-oriented) are more developed both economically and socially than those dependent on periphery or non-basic industries (local-oriented). However, much of the segmented economy literature is based on an industrial or Fordist notion of core and periphery.

There is a need to merge these two traditions of research in the context of a postindustrial and post-Fordist economic structure. The agriculture structure literature has largely treated the non-farm economy as a monolithic whole, failing to recognize the different externalities produced by different economic sectors under postindustrialism. At the same time, the segmented economy literature has produced limited understanding of how postindustrial economic structure affects rural communities, and has virtually ignored the farm economy. This analysis merges these two traditions of research and addresses the methodological shortcomings of each approach in the context of a postindustrial economy and postmodern society.

Although previous researchers have already merged these two traditions of research, they have done in the context of an industrial or Fordist economic structure (Gilles and Dalecki 1988; Green 1985; Lobao 1990; Lobao et al. 1993). Their research leaves several important questions unanswered regarding the interaction between agricultural and industrial structure. Is the agriculture-industry structure hypothesis still relevant in a postindustrial economy increasingly dependent on services and transfers, and where the agricultural base is rapidly declining? Is the hypothesis a historically specific construct of the industrial or Fordist era that no longer holds true in the postindustrial era? Is using occupational structure a better measure of the postindustrial economy than industrial structure? Does the agriculture-industry structure hypothesis hold true when tested using postindustrial definitions of the economy that focuses more on information, communications and advanced producer services? Does an agriculture-industry structure hypothesis hold true when using occupational structure instead of industrial structure? Does the hypothesis also hold true at a more localized unit of analysis?

My dissertation will address these questions, thus filling existing gaps in the poverty, agriculture structure and industry structure literatures. First, my analysis defines economic structure using industrial classifications that better reflect the current postindustrial economy. There is a critical need to reevaluate previous research in light of new and more accurate definitions of the postindustrial economy. Second, my analysis also defines economic structure using occupational classifications that reflect what workers do, not just the type of industry in which they work. Much of the previous research done to date has not looked at occupational structure as the primary organizational principle of the economy. Under postindustrial capitalism, new production systems require workers to possess more diverse skills and better training in order to handle more demanding and sophisticated technologies. Therefore, there is a critical need to reevaluate previous research that incorporates an occupational-based definition of the economy, which better reflects the postindustrial economy.

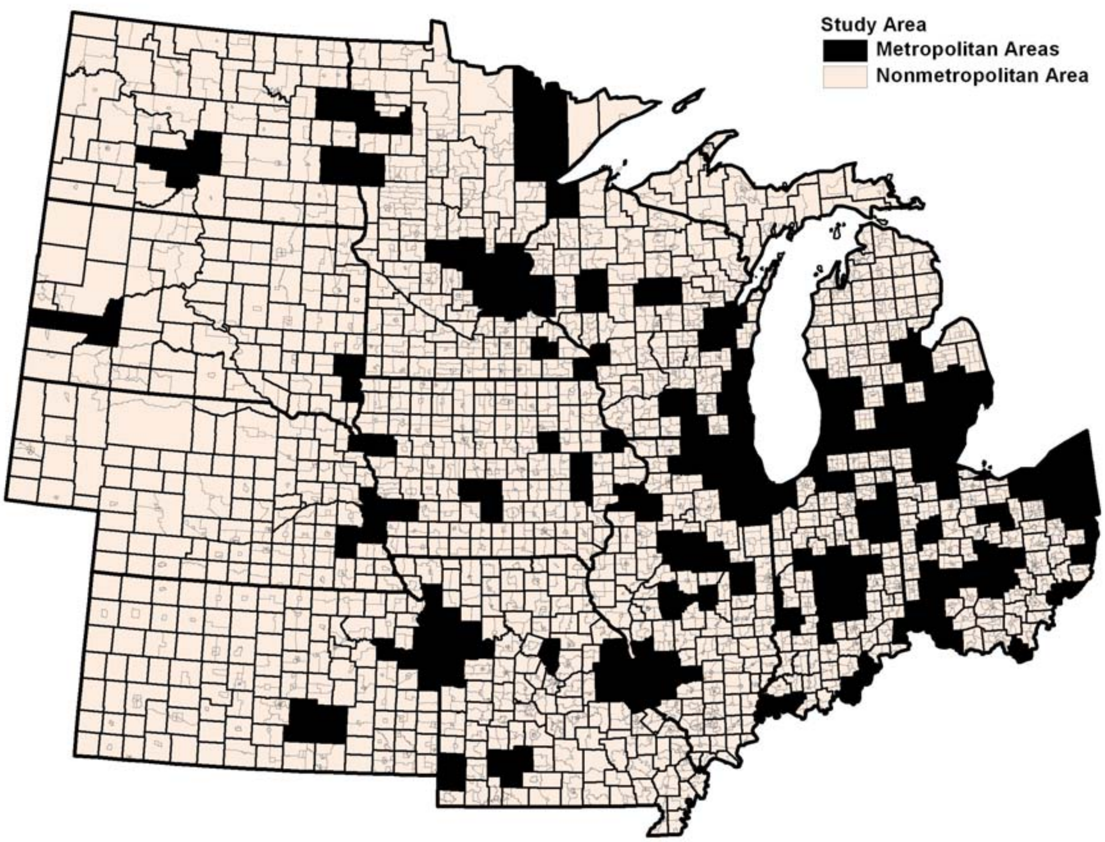
CHAPTER SIX

DATA AND METHODOLOGY

This dissertation seeks to understand poverty clusters in rural America within the context of the postindustrial economy. It is hypothesized that different types of agricultural and economic structures have differential impacts on the level of poverty in rural areas. This chapter describes the data and methods employed to test this research question. The first section reviews the core objectives of this analysis, and then formulates these into specific hypotheses. The second section describes how poverty clusters are identified, starting with a discussion of the cluster analysis method, and then followed by a description of the endogenous variables used in the analysis. The last section describes how poverty clusters can be explained and predicted by taking into account agricultural and economic structure. The section begins with a discussion of logistic regression, which is used to predict the odds of cluster membership, and concludes with a description of the exogenous variables used in the analysis.

The study area for this analysis includes all 4,610 nonmetropolitan census tracts in the north central region of the United States, which includes 12 states (see Figure 11). Rather than using the entire United States as a study area, the north central region was selected for a variety of reasons. Taking a regional approach minimizes error and allows significant statements to be made about the area as a whole. First aggregation into regions is useful in connection with description, because it means that fewer separate numbers or other facts need to be handled and perceived. Second, aggregation is economical in connection with analysis of information; and it is particularly important if there is a good deal of interdependence of units or activities within the area, so that the whole really is more than merely the sum of its parts. Lastly, aggregation is necessary for administration leading to the formulation and implementation of plans and public policies.

FIGURE 11
North Central Region Study Area



Taking this last point further, a normal attribute of a region is a general consciousness of a common regional interest, which makes possible some rational collective efforts to improve regional welfare. The commonality of interests may be reflected in numerous ways, but at its core is the idea of a high degree of correlation of economic experiences among the region's sub-areas and interest groups. The region used in this analysis is analogous to the North Central Regional Center for Rural Development (NCRCRD) area, whose mission is to initiate and facilitate rural development research and education programs to improve the social and economic well-being of rural people in the region. It is hoped that by working through the NCRCRD, this information can then be used to inform collective action within the community and public policy within various units of government.

Hypotheses

The purpose of this analysis is to understand poverty in rural America in the context of agricultural and postindustrial economic structure. In this dissertation, the theoretical approach to understanding poverty is based on the labor market perspective. The labor market approach is a body of theory and research that incorporates both the individual and structural approaches within a spatial context, and has at its heart two core assumptions (Cotter 2002). First, rural poverty is due to the distribution of individual characteristics in the population. Second, rural poverty is also due to the socioeconomic division of labor. Under this rubric, it is posited that poverty is higher in areas with an economic structure concentrated in peripheral/non-basic industries, and lower in areas concentrated in core/basic industries. This determines the level of poverty within an area, with individual characteristics providing the means by which poverty falls more heavily on certain groups.

Both theory and research agree that labor markets dominated by export-oriented core industries of the economy offer better opportunities and rewards than those dominated by peripheral industries dependent on the local economy (Cotter 2002; McLaughlin 2002). However, with the rise of advanced services under postindustrial capitalism old definitions of core and periphery are no longer accurate. The new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Industries that drive this new core include information, publishing, telecommunications, advanced producer services, and professional services (Lash and Urry 1994).

Further, the ascendancy of postindustrial capitalism has led to a new stratification order that is radically different from what existed under industrial capitalism (Lash and Urry 1994, 1987). It is posited that the newly emerging postindustrial class structure is composed of two new large services classes, which include the professional-managerial class and the lower services class. Also included are two smaller classes, which include a stable capitalist class and a much reduced working class – both remnants of industrial capitalism.

Based on this theoretical approach to understanding poverty and economic structure, detailed socioeconomic data are analyzed for all rural census tracts in the north central region of the United States. Specifically, this analysis has four main objectives. The first objective is to identify rural poverty clusters in the north central region using statistically appropriate methods. This analysis employs cluster analysis to group census tracts into homogeneous clusters according to their similarity in poverty rates and changes from a decade ago. Cluster analysis is one of the most appropriate methods to create a typology or classification, where the procedure attempts to mathematically reorganize data into homogenous groups that can be statistically validated. These groupings are termed poverty clusters, which is consistent with the parlance of the cluster analysis, although the clusters are identified in socioeconomic space. Although there are most likely spatial patterns in the clusters, spatial characteristics are not explicitly incorporated into the analysis.

Once poverty clusters are identified, the second objective is to determine how agricultural structure affects membership in a rural poverty cluster. Here the structure of agriculture is defined in terms of the organization of labor relationships. It is posited that greater concentrations of self-employed workers in agriculture reduces poverty. Conversely, it is posited that greater concentrations of workers employed as wage laborers in industrial agriculture increases poverty. The following hypotheses are drawn from the sociology of agriculture literature, and tests whether communities characterized by family farm agriculture are more developed socioeconomically than those characterized by industrial agriculture. Specifically:

H1: Greater concentrations of farmers or workers self-employed in agriculture will reduce the odds of a census tract being in a poverty cluster.

H2: Greater concentrations of agriculture workers employed as wage laborers will increase the odds of a census tract being in a poverty cluster.

The third objective is to determine how postindustrial economic structure affects membership in a rural poverty cluster. It is posited that greater concentrations of workers employed in postindustrial core/basic and semi-core/semi-basic industries reduces poverty. Conversely, it is posited that greater concentrations of workers employed in postindustrial periphery/non-basic industries increases poverty. Analogous to the concepts of basic and non-basic industries in economics, the former are generally export-oriented and dependent on external factors, while the latter is mostly dependent on local markets and conditions. Semi-basic industries sell to both export and local markets, and thus are both basic or non-basic. The following hypotheses are drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by postindustrial core industries are more developed socioeconomically than those characterized by postindustrial periphery industries. Specifically:

H3: Greater concentrations of workers employed in postindustrial core industries will reduce the odds of a census tract being in a poverty cluster. These industries include: (a) information services; (b) finance, insurance, and management of companies services; (c) professional, scientific, and technical services; and (d) manufacturing.

H4: Greater concentrations of workers employed in postindustrial semi-core industries will reduce the odds of a census tract being in a poverty cluster. These industries include: (a) educational services; (b) health care and social assistance; and (c) transportation, warehousing, and utilities.

H5: Greater concentrations of workers employed in postindustrial periphery industries will increase the odds of a census tract being in a poverty cluster. These industries include: (a) construction; (b) trade; (c) real estate, rental, and leasing services; (d) administrative support and waste management services; (e) arts, entertainment, recreation, accommodation, and food services; (f) other services; and (g) public administration.

The fourth objective is to determine how occupational structure affects membership in a rural poverty cluster, and whether the results differ from that of industrial structure. It is posited that greater concentrations of workers employed in postindustrial professional-managerial class and old industrial working class occupations reduces poverty. Conversely, it is posited that greater concentrations of workers employed in postindustrial lower services class occupations increases poverty. The following hypotheses are also drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by the new postindustrial upper class, which mainly includes professional-managerial occupations, are more developed socioeconomically than those characterized by the new postindustrial lower class, which mainly includes lower-skill services occupations. It is assumed that occupational structure reflects class structure. Specifically:

H6: Greater concentrations of workers employed in postindustrial professional-managerial class occupations will reduce the odds of a census tract being in a poverty cluster. These occupations include: (a) management, business, and finance occupations; (b) science and liberal arts professionals; (c) arts, design, entertainment, and media professionals; and (d) health care practitioners and technical occupations.

H7: Greater concentrations of workers employed in postindustrial working class occupations will reduce the odds of a census tract being in a poverty cluster. These occupations include: (a) construction and extraction occupations; (b) installation, maintenance, and repair occupations; (c) production occupations; and (d) transportation and materials moving occupations.

H8: Greater concentrations of workers employed in postindustrial lower service class occupations will increase the odds of a census tract being in a poverty cluster. These occupations include: (a) healthcare support and protective service occupations; (b) food preparation and serving occupations; (c) building and grounds maintenance occupations; (d) personal care and service occupations; and (e) sales, office, and administrative support occupations.

By addressing these objectives, this analysis fills existing gaps in the poverty, sociology of agriculture, and segmented economy literatures. In general, the analysis takes four unique approaches to understanding rural poverty and how it is impacted by local agricultural and economic structures under postindustrialism. First, this analysis identifies clusters or groups of rural poverty using statistically appropriate methods. Second, this analysis examines the relationship between poverty and structures of agricultural and economy at lower levels of aggregation, specifically at the sub-county census tract level.

Third, this analysis defines economic structure using industrial classifications that better reflect the current postindustrial economy. Fourth, this analysis also defines economic structure using occupational classifications that reflect both socioeconomic class and what workers do, not just the type of industry in which they work.

Identifying Poverty Clusters

Cluster Analysis

The first objective of this analysis is to identify rural poverty clusters in the north central region using a statistically appropriate method termed cluster analysis. Cluster analysis is the generic name for a wide array of procedures that can be used to create a classification. These procedures empirically form clusters of highly similar entities. More specifically, a clustering method is a multivariate statistical procedure that starts with data containing information about a sample of entities and attempts to reorganize these entities into relatively homogenous groups. Some confusion may arise in the term clusters, as opposed to groupings. In the parlance of the cluster analysis method, the groupings produced by the method are termed clusters, although they may be identified in socioeconomic space and not geographic space. Although there are most likely spatial patterns in the clusters, spatial characteristics are not explicitly incorporated into the analysis.

Cluster analysis was chosen over other methods, notably factor analysis, for several reasons (Kim and Mueller 1978; Loehlin 1992). Cluster analysis is the most appropriate method for creating a classification or typology, which is one of the main objectives of this analysis. Cluster analysis places very few assumptions on the data, whereas factor analysis assumes that the data must be factorable and correlated. Cluster analysis produces mutually exclusive groupings that can be used in regression-type procedures, such as logistic regression or discriminant function analysis, to statistically test the accuracy of the groupings. By contrast, factor analysis provides no such tests, and the overlapping nature of the factors prohibits the use of such procedures.

All cluster analyses involve four basic steps, which will be used as a framework to discuss the cluster analysis method. The first step involves defining and selecting a set of variables on which to measure the entities in the data sample, which is used as the basis for the clusters. Second, the analyst computes the similarities among the variables selected in the first step. Third, the analyst selects an appropriate cluster analysis method to create groups of similar entities. Finally, the last step involved validation of the resulting cluster solution.

The choice of variables to be used with cluster analysis is one of the most critical steps in the research process, but it is also one of the least well understood parts of cluster analysis. The basic problem is to find that set of variables that best represents the concept of similarity under study. Ideally, variables should be chosen within the context of an explicitly stated theory that is used to support the classification. In practice, however, the theory that supports classification research is often implicit, and therefore it is difficult to assess the relevance of the variables to the problem. Aldenderfer and Blashfield (1984) stress the importance of theory in guiding variable selection as a check against “naïve empiricism”, which is the collection and analysis of as many variables as possible in the hope that the “structure” will emerge if only enough data are used.

As in most statistical analyses, the data used in a cluster analysis are routinely standardized by some appropriate method if the normality of a variable is in question, or if the variables are on different scales (Aldenderfer and Blashfield 1984). However, there is some controversy as to whether standardization should be a routine procedure in cluster analysis. As Everitt (1980) notes, standardization to unit variance and mean of zero can reduce differences between groups on those variables that may be the best discriminators of group differences. The consensus on standardization is far from clear, and in practice the decision to standardize should be made on a problem-to-problem basis. However, one should be aware that any changes may cause the results to differ solely based on the transformation (Aldenderfer and Blashfield 1984; Everitt 1980).

The next step in a cluster analysis is the choice of a similarity measure. In cluster analysis there are four main types of similarity measures: correlation coefficients, distance measures, association coefficients, and probabilistic similarity coefficients. Each measure has its own advantages and disadvantages that must be considered before a decision is made to use one. Although all four measures have been used extensively in the biological sciences, only correlation coefficients and distance measures have had widespread use in the social sciences (Everitt 1980). In this analysis, only distance and correlation measures are used to estimate similarity, which are discussed below.

Because of their intuitive appeal, distance measures have enjoyed widespread popularity in the social sciences. Technically they are best described as dissimilarity measures, where two cases are identical if each one is described by variables with the same magnitudes, which results in the distance between them being zero. Distance measures normally have no upper bounds and are scale-dependent. One of the most serious flaws with distance measures are that the estimation of similarity between cases is strongly affected by elevation differences (i.e. the mean score of the case over all of the variables). Variables with both large size differences and standard deviations can essentially swamp the effects of other variables with smaller absolute sizes and standard deviations. Also, distance measures will not preserve true distance ranking when the scale of measurement is transformed.

One of the most popular representations of distance is Euclidean distance, which measures the distance between two points in a straight line through Euclidean space. There are two variations of Euclidean distance measures: Euclidean distance that is presented in Equation 1, and squared Euclidean distance that is presented in Equation 2. In these two equations, d_{ij} is the distance between cases i and j, x_{ij} is the value of the k^{th} variable for the i^{th} case. To avoid the use of the square root in Equation 1, the value of distance is often squared as in Equation 2 and referred to as squared Euclidean distance.

$$d_{ij} = \sqrt{\sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2} \qquad (1)$$

$$d_{ij}{}^2 = \sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2 \qquad (2)$$

Non-Euclidean metrics are distance measures that are not straight lines but obey certain rules. The Minkowski metric refers to a variety of distance measures that vary by some power (see Equation 3). By increasing r one places more numerical value on the largest distance in terms of elements in the two vectors in question. The Chebychev distance between two points is the maximum distance between the points in any single dimension (see Equation 4). For the equations presented below, the notation follows where d_{ij} is the distance between cases i and j, x_{ij} is the value of the k^{th} variable for the i^{th} case, and r is the r^{th} root of the sum of the absolute differences to the r^{th} power between the values for the items.

$$d_{ij} = \left(\sum_{k=1}^{p} \left| x_{ik} - x_{jk} \right|^r \right)^{\frac{1}{r}} \qquad (3)$$

$$d_{ij} = MAX_{ij} \left| x_{ik} - x_{jk} \right| \qquad (4)$$

Lastly, correlations coefficients are used in cluster analyses in the social sciences to quantitatively classify cases based on the associations between them. Values of this measure range from –1 to 1 with a value of zero indicating no relationship between the cases. Correlation measures are sensitive to the patterns of dips and rises across variables, and are at the same time insensitive to differences in the magnitude of those variables. Although this tends to create groups of highly similar cases in terms of their profiles across variables, they are often not identical because of differences in magnitude. The formula for the correlation coefficient is presented in Equation 5, where x_{ij} is the value of variable *i* for case *j*, and $\overline{X}_j$ is the mean of all values of the variable for case *j*.

$$r_{jk} = \frac{\sum \left(x_{ij} - \overline{X}_j\right)\left(x_{ik} - \overline{X}_k\right)}{\sqrt{\sum \left(x_{ij} - \overline{X}_j\right)^2 \left(x_{ik} - \overline{X}_k\right)^2}} \tag{5}$$

After the similarity measure is chosen, the next step is to select an appropriate cluster analysis method to create groups of similar entities. This analysis exclusively employs hierarchical agglomerative methods, which is the dominant method in both the biological and social sciences (Blashfield and Aldenderfer 1978). Hierarchical agglomerative methods are distinguished primarily by their different rules for the formation of clusters. Some statisticians use the term “sorting strategy” to refer to linkage form. There are many possible linkage rules, each yielding a unique hierarchical method. Cases are combined into clusters based on a similarity matrix between all possible pairs of cases. At the first stage of the hierarchical agglomerative method, all cases are considered separate clusters. At the second step, two of the cases are combined into a single cluster based on the selected clustering method, and the similarity matrix is then recomputed using this new cluster. At the third step, either a third case is added to the cluster formed in the second stage or two other cases are merged into a second new cluster, and the similarity matrix is then recomputed. At each subsequent step this process is repeated, where individual cases are added to existing clusters or two cases are merged to form a new cluster. At the final stage, all cases have been merged into one cluster.

Lance and Williams (1967) have developed a formula that can be used to describe linkage rules in a general form for any hierarchical agglomerative method. The rule is defined in Equation 6, where $d(h,k)$ is the dissimilarity of distance between clusters h and k, where cluster k is the result of combining clusters (or cases) i and j during an agglomerative step. This formula provides a method for calculating the distance between some object (h) and a new cluster (k) that is formed by the merger of objects i and j into a common cluster. The capital letters refer to parameters that define the linkage form.

$$\begin{aligned} d(h,k) = A(i) \bullet d(h,i) + A(j) \bullet d(h,j) + B \bullet d(i,j) + C \bullet \\ ABS(d(h,i) - d(h,j)) \end{aligned} \tag{6}$$

While at least twelve different linkage forms have been proposed, five have become widely popular: single linkage, complete linkage, average linkage, centroid method, and Ward's method. In this analysis, the hierarchical clustering methods used include average within-groups linkage, centroid method, and

Ward's method. The general procedure for all of these methods, which are described in detail below, is that they begin with N clusters each containing one case, thus clusters are denoted as one through N. The first stage finds the most similar pairs of clusters h and k, and this similarity is denoted d_{hk}. In the second stage, the number of clusters is reduced by one through the merger of clusters h and k. This new cluster is denoted p and the similarity matrix S is updated to reflect the revised similarities between the new cluster p and all other clusters denoted by q, after the row and column of S that corresponds to cluster h is deleted. This revised S matrix of similarities between the new cluster p and all other clusters q is denoted as d_{pq}. Stage three performs the previous two stages until all entities are grouped into one cluster.

In average within-groups linkage the distance between two clusters is the average distance between pairs of observations, one in each cluster and between all possible inter or intra cluster pairs. This method tends to join clusters with small variances and is slightly biased towards producing clusters with the same variance. Before the first merge, let SUM_i be equal to zero and N_i be equal to one, which is the number of cases in cluster i. Average linkage updates d_{pq} through the method presented in Equation 7.

$$\begin{aligned} &d_{pq} = d_{hq} + d_{kq} \\ &\qquad Update\, SUM_p \text{ } and \text{ } N_p \text{ } by \\ &\qquad SUM_p = SUM_h + SUM_k + d_{hk} \\ &\qquad N_p = H_h + N_k \end{aligned} \tag{7}$$

In the centroid method the distance between two clusters is defined as the squared Euclidean distance between their centroids or means. This method is more robust to outliers than most other hierarchical methods, but in other respects it has been found not to perform as well as Ward's method or average linkage (Everitt 1980). The centroid method updates d_{pq} through the method presented in Equation 8.

$$d_{pq} = \left(\frac{N_h}{N_h + N_k} d_{hq} \right) + \left(\frac{N_k}{N_h + N_k} d_{kq} \right) - \left(\frac{N_h N_k}{\left(N_h + N_k \right)^2} d_{hk} \right) \qquad (8)$$

In Ward's minimum-variance method, the distance between two clusters is the ANOVA sum of squares between the two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions attainable by merging two clusters from the previous generation. The sums of squares are easier to interpret when they are divided by the total sum of squares to give proportions of variance or squared semipartial correlations. Ward's method joins clusters to maximize the likelihood at each level of the hierarchy under the assumptions of multivariate normality, equal spherical covariance matrices, and equal sampling probabilities. Ward's method tends to join clusters with a small number of observations and is strongly biased towards producing clusters with roughly the same number of observations. It is also very sensitive to outliers. Ward's method updates d_{pq} through the method presented in Equation 9.

$$d_{pq} = \left(\frac{1}{N_p + N_q}\right)\left[\left(\left(N_q + N_h\right)d_{qh}\right) + \left(\left(N_q + N_k\right)d_{qk}\right) - N_q d_{hk}\right] \qquad (9)$$

According to Aldenderfer and Blashfield (1984), the three main criteria for determining an appropriate cluster solution are dendograms, fusion coefficients, and multivariate analysis of variance. Determination of the appropriate number of clusters is difficult since no single agreed upon methodology exists, so cluster determination is a subjective process that is based on these criteria (Everitt 1980). At the most basic level, dendograms are hierarchical trees which permit the researcher to see where cases and clusters merge together to get a better understanding of the underlying structure of the data. Although dendograms are mainly heuristic devices, it provides an important validation of the cluster solution.

Fusion coefficients are an index of the loss of information incurred when merging two clusters. A large loss of information – a jump in the fusion coefficients – implies that two relatively dissimilar clusters have been merged, thus the number of clusters prior to the merger is the most probable cluster solution. The Mojena method is a procedure by which a significant jump in the fusion coefficients can be better defined. Mojena's Stopping Rule is a method of determining clusters based on the mean and standard deviation of all fusion coefficients (Mojena 1977). The rule states that a group level or optimal partition of a hierarchical clustering solution was selected that satisfies the inequality given in Equation 10, where α is the fusion coefficient at stage j, μ is the mean of the fusion coefficients for all stages, k is a constant set at 1.25, and σ is the standard deviation of the fusion coefficients for all stages (Milligan and Cooper 1985).

$$\alpha_{j+1} > \mu_{\alpha} + k\sigma_{\alpha} \tag{10}$$

Finally, the last step in cluster analysis involves validation of the resulting cluster solution. Once cases have been grouped using cluster analysis, the solution is statistically validated using multivariate analysis of variance (MANOVA). MANOVA is a generalization of ANOVA to a situation where there is more than one endogenous variable. MANOVA tests whether mean differences among groups on a combination of endogenous variables are likely to have occurred by chance. In MANOVA, a new endogenous variable that maximizes group differences is created from a set of exogenous variables in order to separate the groups as much as possible, and then ANOVA is run on the new endogenous variable.

In this analysis, MANOVA is used to test if the mean differences among clusters on a combined poverty endogenous variable are larger than would be expected by chance. If so, this indicates that the clusters are statistically different from each other in terms of their scores on the combined poverty endogenous variable, supporting the assertion that the clusters are distinct entities. If this condition is true, then multinomial logistic regression can be used to predict the odds of poverty cluster membership by taking into account the combination of demographic, agricultural, and economic structure variables as predictors.

Endogenous Variables and Models

To identify poverty clusters, cluster analysis is employed to group 4,610 census tracts in the north central region along four poverty variables, which are presented in Table 2. Poverty data is taken from the Summary File 3 (SF3) tables in the decennial census for 2000 and 1990, where the 1990 data was projected to 2000 geographies using GeoLytics Neighborhood Change Database. For Census 2000, SF3 consists of 813 detailed tables of social, economic, and housing characteristics compiled from a sample of approximately 19 million housing units – about one in six households – that received the Census 2000 long-form questionnaire (U.S. Census 2002).

This analysis uses the Census Bureau's definition of poverty, which is also the federal government's official poverty definition (U.S. Census 2002). Census uses a set of money income thresholds that vary by household size and composition to determine who is in poverty. If a household's total income is less than the threshold for that household type, then that household and all individuals within it are in poverty. Money income used to compute poverty status includes income from all sources including: earnings, unemployment and workers' compensation, Social Security and public assistance, pensions and retirement income, dividends and interest, alimony and child support, and an array of other income sources. It does not include noncash benefits, such as food stamps, housing assistance, and Medicaid. A household's money income includes the above sources from all members of the household, excluding non-relatives, and reflects income before taxes that does not include capital gains or losses.

Poverty thresholds are the dollar amounts used to determine poverty status. Each person or family is assigned to one of 48 possible poverty thresholds, which vary according to the size of the family and the ages of its members. If total family income is less than the threshold appropriate for that family, then the family is considered in poverty along with all members of that family. For individuals who do not live within families, their own income is compared with the appropriate threshold. If total family or individual income equals or is greater than the threshold, then that family or individual is not considered to be in poverty. Poverty statistics through the Census Bureau include all people except for institutionalized populations, people in military group quarters, college students in dormitories, and unrelated individuals under 15 years of age.

Thresholds do not vary geographically and are used throughout the United States, thus they do not reflect differences in cost of living. However, thresholds are updated annually for inflation using the Urban Consumer Price Index (CPI-U) calculated by the U.S. Bureau of Labor Statistics. Poverty thresholds were originally derived in the early 1960s as a measure of the required food budget for families under economic distress, and were meant to address the dietary needs of families on an austere budget. Although the current poverty thresholds in some sense reflect family needs, they are intended to be used as a statistical yardstick to measure economic welfare, and not as a complete description of what people and families need to live.

There are four endogenous variables in the analysis that measure the degree of poverty within census tracts, which are presented spatially in Figures 12 through 15. The depth of poverty measure is the ratio between a household's income and the poverty threshold for that household type. Persons below 50 percent of poverty are considered severely poor, those between 50 and 99 percent of poverty are considered poor, and those between 100 and 199 percent of poverty are considered near poor (Proctor and Dalaker 2003). The universe is the population for whom poverty status is determined, which excludes institutionalized populations. POV is the percent of the population whose incomes are under 100 percent of the poverty level in 2000. This variable measures the percent of people living in poverty within a census tract. NPOV is the percent of the population whose incomes are between 100 and 199 percent of the poverty level in 2000. This variable measures the percent of people living in near poverty within the census tract.

Using Census 1990 data that has been converted to Census 2000 geographies, the percent change in the depth of poverty can be measured. DPOV is the percent change in the population whose incomes are under 100 percent of the poverty level between 1990 and 2000. This variable measures the percent of people who either moved into or out of poverty over the last decade, as well as measuring improvements or declines in the rate of poverty. DNPOV is the percent change in the population whose incomes are between 100 and 199 percent of the poverty level between 1990 and 2000. This variable measures the percent of people who either moved into or out of near poverty over the last decade, as well as measuring improvements or declines in the rate of near poverty.

TABLE 2
Endogenous Variables – Depth of Poverty

Variable	***Description***
POV	Percent under 100% of poverty.
NPOV	Percent 100% to 199% of poverty.
DPOV	Percent change under 100% of poverty in 1990-2000.
DNPOV	Percent change 100% to 199% of poverty in 1990-2000.

FIGURE 12
POV – Percent Under 100% of Poverty in 2000

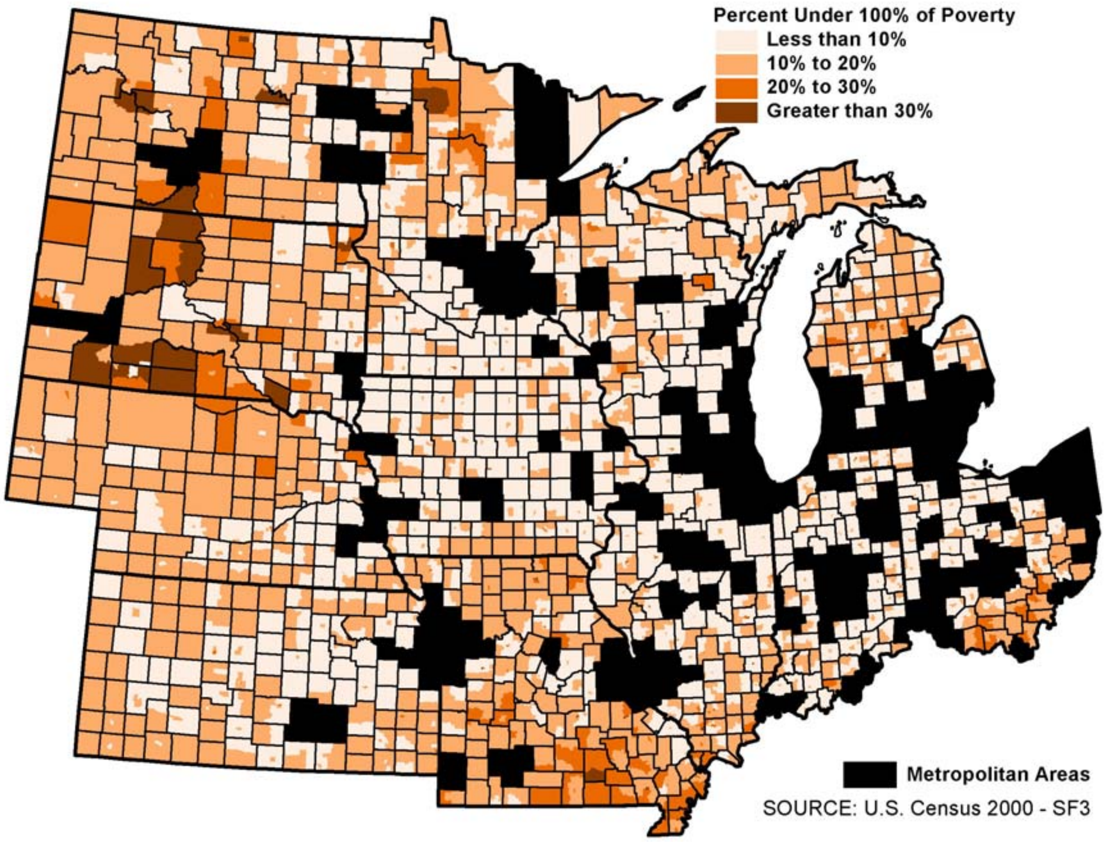


FIGURE 13
DPOV – Percent Change Under 100% of Poverty 1990-2000

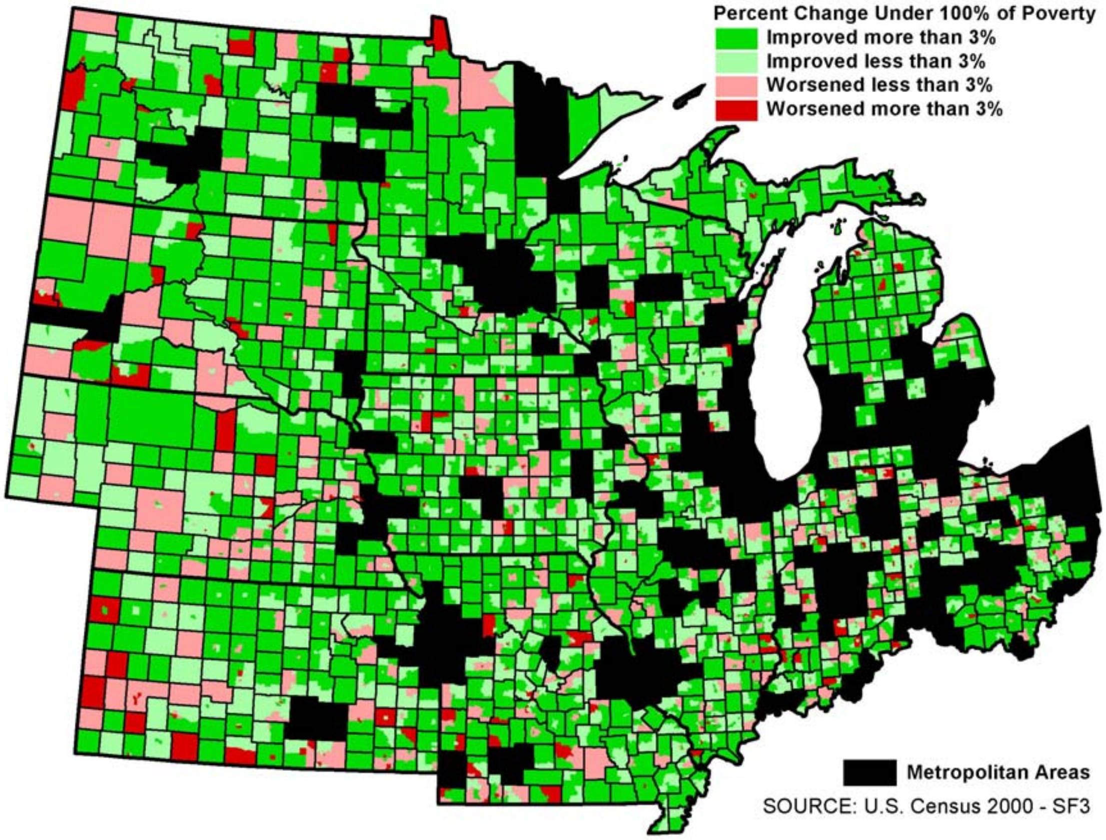


FIGURE 14
NPOV – Percent 100% to 199% of Poverty in 2000

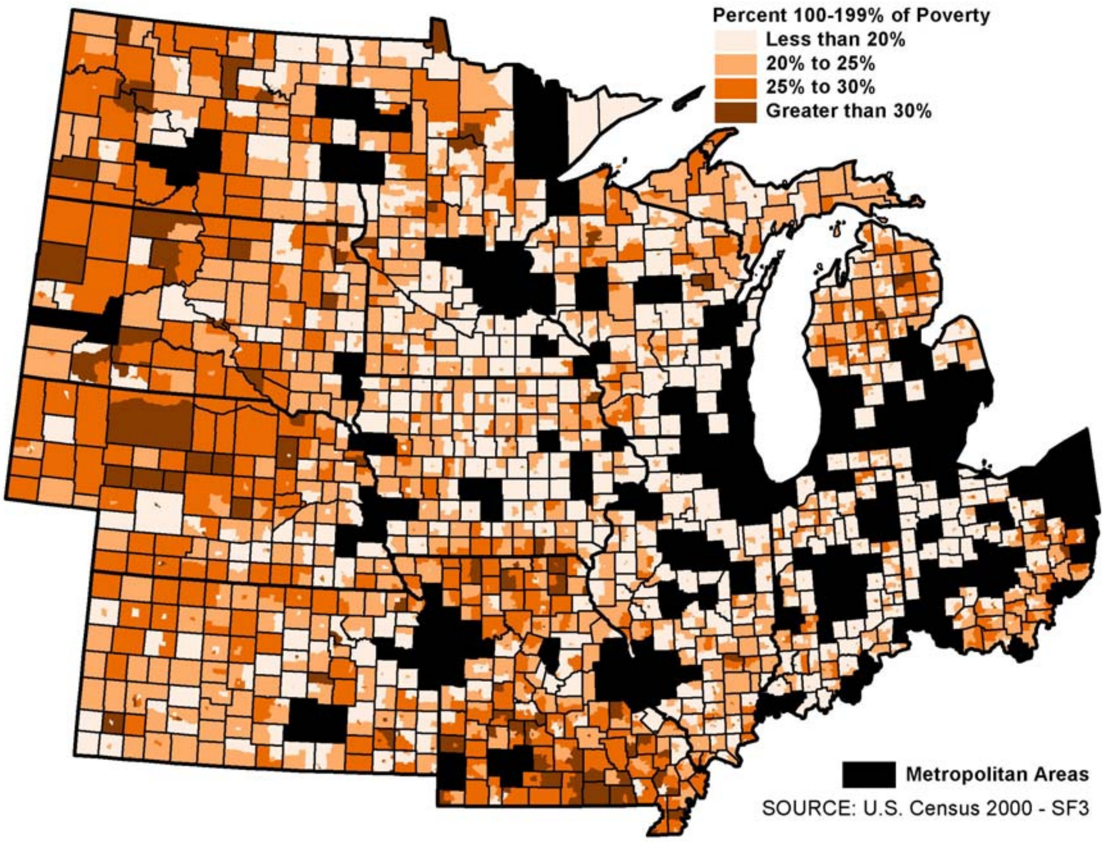
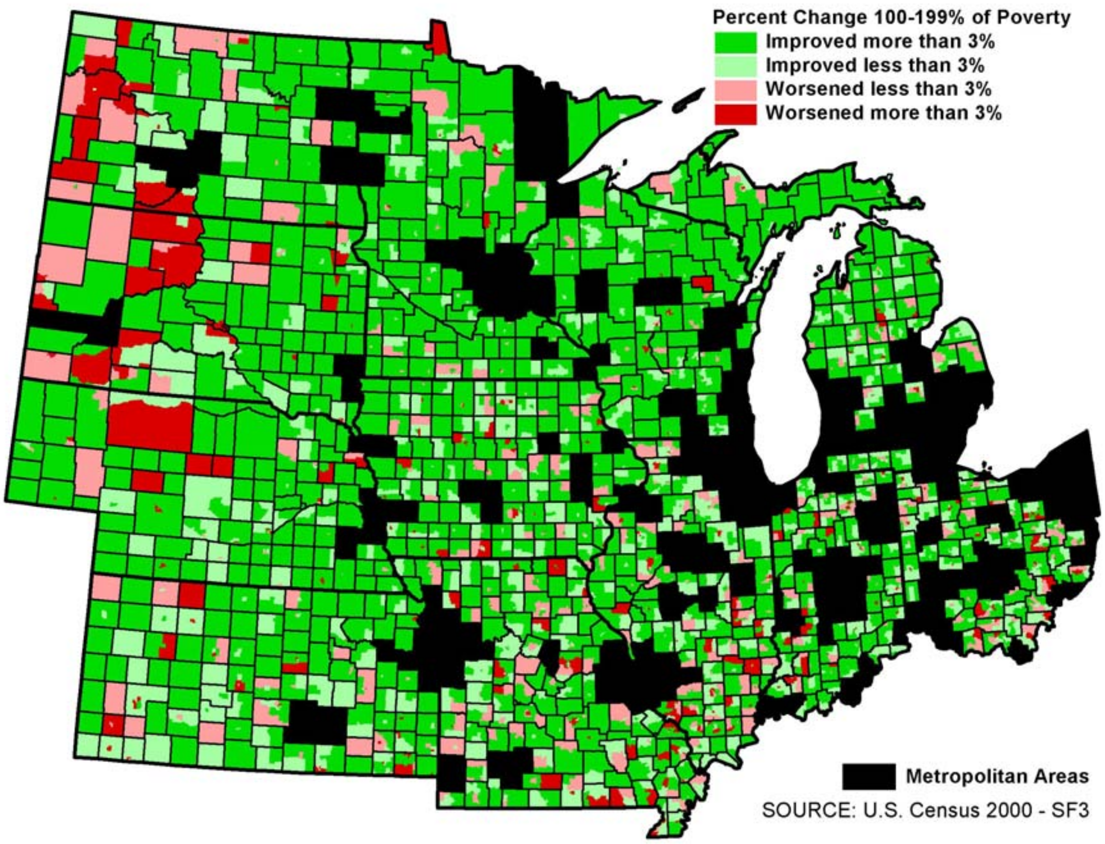


FIGURE 15
DNPOV – Percent Change 100% to 199% of Poverty 1990-2000



Predicting Poverty Clusters

Multinomial Logistic Regression

The second sets of objectives for this analysis are to determine whether agricultural and economic structure determines membership in a rural poverty cluster, after controlling for demographic characteristics. These relationships are tested using multinomial logistic regression, which is a form of regression used when the endogenous variable has multiple categories (i.e. polytomous). Logistic regression can be used to predict an endogenous variable on the basis of continuous and categorical exogenous variables by fitting the model to the data. A good fit means that the logistic model, with covariates, more closely replicates the pattern of observed logit values than a model containing only the intercept. The procedure also ranks the relative importance of exogenous variables, assesses interaction effects, and seeks to understand the impact of covariate control variables.

Logistic regression applies Maximum Likelihood Estimation (MLE) after transforming the endogenous variable into a logit, which is the natural log odds of some outcome on the endogenous variable. In this way, logistic regression estimates the probability of a certain event occurring. Note that logistic regression calculates changes in the log odds of the endogenous variable, not changes in the endogenous variable itself as in least squares regression.

Before proceeding to a more detailed discussion of logistic regression, a short summary of its many analogies to least squares regression is in order

(Gujarati 1995; Tabachnick and Fidell 1996). To start, logit coefficients correspond to least squares beta coefficients, standardized logit coefficients correspond to standardized beta weights, and a pseudo R-squared statistic is available to summarize the strength of the relationship. Unlike OLS regression, however, logistic regression does not assume a linear relationship between the exogenous and the endogenous variables. It also does not require normally distributed variables, does not assume homoscedasticity, and in general has less stringent requirements than least squares regression. Logistic regression does, however, require that the observations be independent and that the logits of the exogenous variables are linearly related to the endogenous variable. The success of the logistic regression can be assessed by looking at goodness-of-fit tests such as model Chi-squared, which is an indicator of model appropriateness or fit. Also, the classification table, showing correct and incorrect classifications of the polytomous endogenous variable, is also useful is assessing the accuracy of the predictive model.

Logistic regression is an extension of linear probability models (LPM), which use a discrete categorical endogenous variable. LPM has all of the assumptions of an Ordinary Least Squares (OLS) model, the only difference is in the interpretation of the model to one that predicts the probability of an occurrence happening. The general form of the LPM is presented in Equation 11, which expresses the dichotomous endogenous variable Y_i as a linear function of the exogenous variables X_i. It is called a linear probability model since $E(Y_i \mid X_i)$ is the conditional expectation of Y_i given X_i, and can be interpreted as the conditional probability that the event will occur given X_i, that is $Pr(Y_i = 1 \mid X_i)$.

$$E(Y_i \mid X_i) = b_0 + b_1 X_1 + \ldots b_p X_p + u_i \quad (11)$$

However, LPM is plagued by several problems that make it unsuitable for analyzing dichotomous or polytomous endogenous variables (Gujarati 1995). These problems include the non-normality of u_i, heteroscedasticity of u_i, the possibility of Y_i lying outside of the zero to one range, the generally lower values of R-squared, and the illogic of using *j-1* LPM regressions for *j-1* endogenous variables for each category of a polytomous endogenous variable (where *j* denotes all categories). Although there are a number of models that can address some of these issues, such as Weighted Least Squares, logistic regression is one of the more accepted and accurate methods.

The logistic regression model assumes that the underlying distribution of probabilities for $P_i = E(Y = 1 \mid X)$ takes the shape of an elongated *s*-curve. More specifically, an *s*-distribution approaches zero at slower and slower rates as *X* gets very large. This has the effect of changing probabilities very little at the two extreme of the distribution, but changing them relatively more in the mid-range of values. The logistic distribution function is *s*-shaped and is relatively easy to estimate. More importantly, the *s*-shaped curve seems to solve the problem of out-of-range predicted values, where the curve is asymptotic to zero and one, but approaches yet never quite reaches those limits. The logistic function is presented in Equation 12.

$$P_i = E(Y = 1 \mid X_i) = \frac{1}{1 + e^{-(b_0 + b_1 X_1 + \ldots b_p X_p)}} \tag{12}$$

Simplified as

$$P_i = \frac{1}{1 + e^{-Z_i}}$$

Where

$$Z_i = (b_0 + b_1 X_1 + \ldots\ b_p X_p)$$

It is easy to verify that as Z_i ranges from $-\infty$ to $+\infty$ P_i ranges between zero and one, and that P_i is not linearly related to Z_i. However, satisfying these requirements creates an estimation problem since P_i is not only nonlinear in the exogenous variables (X) but also in the betas (b) as well. This means that the familiar and convenient least squares regression expression cannot be used unless the equation can be transformed into a linear expression. This can be done through creating a logit model. If P_i is the probability of some event occurring, then the probability of the event not occurring is $1 - P_i$. Now $P_i / (1 - P_i)$ is simply the odds ratio of in favor of the event occurring. Now if the natural log is applied to the odds ratio, denoted L_i and called the log odds ratio, we find that it is not only linear to the exogenous variables but also linear in the beta parameters. Presented in Equation 13, L is called the logit, thus the name logistic models for those based off this procedure.

$$L_i = 1n\left(\frac{P_i}{1-P_i}\right) = b_0 + b_1 X_1 + \ldots\ b_p X_p + u_i \qquad (13)$$

Where

$$P_i = \frac{n_i}{N_i}$$

Several features of logit models should be noted. First, as P_i goes from zero to one (i.e. as Z_i varies from $-\infty$ to $+\infty$) the logit L_i goes from $-\infty$ to $+\infty$. In other words, although the probabilities range between zero and one the logits are not so bounded. Second, although L_i is linear in exogenous variables the probabilities themselves are not. This property is in contrast to the LPM model where the probabilities increase linearly with the exogenous variables. Third, the interpretation of the logit model is as follows, where the slope coefficient b_1 measures the change in the logit L_i for a unit change in the exogenous variable X_i. It tells the log odds in favor of the event occurring per unit increase in the value of the exogenous variable. The intercept b_0 is the value of the log-odds in favor of the event occurring if the value on the exogenous variable is zero. Like most interpretations of intercepts, this coefficient may not have any physical meaning. Lastly, given a certain value on the exogenous variable X_i gives the log-odds of the event occurring, but not the probability of the event not occurring. Probabilities can be estimated once the coefficients of b_0 and b_1 are calculated, which is discussed next.

To estimate the logit model (refer to Equation 13) one needs values on the exogenous variables X_i and also for L_i, which is equivalent of endogenous variable Y_i in least squares regression. Using individual data permits the calculation of L_i directly by using Weighted Least Squares (WLS) to calculate the coefficients. However, when only aggregate data is available this method cannot be used to calculate the coefficients. Since least squares methods cannot be used the logit model resorts to a Maximum Likelihood Estimation (MLE) method. Rather than trying to minimize the error variance as OLS and WLS does, MLE tries to find the set of parameters that best fits the sample of observed data.

In a general sense, MLE starts with some arbitrary set of values for the coefficients and then calculates an overall likelihood that this set of parameters could have generated the observed data, from the logistic model presented in Equation 13. MLE then selects another different set of parameters, and determines the likelihood that this particular set of parameters could have produced the observed data. The process iterates through many sets of parameters, each time calculating their likelihoods. The MLE procedure ends when the process finds a set of parameters with the highest probability of generating the observed sample distributions. Put another way, this is to say that the procedure maximizes the likelihood that a set of parameters fits the observed data.

A logistic regression is evaluated using a variety of diagnostics, including log likelihood ratio tests, goodness-of-fit tests, interpretation of logit coefficients, strength of association estimates, and the accuracy of classification. The following discussion presents each of these diagnostics in detail. To start, a likelihood is the probability that the observed values of the endogenous variable may be predicted from the observed values on the exogenous variables, and like any probability values range from zero to one. The log likelihood (LL) is its log and varies from zero to $-\infty$ because the log of any number less than one is negative. LL is calculated through iteration, using maximum likelihood estimation, and is the basis for tests of a logistic model. The LL of a logistic model is presented in Equation 14, where *B* is the endogenous variable, *m* is the subpopulation of interest, *J* is the category of the endogenous variable, *n* is the sum of the frequency weights, *π* is the cell probability, and *β* is the vector of parameters.

$$
\begin{aligned}
l(B) &= \sum_{i=1}^{m}\sum_{i=1}^{J} n_{ij}\log\left(\pi_{ij}\right) \\
&= \sum_{i=1}^{m}\sum_{i=1}^{J} n_{ij}\log\left(\frac{\exp\left(x_i'\beta_j\right)}{1+\sum_{k=1}^{J-1}\exp\left(x_i'\beta_k\right)}\right)
\end{aligned}
\tag{14}
$$

The log likelihood ratio (–2LL) is a function of log likelihood that is used for assessing the significance of a logistic regression, and when using an approximate Chi-square distribution is analogous to the use of the sum of squared errors in least squares regression. The –2LL statistic reflects the significance of the unexplained variance in the endogenous variable. The log likelihood ratio is not used directly in significance testing, but it is the basis for the –2LL test statistic, which tests the difference between two likelihood ratios.

The log likelihood ratio (–2LL) test statistic estimates the significant difference between the log likelihood ratio for the specified model minus the likelihood ratio for a reduced model. The –2LL test statistic is used in two ways, both to test the overall logit model and to test individual logit model parameters. The first application of this statistic is when the reduced model including only the constant is compared to a covariate model, and tests the significance of the logit model as a whole. A significant well-fitting model means the covariate logit model is significantly different from the one including only the constant term. Thus the likelihood ratio test of the logit model assesses the difference between –2LL for the full model and –2LL for the initial reduced or null model that includes only the intercept. Using a Chi-squared distribution, the –2LL statistic tests the null hypothesis that all population logistic regression coefficients are zero, except the constant. However, this is an overall model test which does not assure that every exogenous variable is significant.

The second application of the –2LL statistic is to tell if particular exogenous variables are more important than others. This is done by comparing the difference in –2LL for the overall model with a nested model that drops one of the exogenous variables. In this situation, the –2LL statistic tests if the logistic regression coefficient for the dropped variable can be treated as zero, thereby justifying dropping the variable from the model. A nonsignificant –2LL statistic indicates no difference between the full and the reduced models, hence justifying dropping the given variable so as to have a more parsimonious model that fits the observations just as well. Note that the –2LL test of individual parameters is a better criterion than the alternative Walds statistic when considering which variables to drop from the logistic regression model. The –2LL statistic is presented in Equation 15, where L_1 is the full model and L_0 is the reduced or simplified model.

$$-2\log\left(\frac{L_0}{L_1}\right) = -2\left[\log(L_0) - \log(L_1)\right] = -2(L_0 - L_1) \tag{15}$$

The performance of a logistic model is assessed by how well it fits the data, not in the percent of the variance explained as in least squares regression. Specifically, it estimates how well the logistic model replicates the pattern of observed values compared to an alternative model including only the intercept. The goodness-of-fit of the logistic model is assessed using two statistics based off a Chi-squared distribution. The Pearson Chi-squared statistic tests the null hypothesis that the logistic model does not fit the data, therefore when this statistic is significant the model is assumed to have adequate fit. By contrast, the deviance/likelihood ratio Chi-squared statistic tests the null hypothesis that the logistic model does fit the data, thus when not significant the model is assumed to have adequate fit. These two goodness-of-fit statistics should be used over the classification tables when assessing the performance of the model. The two Chi-squared equations are presented in Equation 16, where *m* is the subpopulation of interest, *J* is the category of the endogenous variable, *n* is the sum of frequency weights, and π is the maximum likelihood estimate.

Pearson

$$\chi^2 = \sum_{i=1}^{m}\sum_{j=1}^{J}\frac{\left(n_{ij} - n_i\hat{\pi}_{ij}\right)^2}{n_i\hat{\pi}_{ij}} \tag{16}$$

Deviance

$$D = 2\sum_{i=1}^{m}\sum_{j=1}^{J} n_{ij}\log\left(\frac{n_{ij}}{n_i\hat{\pi}_{ij}}\right)$$

Once the overall significance and goodness-of-fit of the logistic model is deemed acceptable, the next step is to interpret the logit coefficients. Also called logits or *b* logistic regression coefficients, logits correspond to beta coefficients in least squares regression and can be used in prediction equations to generate predicted values on the endogenous variable. Logits are the natural log of the odds ratio *(P / 1-P)*. Whereas least squares regression has an identity link function, logistic regression has a logit link function. Put another way, logistic regression calculates changes in the log odds of the endogenous variable, not changes in the endogenous variable itself as with least squares regression.

Logistic regression coefficients, denoted as *b*, are logits of explanatory variables used in the logistic regression equation to estimate the log odds that the endogenous variable equals one in the case of binomial models, or the reference category in the case of polytomous models. Thus, if the logit for a given exogenous variable is b_1, then a one unit change in the exogenous variable is associated with a b_1 change in the log odds of the endogenous variable, where the endogenous is converted to the natural log of the probability that it is equal to one (or the reference category) divided by the probability it is equal to zero.

Logits or logistic *b* coefficients are much easier to interpret when they are converted into an odds ratio using the *exp(b)* function, which is the base of the natural logarithm *e* raised to the power of the logit. The closer the log odds ratio is to one the more the exogenous variable's values are independent of the endogenous variable, with one representing full statistical independence. In multinomial logistic regression, each explanatory variable will have *k – 1* logits, where *k* is the number of categories of the endogenous variable. The logit and log odds ratio formulas are presented in Equation 17.

Logit

$$b = 1n\left(\frac{P(Y=1 \mid X)}{1-P(Y=1 \mid X)}\right) = b_0 + b_1 X_1 \tag{17}$$

Log Odds

$$\exp(b) = \exp\left(1n\left(\frac{P(Y=1 \mid X_i)}{1-P(Y=1 \mid X_i)}\right)\right) = \exp(b_0 + b_1 X_{1i})$$

Logistic *b* coefficients and log odds ratios *exp(b)* can be interpreted in terms of odds or effect size, although the former is the more correct interpretation whereas the latter is the more common interpretation. The log odds ratio can be used to measure effect size, where the ratio of two *exp(b)* values is the ratio of the relative importance of the exogenous variables in terms of effect on the endogenous variable's odds. Most researchers use *exp(b)* ratios as effect size measures and comment on their relative sizes when comparing explanatory variable effects, similar to standardized betas in least squares regression. Other the other hand, log odds ratios are meant to be interpreted in terms of a change in odds. It is important to note that odds are not the same as probabilities. In both cases, the significance of individual logistic regression coefficients for each exogenous variable is assessed using Walds statistic, which tests the null hypothesis that a logit effect is zero, and is analogous to significance testing of beta coefficients in least squares regression.

For dichotomous exogenous variables, a positive log odds ratio *exp(b)* means that as the variable moves from zero to one the log odds of the endogenous variable also increases, and vice versa. For example, if *exp(b)* = 2.31 for having a high school degree regressed on a binary employment endogenous variable, we would say that the odds of a person with a high school degree being employed is 2.3 times the odds of a person without a high school degree. For continuous exogenous variables, when the logit is transformed into a log odds ratio it may be expressed as a percent increase in the odds. For example, if *exp(b)* = 1.08 for the number of years of schooling regressed on a binary employment endogenous variable, we would say that each additional year of schooling increases the odds of employment by 8 percent, controlling for other variables.

To measure the percent of variance explained by the logistic regression is problematic, since there is no widely accepted direct analog to the R-squared measures used in least squares regression. This is because R-squared seeks to make a statement about the percent of the variance explained, but the variance in a logistic regression depends of the frequency distribution of the endogenous variable. For a binomial endogenous variable, for instance, variance is at a maximum for a 50:50 split, and the more lopsided the split the lower the variance. This means that R-squared estimates for logistic regressions with differing marginal distributions of their respective endogenous variables cannot be compared directly, thus making comparisons meaningless.

Nonetheless, a number of logistic R-squared measures have been proposed, all of which should be reported as approximations to OLS R-squared and not as the actual percent of variance explained. More importantly, logistic R-squared measures are not goodness-of-fit tests, but rather an attempt to measure the strength of association. Two R-squared approximations are commonly used in logistic regression. Cox and Snell's R-Squared is an attempt to imitate the interpretation of OLS R-squared based on the likelihood statistic, but its maximum can be more than one which makes interpretation difficult. Nagelkerke's R-Squared is a further modification of the Cox and Snell measure to assure that values vary between zero and one. Therefore, Nagelkerke's measure will normally be higher than the Cox and Snell measure, but will tend to run lower than the corresponding OLS R-squared. Approximate R-squared measures for logistic regression are presented in Equation 18, where π is the maximum likelihood estimate.

Cox and Snell

$$R^2{}_{CS} = 1 - \left(\frac{L(\tilde{\pi})}{L(\hat{\pi})} \right)^{\frac{2}{n}} \tag{18}$$

Nagelkerke

$$R^2{}_N = \frac{R^2{}_{CS}}{1 - L(\tilde{\pi})^{2/n}}$$

Lastly, one feature of logistic regression is the ability to classify cases based on the logistic model. The accuracy of the classification is estimated by the classification tables, which tally correct and incorrect estimates of how well the logistic regression grouped cases. In a perfect model, all cases will be on the diagonal line and the overall percent correct will be at 100 percent. If the logistic model has homoscedasticity, the percent correct will be approximately the same for all rows. It is important to note that classification tables should not be used as goodness-of-fit measures because they ignore actual predicted probabilities and instead use dichotomized predictions based on some cut-off value. For instance, in binary logistic regression the classification table does not reveal how close the correct predictions were to one, nor how close to zero the errors were. However, classification tables are useful in understanding how the logistic model predicts group membership from a set of predictors.

Exogenous Variables and Models

As stated previously, one of the main objectives of this analysis is to determine how demographic, agricultural, and economic structures determine membership in a rural poverty cluster. This approach is grounded in the labor market perspective on poverty, which incorporates both individual and structural approaches within a spatial context. At its core, this approach assumes that rural poverty is due to the distribution of individual characteristics in the population; and that rural poverty is also due to the socioeconomic division of labor. To test these relationships, multinomial logistic regression tests how well a set of demographic and economic variables groups 4,610 census tracts. Data is taken from the Summary File 3 (SF3) tables in the decennial census for 2000, which consists of 813 detailed tables of social, economic, and housing characteristics compiled from a sample of approximately about one in six households that received the Census 2000 long-form questionnaire (U.S. Census 2002).

In this analysis, two multinomial logistic regression models are used to assess the exogenous variables usefulness in predicting cluster membership – an industry structure model and an occupation structure model. The industry structure model, presented in Equation 19, predicts the odds of census tract *j* being classified into a poverty cluster by taking into account a series of exogenous variables that account for individual and structural determinants of poverty, according to the labor market perspective on poverty. In the general form in Equation 19, *DEMO* contains demographic characteristics of the population, *AGORG* contains variables on the structure or organization of labor relations in agriculture, *IND* contains industry structure characteristics of the area, and *STATE* contains dichotomous variables to control for state fixed effects. The corresponding coefficients are denoted by $\alpha 1$, $\beta 1$, $\gamma 1$, $\delta 1$, and $\varepsilon 1$. The long form of the industry structure model is also presented below, with variable descriptions presented in Tables 3, 4, and 5.

$$POVCLU_j = \alpha 1 + \beta 1 DEMO + \gamma 1 AGORG + \delta 1 IND + \varepsilon 1 STATE \tag{19}$$

$$\begin{aligned}
\hat{L}_i = 1n\left(\frac{\hat{P}_i^{\,j-1}}{1-\hat{P}_i^{\,j-1}}\right) = \hat{b}_0 \\
&+ \begin{bmatrix} \hat{b}_1 POP_1 + \hat{\pi}_2 METADJ_2 + \hat{b}_3 MINRTY_3 + \hat{b}_4 DISABL_4 + \hat{b}_5 SHHFAM_5 + \\ \hat{b}_6 HSAA_6 + \hat{b}_7 BAPLUS_7 + \hat{b}_8 UNEMP_8 + \hat{b}_9 POV90_9 \end{bmatrix} \\
&+ \begin{bmatrix} \hat{b}_{10} AGSEMP_{10} + \hat{b}_{11} AGWAGE_{11} \\ \end{bmatrix} \\
&+ \begin{bmatrix} \hat{b}_{12} INFO_{12} + \hat{b}_{13} FINMGM_{13} + \hat{b}_{14} PRFSCI_{14} + \hat{b}_{15} MFGR_{15} + \\ \hat{b}_{16} EDUC_{16} + \hat{b}_{17} HLTHSA_{17} + \hat{b}_{18} TRSUTL_{18} + \hat{b}_{19} CONST_{19} + \\ \hat{b}_{20} TRADE_{20} + \hat{b}_{21} ADMWST_{21} + \hat{b}_{22} LEISUR_{22} + \hat{b}_{23} HHSER_{23} + \\ \hat{b}_{24} PUBADM_{24} \end{bmatrix} \\
&+ \begin{bmatrix} \hat{\pi}_{25} IL_{25} + \hat{\pi}_{26} IN_{26} + \hat{\pi}_{27} IA_{27} + \hat{\pi}_{28} KS_{28} + \hat{\pi}_{29} MI_{29} + \hat{\pi}_{30} MN_{30} + \\ \hat{\pi}_{31} NE_{31} + \hat{\pi}_{32} ND_{32} + \hat{\pi}_{33} OH_{33} + \hat{\pi}_{34} SD_{34} + \hat{\pi}_{35} WI_{35} \end{bmatrix}
\end{aligned}$$

The occupation structure model, presented in Equation 20, predicts the odds of census tract *j* being classified into a poverty cluster by taking into account a series of exogenous variables that account for individual and occupational determinants of poverty, and is very similar to the industry structure model. In the general form in Equation 20, *DEMO* contains demographic characteristics of the population, *AGORG* contains variables on the structure or organization of labor relations in agriculture, *OCC* contains occupation structure characteristics of the area, and *STATE* contains dichotomous variables to control for state fixed effects. The corresponding coefficients are denoted by $\alpha 1$, $\beta 1$, $\gamma 1$, $\delta 1$, and $\varepsilon 1$. The long form of the occupation structure model is also presented below, with variable descriptions presented in Tables 3, 4, and 6.

$$POVCLU_j = \alpha 1 + \beta 1 DEMO + \gamma 1 AGORG + \delta 1 OCC + \varepsilon 1 STATE \qquad (20)$$

$$\begin{aligned}
\hat{L}_i = 1n\left(\frac{\hat{P}_i^{\,j-1}}{1-\hat{P}_i^{\,j-1}}\right) &= \hat{b}_0 \\
&+ \begin{bmatrix} \hat{b}_1 POP_1 + \hat{\pi}_2 METADJ_2 + \hat{b}_3 MINRTY_3 + \hat{b}_4 DISABL_4 + \hat{b}_5 SHHFAM_5 + \\ \hat{b}_6 HSAA_6 + \hat{b}_7 BAPLUS_7 + \hat{b}_8 UNEMP_8 + \hat{b}_9 POV90_9 \end{bmatrix} \\
&+ \begin{bmatrix} \hat{b}_{10} FARMER_{10} + \hat{b}_{11} AGRFOR_{11} \\ \end{bmatrix} \\
&+ \begin{bmatrix} \hat{b}_{12} PRFBUS_{12} + \hat{b}_{13} ARTENT_{13} + \hat{b}_{14} HEALTH_{14} + \hat{b}_{15} CONEXT_{15} + \\ \hat{b}_{16} MAINRP_{16} + \hat{b}_{17} PROD_{17} + \hat{b}_{18} TRANS_{18} + \hat{b}_{19} HLTPRT_{19} + \\ \hat{b}_{20} FOOD_{20} + \hat{b}_{21} BLDGRD_{21} + \hat{b}_{22} PERSER_{22} + \hat{b}_{23} SALEOF_{23} \end{bmatrix} \\
&+ \begin{bmatrix} \hat{\pi}_{24} IL_{24} + \hat{\pi}_{25} IN_{25} + \hat{\pi}_{26} IA_{26} + \hat{\pi}_{27} KS_{27} + \hat{\pi}_{28} MI_{28} + \hat{\pi}_{29} MN_{29} + \\ \hat{\pi}_{30} NE_{30} + \hat{\pi}_{31} ND_{31} + \hat{\pi}_{32} OH_{32} + \hat{\pi}_{33} SD_{33} + \hat{\pi}_{34} WI_{34} \end{bmatrix}
\end{aligned}$$

These exogenous variables were selected using the poverty, sociology of agriculture, and postindustrial literatures as a theoretical base. Demographic and economic structure variable selection was heavily guided by the labor market perspective in the rural poverty literature. This body of work assumes that rural poverty is due to the distribution of individual characteristics in the population, which is consistent with individual approaches; and at the same time rural poverty is also due to the socioeconomic division of labor, which represents structural approaches. Accordingly, poverty is posited to be lower in areas with an economic structure concentrated in core or basic industries, and higher in areas concentrated in periphery or non-basic industries. In short, structure determines the level of poverty within an area, with individual characteristics providing the means by which poverty falls more heavily on certain groups.

To account for the individual characteristics that affect poverty, nine demographic exogenous variables are selected for the analysis and are presented in Table 3. Geographic and size controls comprise two variables in the demographic block (see Figure 16). POP is the percent of the total nonmetropolitan north central population in that tract in 2000. METADJ is a dichotomous variable indicating that the census tract is in a county adjacent to a metropolitan area in 2000, and is taken from the rural-urban continuum codes produced by the Economic Research Service at the U.S. Department of Agriculture.

Demographic structure is measured using five variables (see Figures 17 through 21). MINRTY is the percent of the total population that is African-American, American Indian, Asian, Pacific Islander, Hispanic of any race, or any combination of these in 2000. DISABL is the percent of the non-institutionalized population 16 years and over that has an employment disability in 2000. SHHFAM is the percent of households that are families with children headed by a single adult in 2000. HSAA is the percent of the population 25 years and over with a high school degree or equivalency, some college, or an associate's degree in 2000. BAPLUS is the percent of the population 25 years and over with a bachelor's degree or higher in 2000.

Economic conditions in the area comprise two variables in the demographic block (see Figures 22 and 23). UNEMP is the percent of the civilian labor force 16 years and over that is unemployed in 2000. POV90 is the percent of the population whose incomes were under 100 percent of the poverty level in 1990, adjusted to Census 2000 geographies. Inclusion of POV90 presents no issues with the endogenous variable, since 19990 poverty is only expressed as a percent change from 2000.

TABLE 3
Exogenous Variables – Demographic Structure

Variable	***Description***
POP	Percent population of the nonmetropolitan north central region.
METADJ	Metropolitan adjacency.
MINRTY	Percent minority.
DISABL	Percent employment disabled.
SHHFAM	Percent single headed family households with children.
HSAA	Percent high school degree, some college, or associate's degree.
BAPLUS	Percent bachelor's degree or higher.
UNEMP	Percent unemployed.
POV90	Percent under 100% of poverty in 1990.

FIGURE 16
POP – Percent Nonmetropolitan Population in 2000

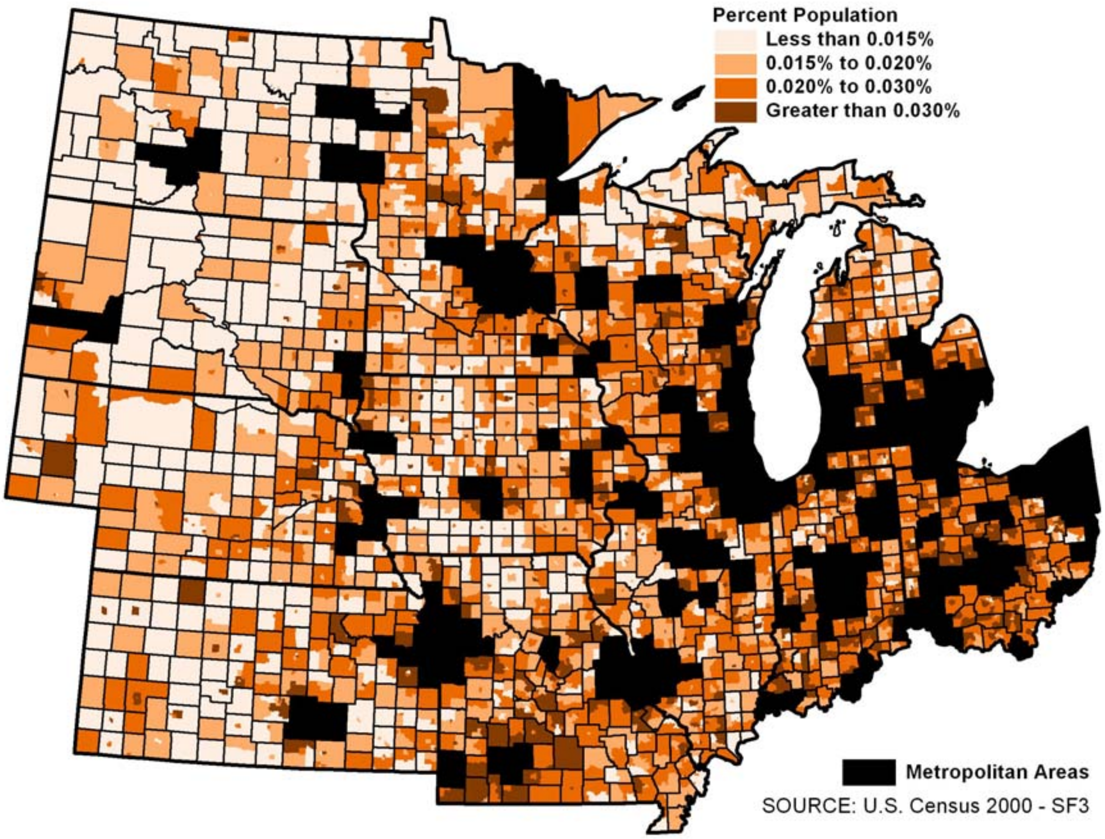


FIGURE 17
MINRTY – Percent Minority Population in 2000

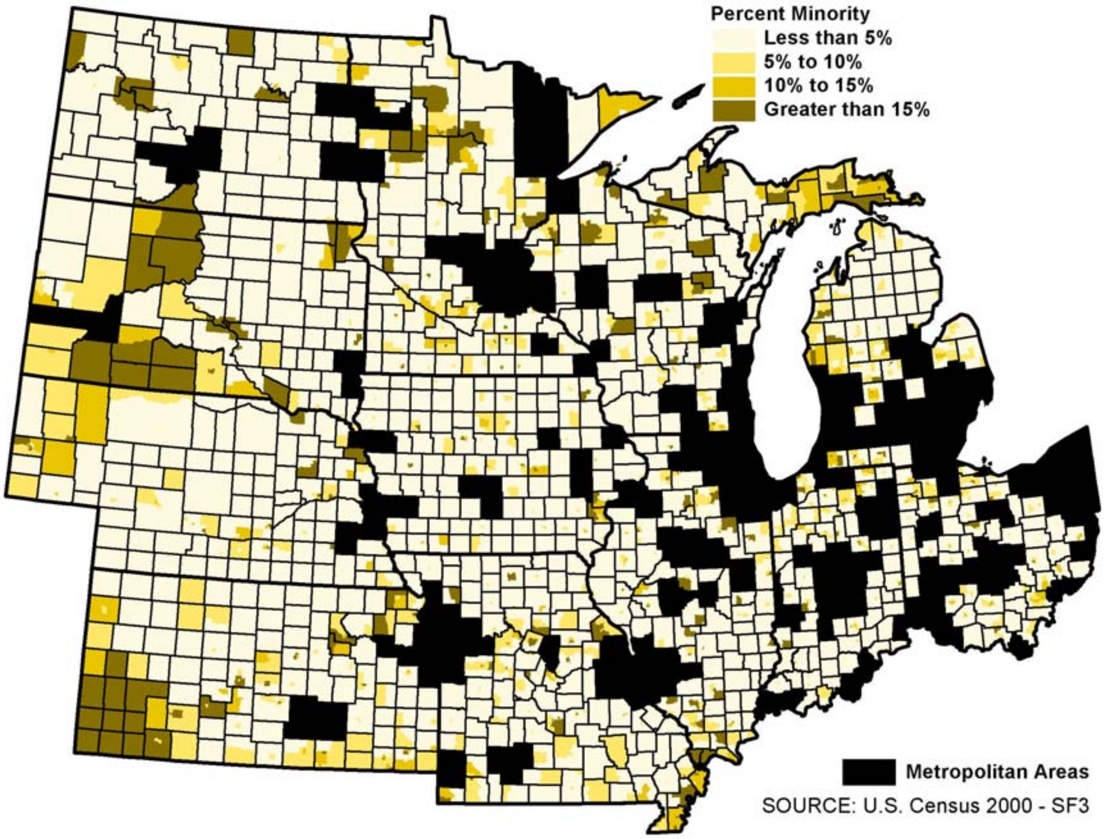


FIGURE 18
DISABL – Percent Employment Disabled in 2000

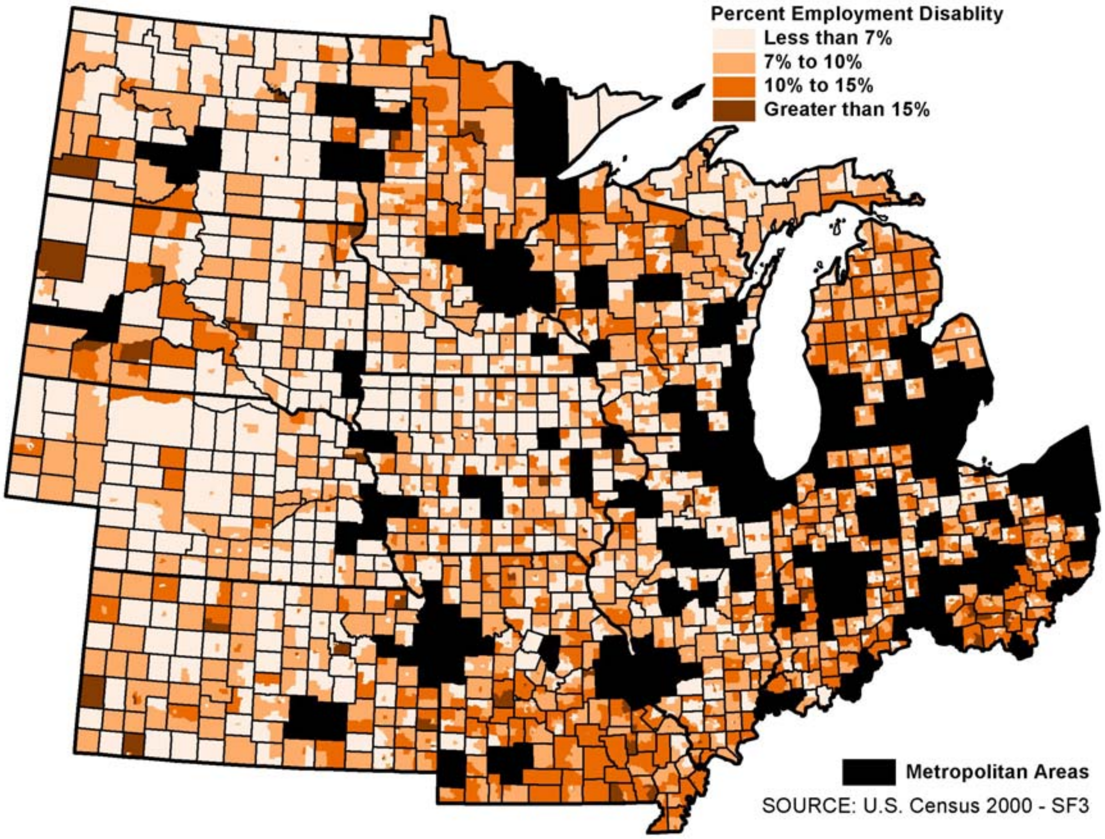


FIGURE 19
SHHFAM – Percent Single Headed Families with Children in 2000

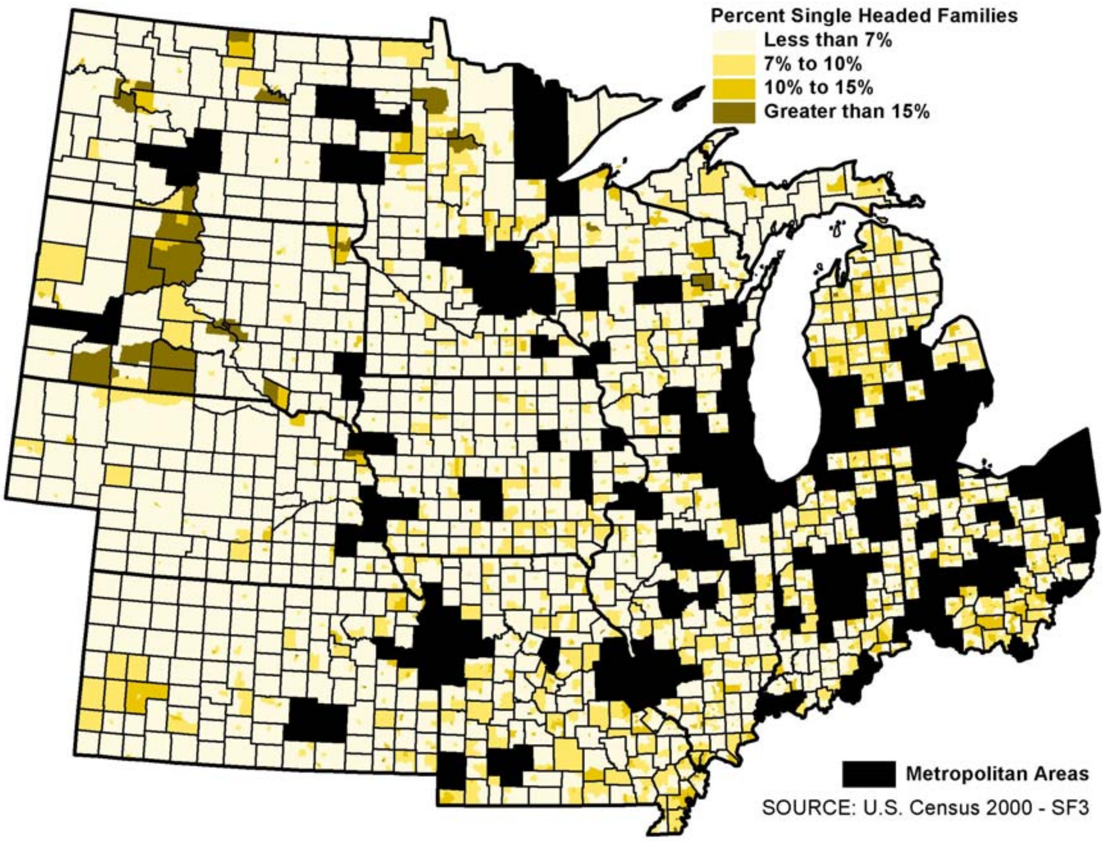


FIGURE 20
HSAA – Percent High School Degree, Some College, or Associate's Degree in 2000

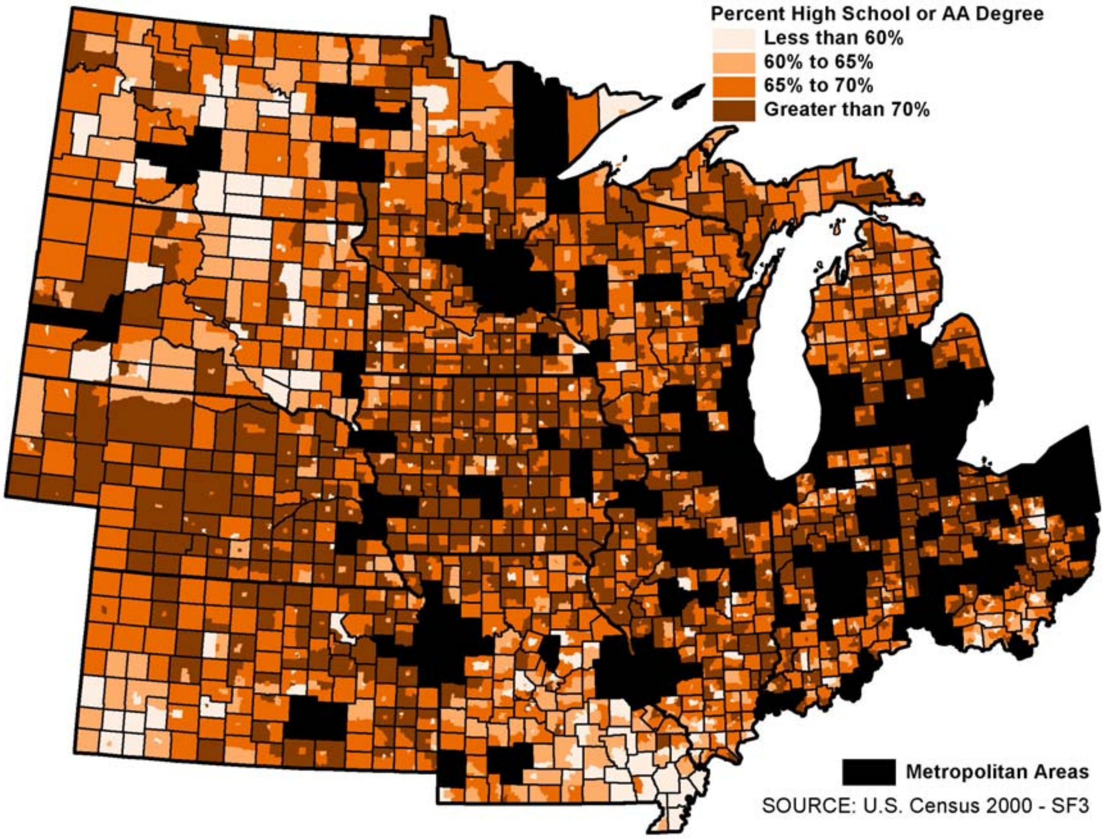


FIGURE 21
BAPLUS – Percent Bachelor's Degree or Higher in 2000

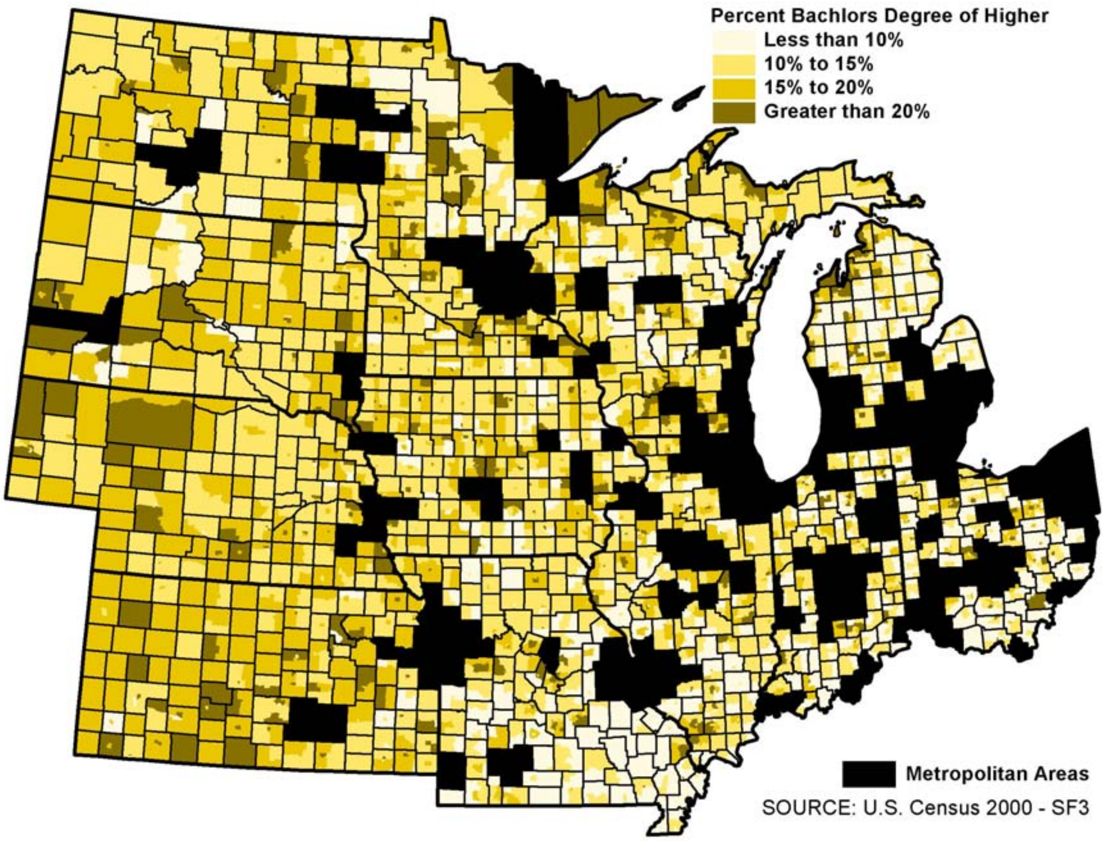


FIGURE 22
UNEMP – Percent Unemployed in 2000

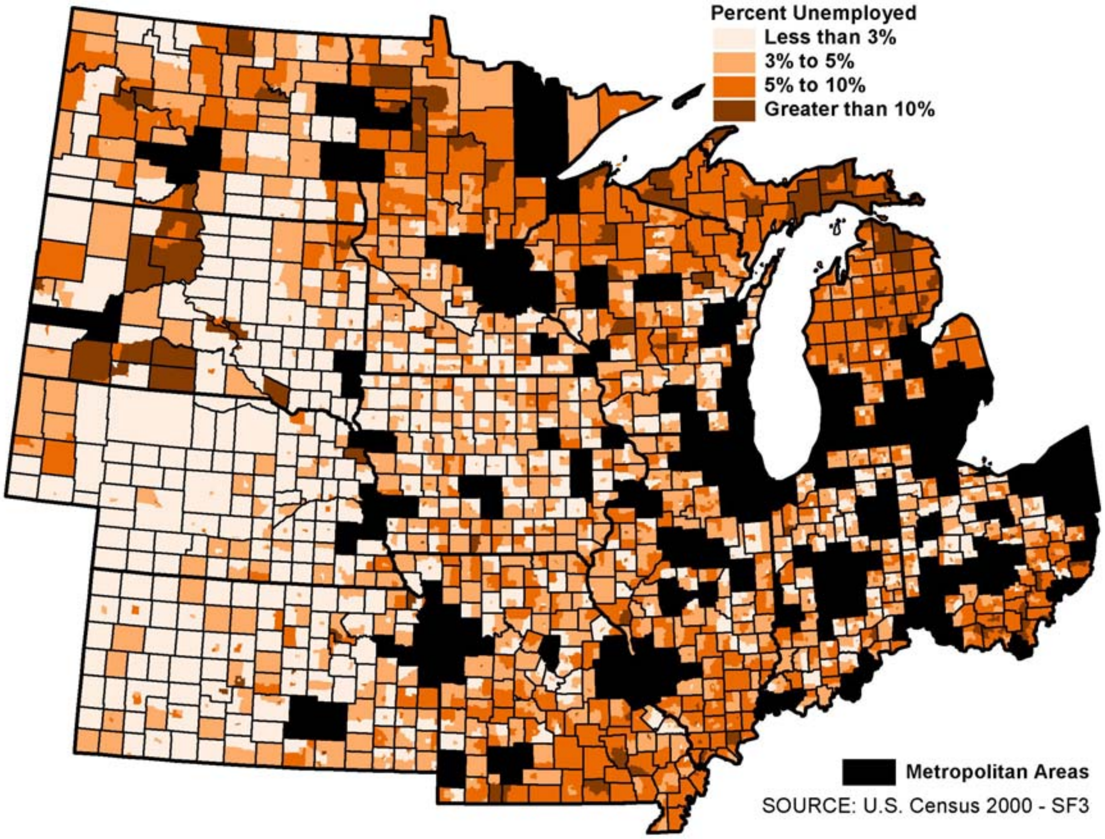
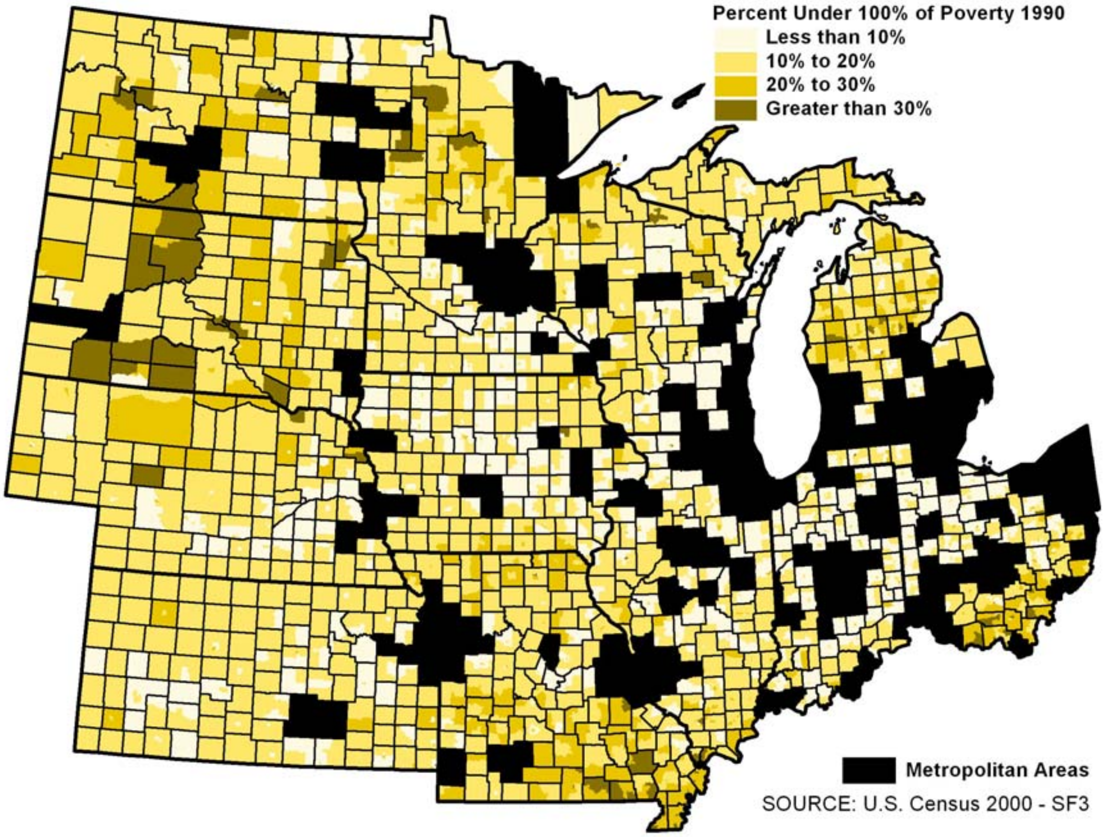


FIGURE 23
POV90 – Percent Under 100% of Poverty in 1990



Agriculture structure is defined using the sociology of agriculture literature, which specifically links the organization of labor in agriculture to the economic and social conditions within a community. Often termed the Goldschmidt hypothesis, this literature argues that communities with absentee-owned industrial farms are less developed both economically and socially than similar communities composed mainly of family farms. To measure the structure or labor organization within agriculture, four variables are selected that describe the ownership and labor relations of residents by separating those who were self-employed from those working as wage earners.

Presented in Table 4, the variables measure class of worker and the occupation of the worker by place of residence for the employed civilian population 16 years of age and older (see Figures 24 through 27). AGSEMP is the percent who are self-employed (including those in an incorporated business) in agriculture, forestry, and fishing in 2000. AGWAGE is the percent who are employed as wage and salary employees in agriculture, forestry, and fishing in 2000. FARMER is the percent employed in farm operator and farm management occupations in 2000 (SOC 11901). AGRFOR is the percent employed in farming, fishing, and forestry occupations in 2000 (SOC 45). Standard Occupational Classifications (SOCs) are explained under the occupational variables section.

TABLE 4
Exogenous Variables – Agriculture Structure

Variable	*Description*
AGSEMP	Percent self-employed in agriculture.
AGWAGE	Percent wage and salary workers in agriculture.
FARMER	Percent farmers and farm managers.
AGRFOR	Percent farming, forestry, and fishing occupations.

FIGURE 24
AGSEMP and FARMER – Percent Agriculture Self-Employment in 2000

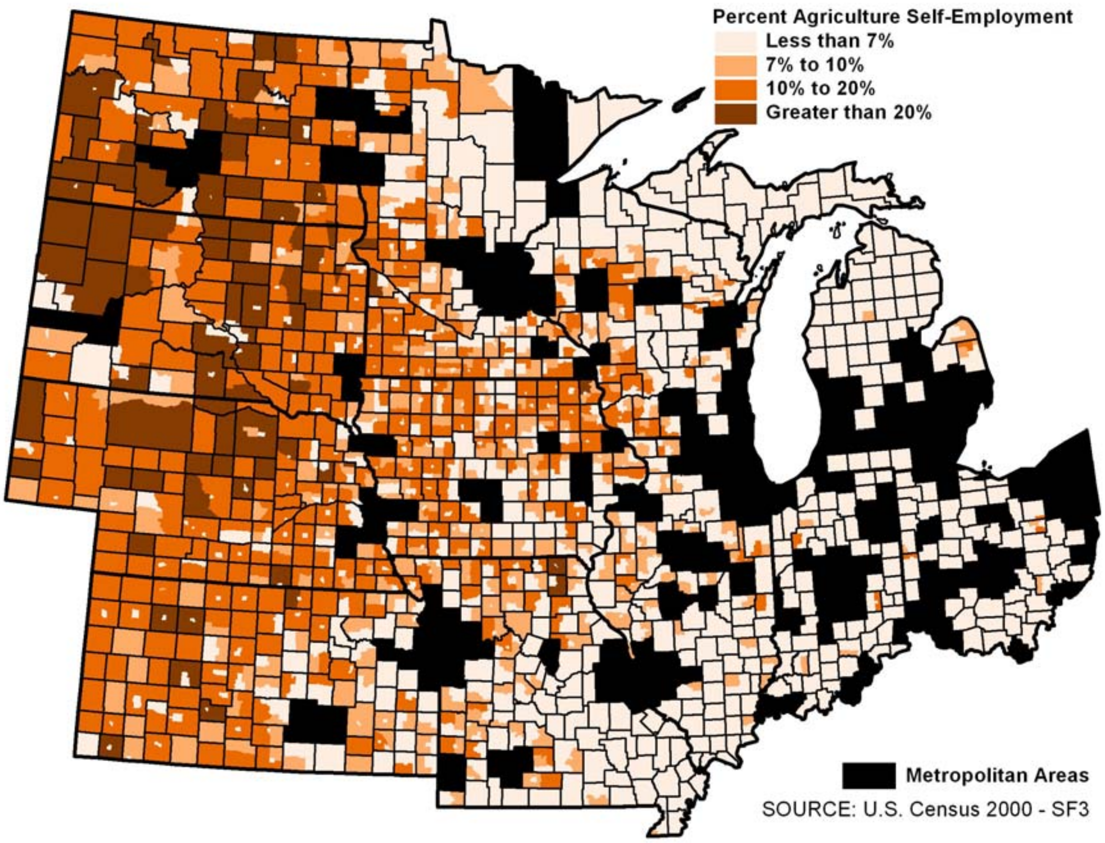
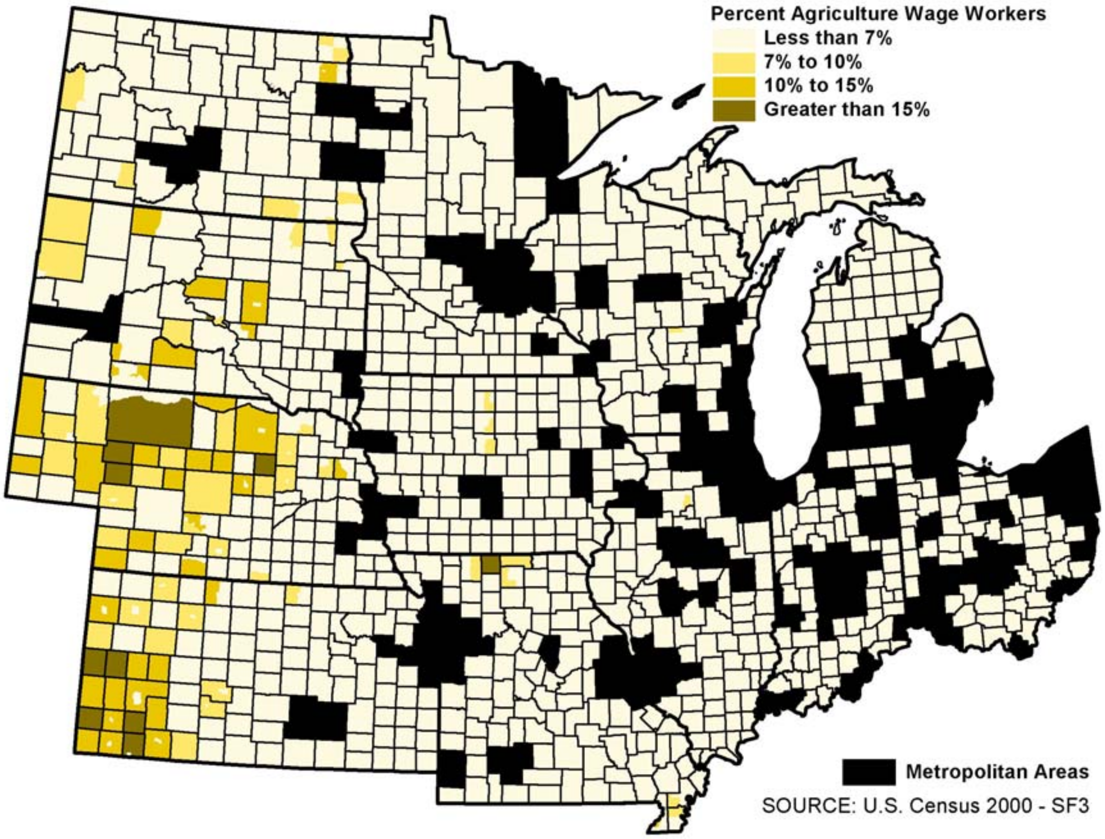


FIGURE 25
AGWAGE and AGRFOR – Percent Agriculture Wage and Salary Workers in 2000



To measure industry structure from a postindustrial perspective, 13 exogenous variables are selected that describe the local economic structure by place of residence. Based on the work of Lash and Urry (1994), industries are grouped according to their economic importance under postindustrialism into core, semi-core, and periphery. Termed dual or segmented economy theory, this framework states that uneven development of certain industries results in three distinct categories (Edwards 1979; Hodson 1984; Lobao 1990). First, core or basic industries are export-oriented segments of the economy that depend entirely on factors external to the local economy. Second, periphery or non-basic industries have internal markets that depend on local economic conditions. However, some industries sell both to export and local markets, and these segments of the economy are termed semi-core industries.

Demarcations between core, semi-core, and periphery are identified using the assumption technique in economic base theory, where broad assumptions are made about which market an industry operates in and is guided by theory (Ullman et al. 1971). According to Lash and Urry (1994, 1987), the new core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Industries that drive this new core include information, publishing, telecommunications, advanced producer services, and professional services. The semi-core consists of industries that serve not only local markets, as was the case under industrial capitalism, but increasingly are serving external markets.

Examples include education and health care, where consumers are spending increasing amounts of money and which draws consumers from outside the local economy. Lastly, periphery industries are those that serve a mainly local market.

Industries are classified based on the North American Industry Classification System (NAICS) used by the federal government (U.S. OMB 2002), which reflects the primary economic activity of the establishment. NAICS is a production-oriented or supply-based conceptual framework that groups establishments into industries according to the similarity in processes used to produce goods and services. NAICS replaces the old Standard Industrial Classifications (SIC) that were first developed in the 1930s, and later revised in the late 1980s. Rapid changes in both the United States and world economies brought the SIC system under increasing criticism that it no longer reflected the present economy accurately. These changes included the creation and destruction of industries since the 1980s, changes in technology and production practices, and the general shift from a goods-producing to a services-producing economy (U.S. OMB 2002).

Presented in Table 5, data are for the employed civilian population 16 years and older, where employment counts are by place of residence and not by place of work. Thus, the data reflect the industries in which residents work, not the types of industries located in the area. The postindustrial economic core consists of four industry groups, and is presented spatially in Figure 26. INFO is the percent employed in the information industry in 2000 (NAICS 51). FINMGM is the percent employed in the finance, insurance, and management of companies industries in 2000 (NAICS 52,55). PRFSCI is the percent employed in the professional, scientific, and technical services industries in 2000 (NAICS 54). MFGR is the percent employed in the manufacturing industry in 2000 (NAICS 31,32,33).

The postindustrial semi-core consists of three industry groups, and is presented spatially in Figure 27. EDUC is the percent employed in the educational services industry in 2000, including public entities (NAICS 61). HLTHSA is the percent employed in the health care and social assistance industries in 2000, including public entities (NAICS 62). TRSUTL is the percent employed in the transportation, warehousing, and utilities industries in 2000 (NAICS 22,48,49).

The postindustrial periphery consists of six industry groups, and is presented spatially in Figure 28. CONST is the percent employed in the construction industry in 2000 (NAICS 23). TRADE is the percent employed in the wholesale and retail trade industries in 2000 (NAICS 42,44,45). ADMWST is the percent employed in administrative support services and waste management industries in 2000 (NAICS 56). LEISUR is the percent employed in the arts, entertainment, recreation, accommodation, and food services industries in 2000 (NAICS 71,72). HHSERV is the percent employed in the real estate, rental, leasing, and other service industries in 2000 (NAICS 53,81). PUBADM is the percent employed in public administration in 2000, and only includes regular government functions (NAICS 92).

TABLE 5
Exogenous Variables - Industry Structure

Variable	***Description***
INFO	Percent information services.
FINMGM	Percent finance, insurance, and management of companies.
PRFSCI	Percent professional, scientific, and technical services.
MFGR	Percent manufacturing.
EDUC	Percent educational services.
HLTHSA	Percent health care and social assistance.
TRSUTL	Percent transportation, warehousing, and utilities.
CONST	Percent construction.
TRADE	Percent wholesale and retail trade.
ADMWST	Percent administrative support service and waste management.
LEISUR	Percent arts, entertainment, recreation, accommodation, and food services.
HHSERV	Percent real estate, rental, leasing, and other services.
PUBADM	Percent public administration.

FIGURE 26
Percent Core Industry Employment in 2000

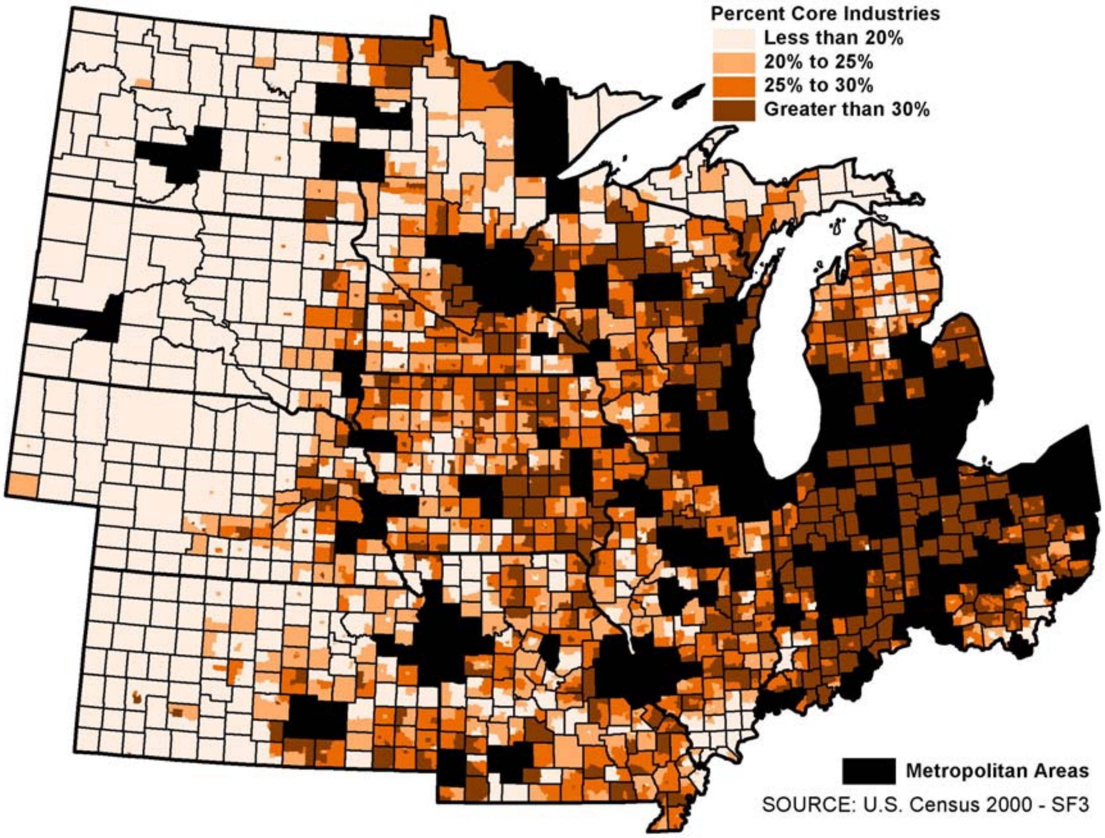


FIGURE 27
Percent Semi-Core Industry Employment in 2000

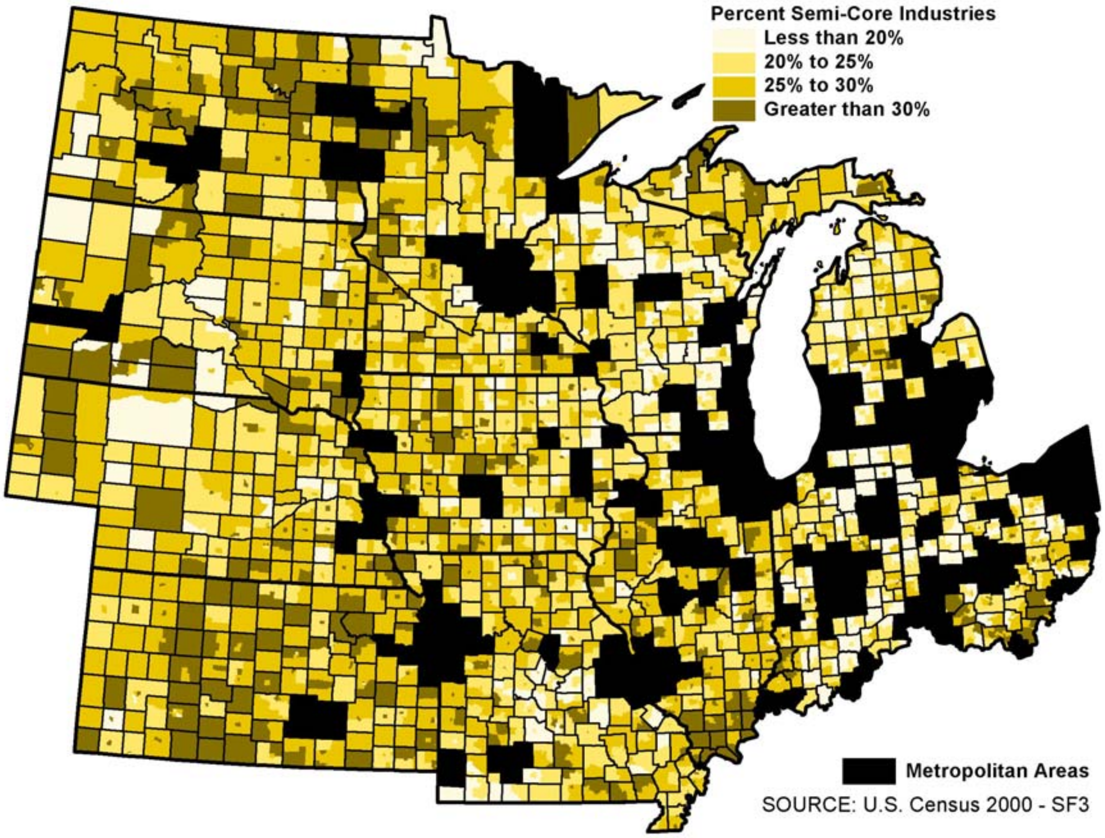
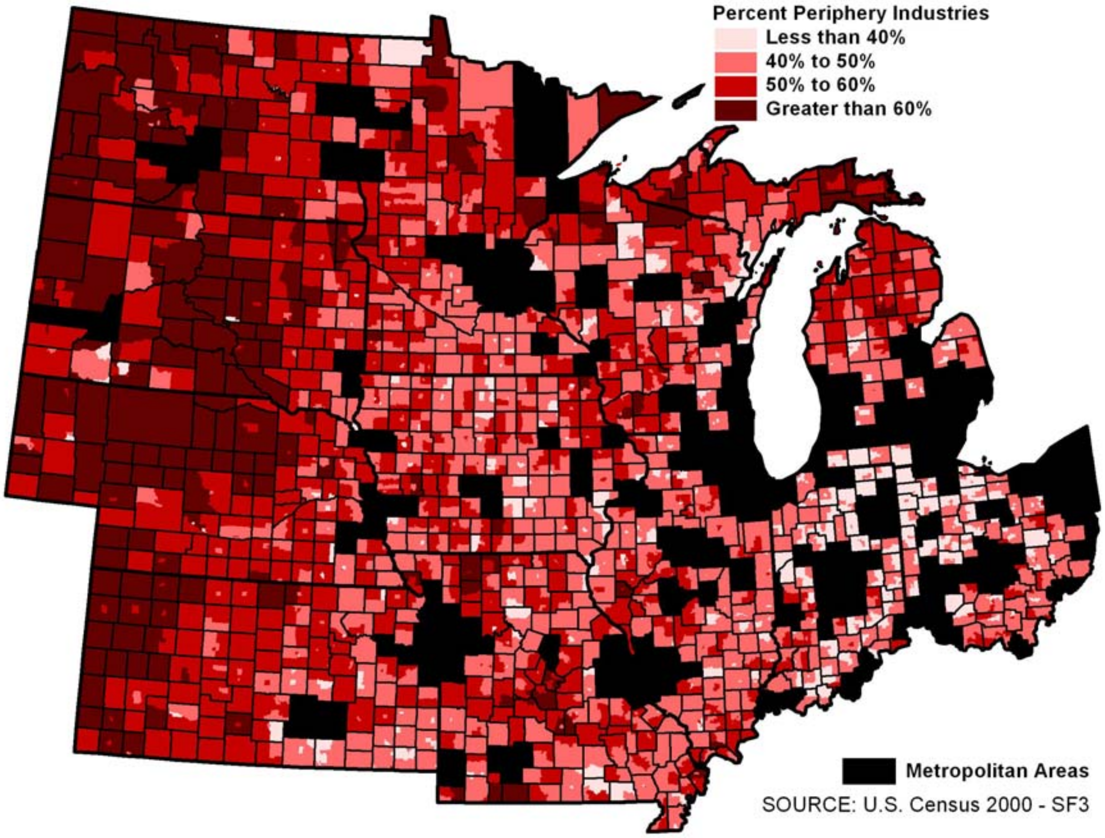


FIGURE 28
Percent Periphery Industry Employment in 2000



To measure occupation structure, 12 exogenous variables are selected that describe the local occupation structure by place of residence. In terms of postindustrial class structures, Lash and Urry (1994, 1987) argue that the ascendancy of postindustrial capitalism has led to a new stratification order that is different from what existed under industrial capitalism. The new class structure is dominated by two large services classes, which include the professional-managerial class and the lower services class. In addition, there also exists a small working class that has been greatly diminished from previous capitalist periods. In this analysis, occupation is used as a proxy for socioeconomic class.

Occupations are classified based on the Standard Occupation Classifications (SOC) used by the federal government (U.S. OMB 2000), which reflects the primary type of activities an individual performs at work. Developed in 2000, SOCs cover all occupations in which work is performed for pay or profit, including work performed in family-operated enterprises by family members who are not directly compensated. Occupations are classified based on the work performed and on the required skills, education, training, and credentials. Presented in Table 6, data are for the employed civilian population 16 years and older, where employment counts are by place of residence and not by place of work. Thus, the data reflect the occupations of area residents, not the types of occupations in local establishments.

The professional-managerial class is composed of three occupational groups, and is presented spatially in Figure 29. PRFBUS is the percent employed in management, business, financial, and professional occupations – including the fields of computer science and mathematics, architecture and engineering, life and physical science, community and social services, education and social science, and law – in 2000 (SOC 11,13 15,17,19,21,23,25). ARTENT is the percent employed in arts, design, entertainment, sports, and media occupations in 2000 (SOC 27). HEALTH is the percent employed in health practitioner and technical occupations in 2000 (SOC 29).

The working class is composed of four occupational groups, and is presented spatially in Figure 30. CONEXT is the percent employed in construction and extraction occupations in 2000 (SOC 47). MAINRP is the percent employed in installation, maintenance, and repair occupations in 2000 (SOC 49). PROD is the percent employed in production occupations in 2000 (SOC 51). TRANS is the percent employed in transportation and materials moving occupations in 2000 (SOC 53).

The new lower services class is composed of five occupational groups, and is presented spatially in Figure 31. HLTPRT is the percent employed in healthcare support and protective service occupations in 2000 (SOC 31,33). FOOD is the percent employed in food preparation and serving occupations in 2000 (SOC 35). BLDGRD is the percent employed in building and grounds cleaning and maintenance occupations in 2000 (SOC 37). PERSER is the percent employed in personal care and services occupations in 2000 (SOC 39).

SALEOF is the percent employed in sales, office, and administrative support occupations in 2000 (SOC 41,43).

TABLE 6
Exogenous Variables - Occupation Structure

Variable	***Description***
PRFBUS	Percent management, business, and other professional occupations.
ARTENT	Percent arts, design, entertainment, sports, and media occupations.
HEALTH	Percent health practitioners and technical occupations.
CONEXT	Percent construction and extraction occupations.
MAINRP	Percent installation, maintenance, and repair occupations.
PROD	Percent production occupations.
TRANS	Percent transportation and material moving occupations.
HLTPRT	Percent healthcare support and protective service occupations.
FOOD	Percent food preparation and serving occupations.
BLDGRD	Percent building, grounds, and maintenance occupations.
PERSER	Percent personal care and service occupations.
SALEOF	Percent sales and office occupations.

FIGURE 29
Percent Professional-Managerial Class Employment in 2000

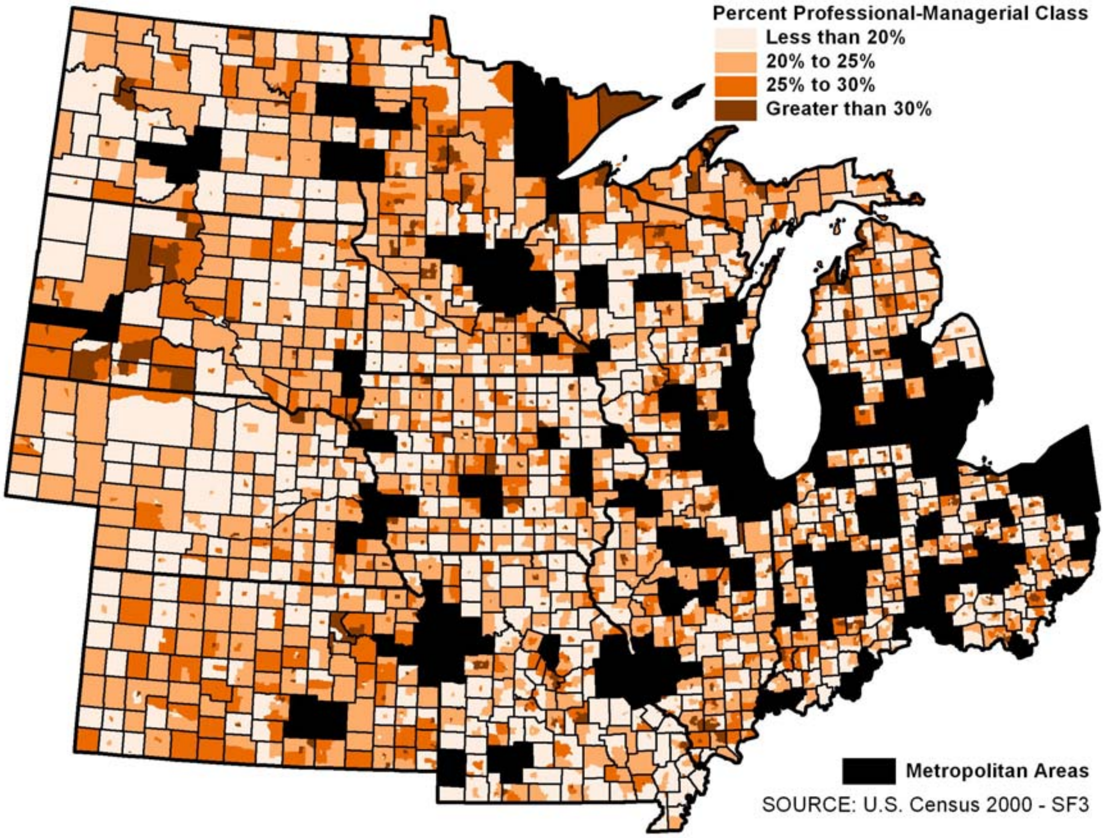


FIGURE 30
Percent Working Class Employment in 2000

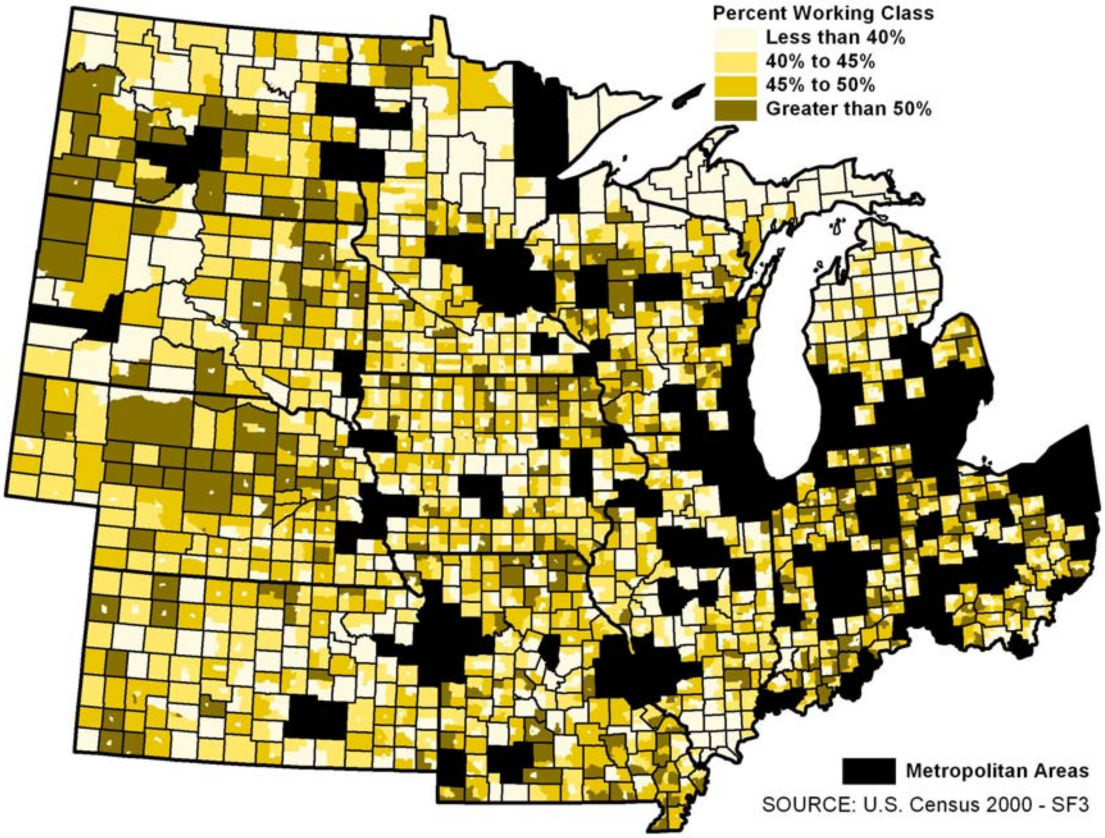
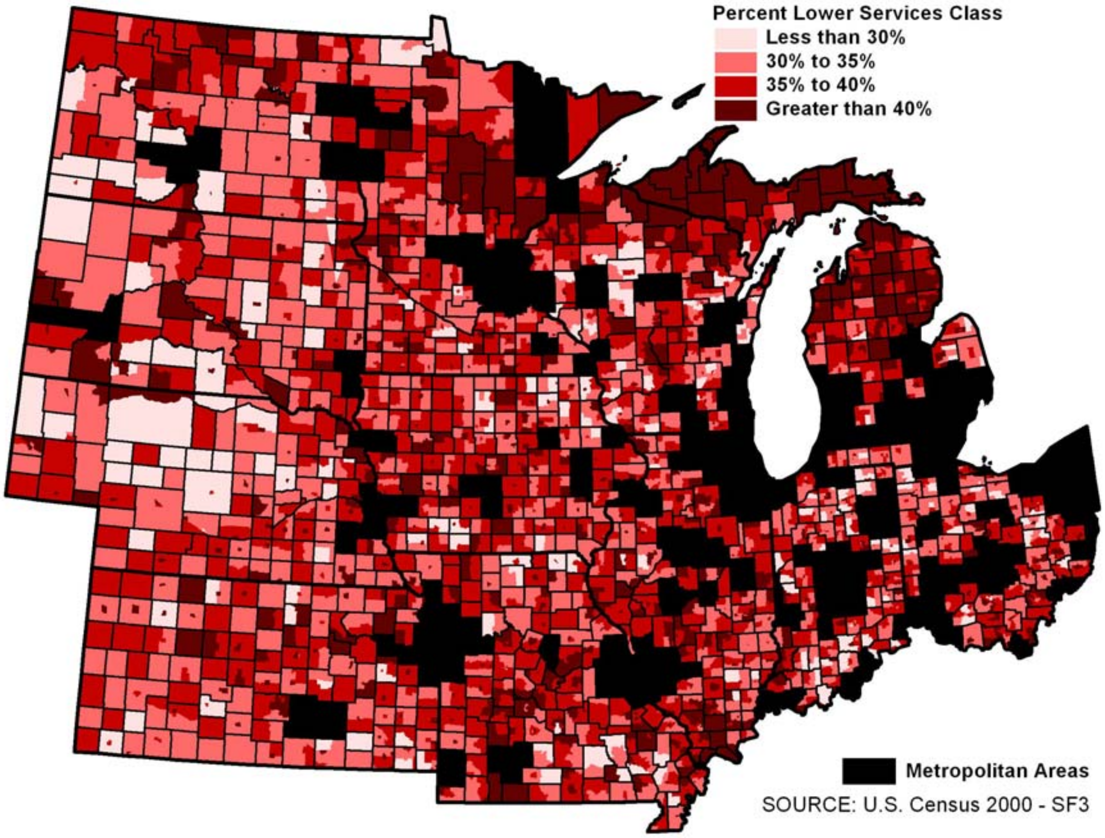


FIGURE 31
Percent Lower Services Class Employment in 2000



State fixed effects account for the poverty effects of omitted state-level variables, which if correlated with the included exogenous variables would otherwise bias the coefficients of the remaining variables by their omission. Omitted factors may include cost of living, amenity effects, cultural influences, and state government policies including welfare and economic development programs. State fixed effects are estimated using a series of 11 dichotomous variables, one for each state in the analysis except for Missouri which is the control state.

Assumptions and Data Screening

Prior to analysis, the data were screened in terms of missing data, outliers, normality, and multicollinearity. Of the initial 4,610 cases, 21 were deleted from the data leaving a final total of 4,589 census tracts for analysis. In terms of missing data, it is the pattern of missing cases that is more important than the actual number of cases. Missing data scattered randomly throughout the data poses less serious a problem in terms of the generalizability of the results (Gujarati 1995). In this analysis, 14 census tracts were removed from the data because they had zero population. Of these zero population tracts, eight were in South Dakota, two in Michigan, two in North Dakota, one in Iowa, and one in Wisconsin. Exclusion of these tracts is not deemed a problem because they are too few in number to affect the analysis (14 out of 4,610 tracts), and because they are the result of zero population and not due to any response bias (for example, not due to the systematic non-response to certain variables).

Outliers are cases with such extreme values on one variable or combinations of variables that they distort statistics, causing both Type I and Type II errors, which leads to non-generalizable results because they are overly determined by the outliers. Multivariate outliers were identified using a k-means cluster analysis including all endogenous and exogenous variables, which is a method suggested by Gujarati (1995) and Tabachnick and Fidell (1996). A k-means cluster analysis simply involves the reassignment of cases to the cluster with the nearest centroid, where the number of clusters is set a priori. To identify outliers, a separate k-means 10 cluster solution was run on all variables in the industry structure model (see Equation 19) and in the occupation structure model (see Equation 20). Both runs identified the same six census tracts as outliers, with each tract constituting its own cluster. These tracts were mostly located on Indian reservations, with four in South Dakota, two in North Dakota, and one in Missouri. These tracts were removed from the analysis.

In terms of the normal distribution of variables, inspection of the exogenous variable descriptive statistics presented in Tables 7 through 10 indicate that non-normality may be a problem for three variables based on skewness, and for nine variables based on kurtosis. According to Gujarati (1995), skewness is more of a problem in terms of linearity than the flatness or steepness of the distribution (i.e. kurtosis). In terms of multicollinearity and singularity, examination of the correlation matrices indicated that almost all variables were linear. However, two variables in the data exhibited high correlations above $r < 0.70$, which may indicate multicollinearity (Gujarati 1995). First, BAPLUS was dropped from the occupation structure model due to extremely high correlations ($r > 0.76$) with PRFBUS. Second, AGRFOR was also dropped from the occupation structure model due to high correlations with FARMER ($r = 0.69$). The other agriculture structure variables were also highly correlated with each other, yet were kept in the analysis because they were below the threshold (AGWAGE and AGSEMP $r = 0.64$). The correlation matrix is presented in the Appendix.

Logistic regression is a popular alternative to linear probability models because it has less restrictive assumptions than other least squares methods. Logistic regression does not assume a linear relationship between endogenous and exogenous variables. Although the endogenous variable need not be normally distributed, logistic regression does assume that its distribution is within the range of the exponential family of distributions. The endogenous variable also need not be homoscedastic for each level for the exogenous variables, meaning that there is no homogeneity of variance assumption. Normally distributed error terms are also not assumed. Lastly, logistic regression does not require the exogenous variables to be internal or unbounded.

However, logistic regression still makes several assumptions about the data that need to be met for the results to be considered acceptable. First, the endogenous variable must have meaningful coding. This assumption is met since this analysis uses cluster analysis to identify groupings of census tracts. Second, all relevant variables must be included while all irrelevant ones must also be excluded. This model specification assumption is met because variable selection was guided by relevant theory and research. Third, the assumption of independent error terms and low error in the explanatory variables is assumed to be met, since this analysis uses data from the U.S. Census Bureau. Fourth, there must be linearity between exogenous variables and the logits of the endogenous variable, and this assumption is satisfied through normally distributed exogenous variables (Gujarati 1995; Tabachnick and Fidell 1996). Although roughly one-quarter of the exogenous variables are non-normally distributed, this has the effect on generating Type II errors which underestimate the degree of relationship between the exogenous and endogenous variables. Fifth, there must be no multicollinearity among predictors and interactions must be additive. This assumption is met through the inspection of the correlation matrix and the removal of all correlations above $r = 0.70$. Sixth, the assumption of no outliers in the data is met, through the removal of extreme cases using k-means cluster analysis described above. Lastly, logistic regression assumes large samples. This is met through the large number of census tracts in the analysis, each with a relatively equal population size due to U.S. Census Bureau sampling methodologies.

TABLE 7
Descriptive Statistics - Endogenous Variables

Variable	*Mean*	*Minimum*	*Maximum*	*Variance*	*Skewness*	*Kurtosis*
POV	11.348	0.000	100.000	54.945	3.391	21.242
NPOV	20.441	0.000	57.252	33.768	0.445	1.659
DPOV	(2.857)	(68.487)	54.441	21.641	0.363	27.022
NDPOV	(3.596)	(48.111)	45.455	28.617	0.565	7.140

TABLE 8
Descriptive Statistics – Demographic and Agriculture Structure Exogenous Variables

Variable	*Mean*	*Minimum*	*Maximum*	*Variance*	*Skewness*	*Kurtosis*
POP	0.022	0.000	0.069	0.000	0.784	1.476
METADJ	0.492	0.000	1.000	0.250	0.033	(2.000)
MINRTY	6.928	0.000	100.000	128.017	4.485	24.492
DISABL	8.338	0.000	64.925	9.257	2.074	26.843
SHHFAM	7.309	0.000	62.712	12.966	2.784	21.017
HSAA	66.448	0.000	100.000	48.092	(1.729)	7.873
BAPLUS	14.874	0.000	100.000	62.814	2.657	13.376
UNEMP	5.208	0.000	49.183	11.663	3.407	24.534
POV90	14.205	0.000	85.464	65.941	2.312	9.548
AGSEMP	4.130	0.000	43.359	28.277	2.360	7.795
AGWAGE	1.771	0.000	50.000	5.017	5.535	73.325
FARMER	4.019	0.000	57.143	28.037	2.478	9.447
AGRFOR	1.814	0.000	40.000	4.452	4.497	48.363

TABLE 9
Descriptive Statistics – Economic Exogenous Variables

Variable	*Mean*	*Minimum*	*Maximum*	*Variance*	*Skewness*	*Kurtosis*
INFO	1.732	0.000	13.709	1.305	2.103	11.193
FINMGM	3.184	0.000	25.000	2.623	1.777	11.071
PRFSCI	2.230	0.000	12.566	1.610	1.303	3.982
MFGR	19.927	0.000	65.735	99.180	0.304	(0.139)
EDUC	8.755	0.000	65.263	25.295	3.723	22.048
HLTHSA	11.845	0.000	40.000	13.106	0.793	2.362
TRSUTL	5.202	0.000	28.313	5.838	1.802	9.453
CONST	6.809	0.000	25.000	6.468	0.671	1.537
TRADE	14.482	0.000	57.143	12.107	0.717	6.882
ADMWST	1.959	0.000	14.454	1.325	1.583	6.461
LEISUR	7.125	0.000	35.175	14.274	2.016	6.670
HHSERV	5.531	0.000	47.368	3.121	3.357	69.501
PUBADM	4.325	0.000	100.000	12.105	7.958	156.710
PRFBUS	17.902	0.000	67.895	31.301	1.453	5.665
ARTENT	0.996	0.000	8.345	0.592	1.929	8.116
HEALTH	4.201	0.000	33.333	3.335	1.740	16.051
CONEXT	6.010	0.000	31.250	5.391	1.101	5.957
MAINRP	4.667	0.000	100.000	4.605	19.292	849.195
PROD	13.601	0.000	47.934	40.238	0.462	0.404
TRANS	8.220	0.000	26.446	7.480	0.310	0.952
HLTPRT	4.264	0.000	46.667	4.229	3.828	56.554
FOOD	5.389	0.000	21.654	4.761	1.603	5.413
BLDGRD	3.402	0.000	18.072	1.983	1.306	5.667
PERSER	2.905	0.000	40.000	2.073	5.003	100.874
SALEOF	22.588	0.000	62.500	17.478	0.477	4.373

TABLE 10
Descriptive Statistics – State Effects Exogenous Variables

Variable	***Mean***	***Minimum***	***Maximum***	***Variance***	***Skewness***	***Kurtosis***
IL	0.115	0.000	1.000	0.102	2.414	3.827
IN	0.091	0.000	1.000	0.082	2.852	6.139
IA	0.101	0.000	1.000	0.091	2.651	5.030
KS	0.071	0.000	1.000	0.066	3.334	9.122
MI	0.108	0.000	1.000	0.096	2.533	4.416
MN	0.088	0.000	1.000	0.081	2.899	6.408
NE	0.054	0.000	1.000	0.051	3.937	13.503
ND	0.034	0.000	1.000	0.033	5.109	24.108
OH	0.108	0.000	1.000	0.096	2.533	4.416
SD	0.037	0.000	1.000	0.036	4.904	22.058
WI	0.095	0.000	1.000	0.086	2.763	5.638

CHAPTER SEVEN

RESULTS

This chapter presents and discusses the results of the analysis, using the data and methods presented in the previous chapter. As stated previously, this analysis has four main objectives. The first is to identify rural poverty clusters using appropriate statistical methods. The first section of this chapter addresses this objective, by using statistical cluster analysis to group census tracts according to their similarity along four poverty measures. The second and third objectives seek to understand how agricultural and postindustrial economic structure affects membership in the poverty clusters identified in the first section. These two objectives are addressed in the second section of this chapter, where the agriculture and industry model is regressed on the poverty clusters to determine which economic factors increase the likelihood of poverty cluster membership. The fourth objective is to determine how agricultural and occupational structure determines membership in a poverty cluster. This objective is addressed in the last section of this chapter, where a series of occupational and agricultural structure variables are used to predict poverty cluster membership.

Poverty Clusters

The first objective of this analysis is to identify rural poverty clusters using statistically appropriate methods. Cluster analysis is used to identify rural poverty clusters in the north central region by grouping 4,589 nonmetropolitan census tracts based on their similarity along four poverty variables measuring poverty, near poverty, and rates of change. POV is the percent of the population whose incomes are under 100 percent of the poverty level in 2000. NPOV is the percent of the population whose incomes are between 100 and 199 percent of the poverty level in 2000. DPOV is the percent change in the population whose incomes are under 100 percent of poverty between 1990 and 2000. DNPOV is the percent change in the population whose incomes are between 100 and 199 percent of poverty between 1990 and 2000.

In this analysis, the poverty clusters are identified using squared Euclidean distance grouped by Ward's Method. According to Aldenderfer and Blashfield (1984), the three main criteria for determining an appropriate cluster solution are fusion coefficients, dendograms, and multivariate analysis of variance (MANOVA). Determination of the appropriate number of clusters is difficult since no single agreed upon methodology exists, so cluster determination is a subjective process that is based on these criteria (Everitt 1980).

Fusion coefficients are an index of the loss of information incurred when merging two clusters. A large loss of information – a jump in the fusion coefficients – implies that two relatively dissimilar clusters have been merged, thus the number of clusters prior to the merger is the most probable cluster solution. There are several methods to assess a jump in the fusion coefficients, including numeric change, z-standardized change, percent change (slope), percent change in slope, and Mojena's Stopping Rule. The agglomeration schedule, presented in Table 11, indicates the presence of between 7 and 10 clusters. There is a large jump in the fusion coefficients at the sixth cluster stage, indicated by high numeric change (20,460.81), high z-standardized change (7.34), high slope or percent change (43.27%), and high change in slope (41.74%). Taking the previous cluster stage results in a seven cluster solution. However, the Mojena value exceeds the fusion coefficient at the ninth cluster stage, indicating the presence of 10 clusters. A seven cluster solution is deemed most appropriate given that most of the change metrics suggest such a solution.

Examination of the dendogram also suggests the presence of seven clusters. Dendograms are hierarchical trees that permit the researcher to see where cases and clusters merge together to get a better understanding of the underlying structure of the data. Interpretation is fairly straightforward, where census tracts are represented as nodes in the dendogram and the branches illustrate when the cluster method joins other tracts containing that object. The length of the branch indicates the distance between the tracts when they are joined. Although dendograms are mainly heuristic devices, it provides an important validation of the cluster solution.

TABLE 11
Cluster Analysis Agglomeration Schedule

Cluster	*Fusion Coefficient*	*Fusion Change*	*z – Fusion Change*	*Slope*	*Slope Change*	*Mojena*
30	138655.384	2471.985	0.842	2.825	2.241	248858.856
29	141127.924	2472.540	0.843	0.022	(2.802)	248858.856
28	143653.550	2525.626	0.862	2.147	2.125	248858.856
27	146247.046	2593.496	0.886	2.687	0.540	248858.856
26	149008.464	2761.417	0.947	6.475	3.787	248858.856
25	152368.584	3360.120	1.163	21.681	15.206	248858.856
24	155964.839	3596.256	1.248	7.028	(14.653)	248858.856
23	159583.158	3618.319	1.256	0.613	(6.414)	248858.856
22	163300.424	3717.265	1.292	2.735	2.121	248858.856
21	167444.460	4144.036	1.446	11.481	8.746	248858.856
20	171836.095	4391.635	1.535	5.975	(5.506)	248858.856
19	177039.246	5203.152	1.828	18.479	12.504	248858.856
18	182377.119	5337.873	1.877	2.589	(15.889)	248858.856
17	187770.837	5393.718	1.897	1.046	(1.543)	248858.856
16	193819.107	6048.270	2.134	12.135	11.089	248858.856
15	200251.700	6432.593	2.272	6.354	(5.781)	248858.856
14	207572.363	7320.663	2.593	13.806	7.452	248858.856
13	214936.329	7363.967	2.609	0.592	(13.214)	248858.856
12	222447.368	7511.038	2.662	1.997	1.406	248858.856
11	231868.090	9420.723	3.351	25.425	23.428	248858.856
10	242742.791	10874.701	3.876	15.434	(9.991)	248858.856
9	254665.050	11922.258	4.254	9.633	(5.801)	248858.856
8	268733.602	14068.553	5.029	18.002	8.369	248858.856
7	283015.898	14282.296	5.107	1.519	(16.483)	248858.856
6	303476.712	20460.813	7.337	43.260	41.741	248858.856
5	326702.167	23225.455	8.336	13.512	(29.748)	248858.856
4	351402.888	24700.722	8.868	6.352	(7.160)	248858.856
3	394642.493	43239.605	15.562	75.054	68.702	248858.856
2	493395.920	98753.427	35.606	128.387	53.333	248858.856
1	637598.590	144202.670	52.016	46.023	(82.364)	248858.856

The seven cluster solution is statistically validated using multivariate analysis of variance (MANOVA). MANOVA is a generalization of ANOVA to a situation where there is more than one endogenous variable. MANOVA tests whether mean differences among groups on a combination of endogenous variables are likely to have occurred by chance. In this analysis, MANOVA is used to test if there are mean differences between the seven clusters on a combined poverty endogenous variable consisting of four measures. If significant, this indicates that the clusters are statistically different from each other in terms of their scores on the combined poverty endogenous variables, supporting the assertion that the clusters are distinct entities. Once this assertion is supported, then multinomial logistic regression analysis can be used to predict cluster membership by taking into account the combination of demographic, agricultural, and economic structure variables as predictors.

Results of the MANOVA found that the mean differences across all four poverty variables are significantly different from each other across the seven clusters. This is indicated through global multivariate tests of significant differences (with an approximate F statistic) using Pillai's Trace Criterion ($F_{(24,18328)} = 543.43$, $p<0.000$), Wilks' Lambda ($F_{(24,15975)} = 747.14$, $p<0.000$), Hotelling's Trace Criterion ($F_{(24,18310)} = 935.67$, $p<0.000$), and Roy's Largest Root Criterion ($F_{(6,4582)} = 2534.27$, $p<0.000$) statistics.

MANOVA also indicates that each of the four endogenous poverty variables are statistically significant in discriminating between the seven clusters.

Presented in Table 12, poverty rates ($F_{(6,4582)}$ = 2208.79, p<0.000), near poverty rates ($F_{(6,4582)}$ = 1081.45, p<0.000), change in poverty rates ($F_{(6,4582)}$ = 349.64, p<0.000), and change in near poverty rates ($F_{(6,4582)}$ = 401.91, p<0.000) are all highly significant. The Type III method in MANOVA calculates the sums of squares of an effect in the design as the sums of squares adjusted for any other effects that do not contain it, and orthogonal to any effect that contain it. The Type III sums of squares have one major advantage in that they are invariant with respect to the cell frequencies as long as the general form of estimation remains constant. Therefore, this type is often considered useful for an unbalanced model with no missing cells.

TABLE 12
Multivariate Analysis of Variance by Clusters and Endogenous Variables

Variable	*df*	*Type III Sum of Squares*	*Mean Squares*	*F Statistic*		*R Squared*
POV	6	187323.696	31220.616	2208.786	***	0.743
NPOV	6	90804.867	15134.144	1081.451	***	0.586
DPOV	6	31182.198	5197.033	349.639	***	0.313
DNPOV	6	45271.931	7545.322	401.905	***	0.345

NOTE: * Significant at p<0.10. ** Significant at p<0.05. *** Significant at p<0.01.

Looking at the MANOVA results in more detail, nearly all of the four endogenous variables are significantly different between all pairs of clusters. Significance is estimated using the least significant difference (LSD) test, which is a multiple pair-wise comparison test that is equivalent to multiple individual *t* tests between all pairs of clusters. LSD tests indicate that POV is significantly different among all seven clusters. DPOV is not significantly different between clusters one and five, and between clusters three and five. NPOV is significantly different among all pairs of clusters except between cluster four and six. DNPOV is not significantly different between clusters one and seven, and between clusters two and five. Scheffe's test was also used to test for all possible linear combinations of cluster means, not just pair-wise comparisons, which results in this test being more conservative than LSD as larger mean differences are required. The results of both the LSD and Scheffe tests are presented in the Appendix.

The results of this cluster solution using squared Euclidean distance grouped by Ward's Method are similar to other solutions using different grouping methods. This indicates that there is inherent structure in the data and that the cluster solution is robust across methods. The solution using squared Euclidean distance grouped by average within-groups linkage results in nine to ten clusters. These clusters are similar in membership to that using Ward's method, but tended to break out the clusters in more detail with smaller numbers of tracts. Using the centroid method produces four to seven clusters, which are also similar to the solution using Ward's method. Lastly, the solution using Pearson's correlation grouped by average within-groups linkage produces very dissimilar clusters compared to Ward's Method. Although the results indicated the presence of eight clusters, nearly all the tracts were grouped into the first cluster, with the remaining clusters consisting of no more than 10 tracts each. This solution is not considered further.

Once the seven cluster solution has been statistically validated using the above techniques, the clusters can then be described and named according to their means along the four endogenous poverty variables, which is presented in Table 13 and graphically in Figure 32. The distribution of all clusters at the census tract level is presented spatially in Figure 35, using the names discussed below. The cluster solution indicates the presence of three poverty clusters, which are presented spatially in Figure 33. Cluster five consists of 130 census tracts that have high poverty rates, where over 30 percent of the population is poor. However, over the last decade poverty rates have improved slowly, declining by over two percent since 1990. These tracts also have high rates of near poverty, where over 25 percent of the population was between 100 and 199 percent of poverty. Near poverty rates did not change much during the 1990s. Termed the *High Poverty and Near Poverty Cluster*, tracts in this group contain 447,962 people accounting for a little over two and a half percent of the north central region's nonmetropolitan population.

Within the *High Poverty and Near Poverty Cluster*, 21 percent of the tracts are located in Missouri, 14 percent in South Dakota, and 12 percent each in Ohio and Illinois. In Missouri, these tracts are located in areas that have large postsecondary student populations (such as Kirksville and Maryville in the north, Warrensburg and Rolla in the central, and Cape Girardeau in the southeast), or are located in public forest areas (Mark Twain National Forest) in the south central area, or are located in the "Bootheel" area of extreme southeastern Missouri. In South Dakota, tracts are almost exclusively located on Native American reservations or areas adjacent to them (such as Standing Rock, Cheyenne River, Pine Ridge and Yankton Indian Reservations), or are located on public lands in the west (Black Hills National Forest), or near the town of Sisseton in the east. In Ohio, poverty clusters are principally located on or near Wayne National Forest in southern and southeastern Ohio, especially Gallia and Meigs counties. In Illinois, tracts are either located in areas with postsecondary institutions (such as Carbondale in the south, Charleston in the east, and Macomb in the west) or in the southern tip of the state around Pulaski County.

The *High Poverty and Near Poverty Cluster* is also unique in its socioeconomic characteristics. Referring to Tables 14 through 16, the cluster has one of the highest rates of urban population, yet one of the lowest rates of metropolitan adjacency – indicating that these tracts are principally located in rural towns. On average, tracts in this cluster have large minority populations and a large number of families headed by single parents. Unemployment in these tracts averages over 11 percent, and poverty in 1990 stood at a high rate of over 34 percent of the population.

In terms of labor relations, this cluster has some of the lowest rates of self-employment and wage employment in agriculture, yet at the same time has an average rate of self-employment in other industries. Of those employed, most worked in education, health care and social assistance, the leisure industries (amusement, recreation, food, and accommodation), and manufacturing. In fact, compared to other clusters this one has some of the highest rates of employment in education, health care and social assistance, leisure, information, administrative services, and real estate and rental services. However, the cluster also has some of the lowest rates of employment in manufacturing and natural resources. Looking at employment by occupation, we find above average employment rates in arts and entertainment jobs, healthcare support and protective service jobs, food preparation and serving jobs, and personal service workers. By contrast, below average employment rates are found among business and management occupations and farmers.

Cluster seven consists of 34 census tracts that have extremely high poverty rates nearing 60 percent of the population. Worse still, over the last decade poverty rates have dramatically worsened in these areas, growing by over eight percent since 1990. However, rates of near poverty in these tracts are close to the regional average, standing around 20 percent of the population. Near poverty rates improved somewhat during the 1990s, declining by over one percent. Termed the *High Poverty Cluster*, tracts in this group contain only 78,994 people equaling one half of one percent of the north central region's nonmetropolitan population.

Within the *High Poverty Cluster* over 40 percent of tracts in this small group are located in South Dakota, 18 percent are in Illinois, and 12 percent in Ohio. In South Dakota, tracts are almost exclusively located on Native American reservations or areas adjacent to them, specifically northeast Standing Rock, southwest Cheyenne River, all of Crow Creek, and most of Pine Ridge and Rosebud (including Bennett County which lies between the two). In both Illinois and Ohio, tracts in this poverty cluster are principally in towns with postsecondary institutions, such as Macomb in western Illinois, Charleston in eastern Illinois, Carbondale in southern Illinois, Wooster in northeast Ohio, and Athens in southeast Ohio.

The *High Poverty Cluster* has some of the most extreme socioeconomic characteristics compared to the other clusters. Referring to Tables 14 through 16, this cluster has one of the lowest rates of metropolitan adjacency and the smallest population base. In terms of demographics, tracts in this cluster have the smallest percent of the population over 64 years of age (under 6 percent), the largest minority population (close to 50 percent), the largest number of families headed by single parents (nearly 16 percent), and has one of the lowest rates of high school educational attainment while at the same time having the largest percentage of college graduates (under 55 percent and over 26 percent, respectively). Unemployment in these tracts stands near 18 percent, while over 27 percent of the working age population does not have a full-time and full-year job. These tracts also seem to be in persistent poverty, where almost 50 percent of the population was living in poverty in 1990.

In terms of economic structure, this cluster has the lowest rate of self-employment in other industries. Of those employed, most worked in education, the leisure industries, and trade. This cluster is a case of extremes, having some of the highest rates of industry employment in education, leisure, public administration, information, and real estate and rental services. Conversely, the cluster also has the lowest rates of employment in trade, construction, manufacturing, other services, transportation and utilities, professional and scientific services, and finance and management services. In terms of occupational structure, we find some of the highest employment rates in professional occupations, food preparation and serving jobs, personal service jobs, building and grounds jobs, natural resource jobs, and arts and entertainment jobs. By contrast, these tracts have very low numbers of business and management occupations, transportation jobs, production jobs, healthcare practitioners and support professions, and maintenance and repair jobs.

Cluster two consists of 695 census tracts that have extremely high rates of near poverty, standing at close to 30 percent of the population. Worse still, over the last decade near poverty rates have slowly worsened in these areas, growing by over one percent since 1990. However, poverty rates in these tracts are close to the regional average, standing around 14 percent of the population. Encouragingly, poverty rates improved dramatically during the last decade, declining by over seven percent since 1990. Termed the *High Near Poverty Cluster*, tracts in this group contain 2.31 million people accounting for over 13 percent of the north central region's nonmetropolitan population.

Within the *High Near Poverty Cluster*, 19 percent of the tracts are located in Missouri, 12 percent are each located in Illinois and Ohio, and 10 percent are located in Michigan. In Missouri, most of these tracts are located in the southern and southeastern part of the state, characterized by large public forests and persistently poor areas in the Bootheel. In addition, near poverty tracts are also located in the west central part of the state and in the more remote northern one-quarter of the state, both characterized by intensive farming. In Illinois, near poverty tracts are concentrated in the southern half of the state, principally dominated by large public forests; and also in the west central part of the state that is more farming dependent. In Ohio, near poverty is almost all located in state and national forest areas and in the Appalachian foothills in eastern, southern, and southeastern Ohio. Lastly, in Michigan near poverty affects the northern part of the state in both the upper and lower peninsulas, primarily in areas dominated by state and national forests.

The socioeconomic characteristics of the *High Near Poverty Cluster* are presented in Tables 14 through 16. In terms of demographics, the only distinguishing feature of tracts in the near poverty cluster is that they have a very low percentage of college graduates, standing at under 12 percent of the population. In terms of labor relations, this cluster has the highest rate of wage employment in agriculture. Looking at the average industry structure of near poverty tracts, we find that of those employed most worked in manufacturing, trade, and healthcare and social assistance. Compared to other clusters, the near poverty cluster has above average employment rates in trade, healthcare and social assistance, agriculture and other resource industries, and transportation and utilities. On the other hand, the cluster also has the lowest rates of employment in education services and information services. Looking next at occupational structure, the near poverty cluster is characterized by above average employment in construction and extraction occupations, farmers, wage workers in agriculture, and other resource-based jobs. By contrast, this cluster has the lowest employment rates in arts, entertainment and recreation jobs compared to all other clusters.

In addition, the cluster solution also identified the presence of four non-poverty clusters that can be contrasted with the poverty clusters described above, and which are presented spatially in Figure 34 with socioeconomic data presented in Tables 14 through 16. Cluster four consists of 962 census tracts that have poverty rates near the regional average, where a little under 15 percent of the population is poor. Over the last decade poverty rates have not changed much since 1990. These tracts also have average rates of near poverty, where a little over 20 percent of the population is between 100 and 199 percent of poverty. However, rates of near poverty improved fairly well during the 1990s, experiencing a decline of over three percent. Termed the *Average Poverty – Slow Decline Cluster*, tracts in this group contain 3.65 million people equaling nearly 22 percent of the north central region's nonmetropolitan population. Spatially, 16 percent of the tracts are located in Missouri, 14 percent in Illinois, and 10 percent in Ohio.

Cluster six consists of 1,034 census tracts that have poverty rates slightly below the regional average, where roughly 10 percent of the population is poor. Encouragingly, poverty rates showed marked improvement during the 1990s, dropping by well over four percent. Rates of near poverty are also close to the regional average, accounting for a little over 20 percent of the population. As is the case for poverty, rates of near poverty improved over the last decade, declining by four percent since 1990. Termed the *Average Poverty – Fast Decline Cluster*, tracts in this group contain 3.56 million people accounting for 21 percent of the north central region's nonmetropolitan population. In terms of geography, 16 percent of the tracts are located in Michigan, 12 percent in Iowa, and 10 percent each in Minnesota and Wisconsin.

Cluster one consists of 607 census tracts that have very low rates of poverty, where under six percent of the population is considered poor. In addition, this low poverty rate improved during the 1990s, declining by one and a half percent. Rates of near poverty are also well below the regional average, accounting for about 14 percent of the population. Mirroring the trend for poverty, rates of near poverty also improved during the last decade, dropping about one and a half percent since 1990. Termed the *Low Poverty – Slow Decline Cluster*, tracts in this group contain 2.63 million people equaling over 15 percent of the north central region's nonmetropolitan population. These tracts are distributed across the region, with 20 percent of the tracts being located in Ohio, 17 percent in Illinois, 14 percent in Indiana, 12 percent in Wisconsin, and 10 percent in Iowa.

Lastly, cluster three consists of 1,127 census tracts that also have very low rates of poverty, where only eight percent of the population is living below poverty. Added to this already low rate, poverty also improved over the last decade, dropping by well over two percent since 1990. Rates of near poverty are also well below the regional average, where about 16 percent of the population is considered near poor. Tracts in this cluster experienced a vast improvement in near poverty during the 1990s, with rates declining over eight percent during the last decade. Termed the *Low Poverty – Fast Decline Cluster*, tracts in this group contain 4.21 million people accounting for 25 percent of the north central region's nonmetropolitan population. Spatially, 16 percent of the tracts are located in Wisconsin, 15 percent in Minnesota, and 11 percent in Indiana.

TABLE 13
Cluster Means and Standard Deviations by Endogenous Variables

Variable	***Cluster 1***	***Cluster 2***	***Cluster 3***	***Cluster 4***	***Cluster 5***	***Cluster 6***	***Cluster 7***
POV							
Mean	5.753	14.348	7.519	14.725	31.943	9.502	58.597
Standard Deviation	2.036	5.399	2.482	3.880	6.336	2.811	14.837
N	607	695	1127	962	130	1034	34
NPOV							
Mean	14.203	27.499	15.870	22.263	25.414	22.028	20.165
Standard Deviation	3.189	4.771	3.236	4.118	5.831	2.585	9.159
N	607	695	1127	962	130	1034	34
DPOV							
Mean	(1.599)	(7.292)	(2.331)	0.180	(2.172)	(4.479)	8.752
Standard Deviation	2.618	5.183	2.887	3.087	7.076	2.863	18.930
N	607	695	1127	962	130	1034	34
DNPOV							
Mean	(1.403)	1.220	(8.143)	(3.322)	0.768	(4.040)	(1.336)
Standard Deviation	2.471	5.393	3.496	3.961	5.429	4.767	13.488
N	607	695	1127	962	130	1034	34

FIGURE 32
Cluster Means by Endogenous Variables

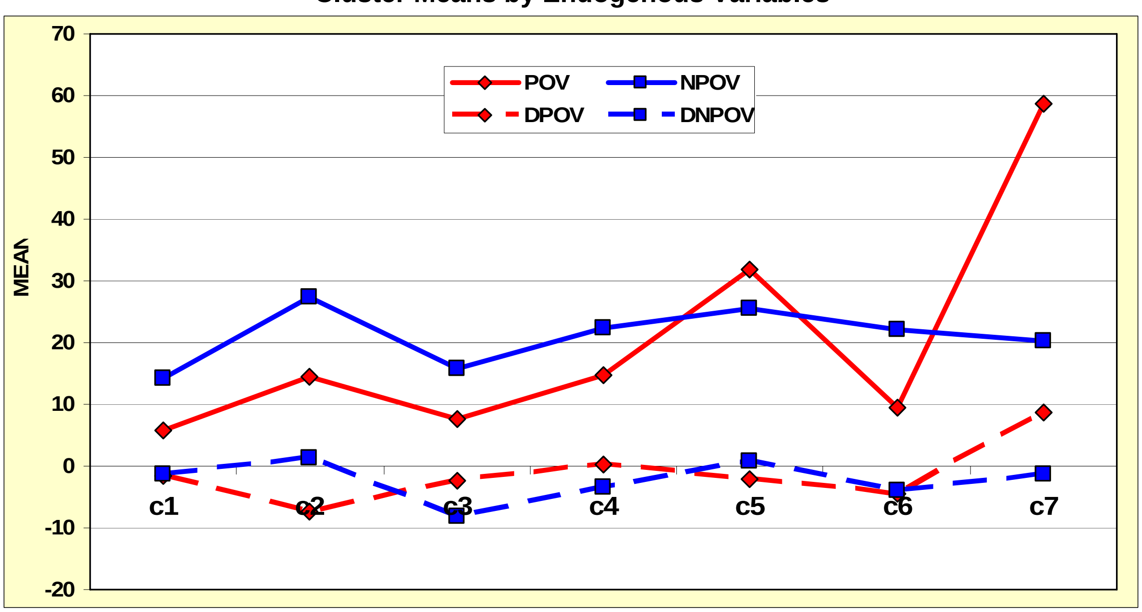


FIGURE 33
Poverty Clusters

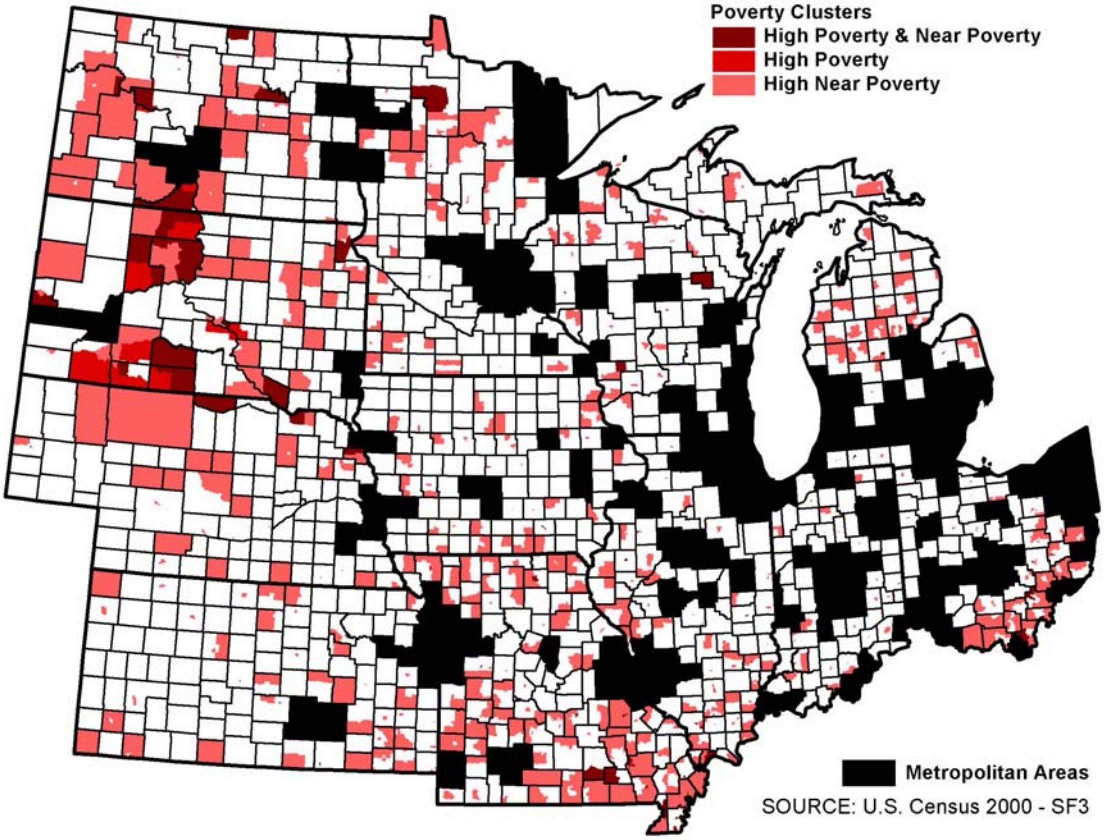


FIGURE 34
Non-Poverty Clusters

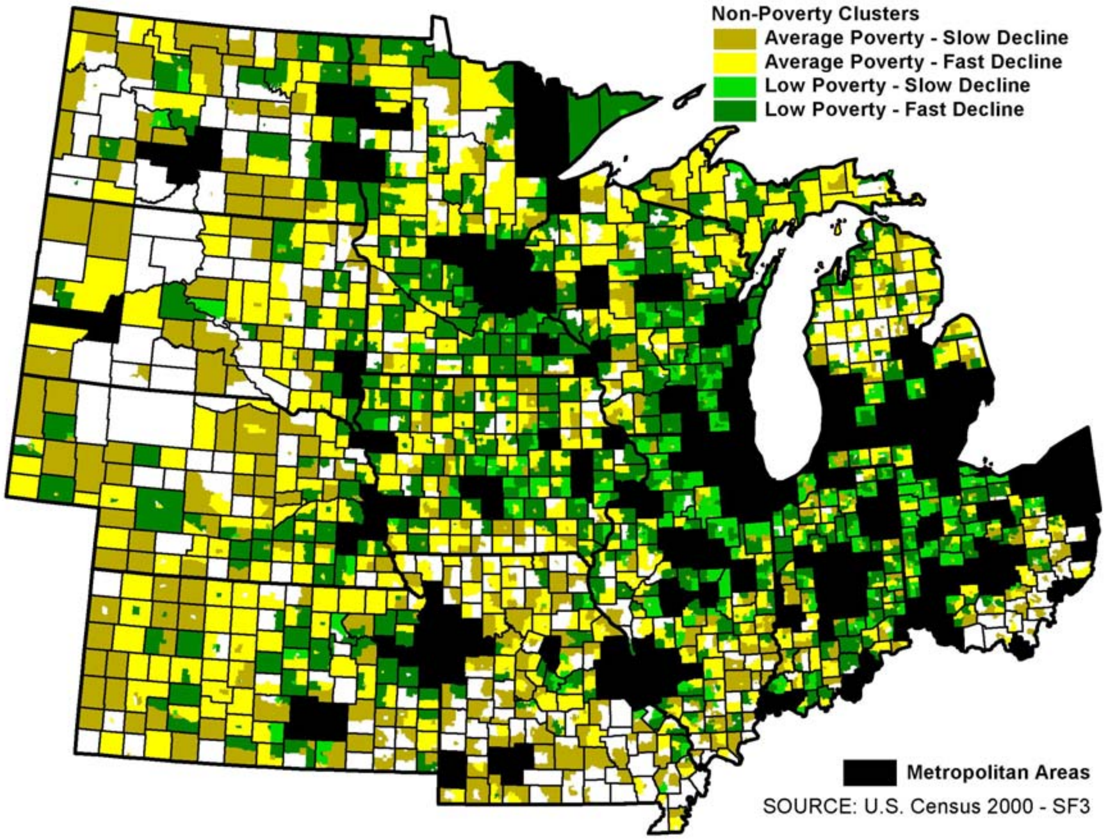


TABLE 14
Cluster Means by Demographic and Agriculture Structure Exogenous Variables

Variable	*High Poverty & Near Poverty Cluster*	*High Poverty Cluster*	*High Near Poverty Cluster*	*Average Poverty-Slow Decline Cluster*	*Average Poverty-Fast Decline Cluster*	*Low Poverty-Slow Decline Cluster*	*Low Poverty-Fast Decline Cluster*
POP	0.020	0.014	0.020	0.022	0.020	0.026	0.022
METADJ	0.338	0.206	0.350	0.448	0.439	0.713	0.571
MINRTY	29.215	49.128	9.703	8.034	4.471	4.571	3.951
DISABL	9.469	8.799	9.763	9.024	8.237	7.001	7.542
SHHFAM	12.703	15.848	8.396	8.463	6.540	6.178	6.089
HSAA	57.674	54.976	64.995	64.972	68.100	66.268	68.542
BAPLUS	18.245	26.108	11.643	13.891	13.400	19.755	15.701
UNEMP	11.008	17.850	6.333	5.785	4.950	3.667	4.039
POV90	34.116	49.845	21.640	14.546	13.983	7.353	9.851
AGSEMP	2.813	4.370	4.742	3.842	5.257	2.034	4.237
AGWAGE	1.148	1.437	2.062	1.831	2.101	0.929	1.771
FARMER	2.701	4.342	4.601	3.762	5.091	2.012	4.118
AGRFOR	1.387	2.923	2.168	1.861	2.171	0.873	1.749

TABLE 15
Cluster Means by Industry Structure Exogenous Variables

Variable	*High Poverty & Near Poverty Cluster*	*High Poverty Cluster*	*High Near Poverty Cluster*	*Average Poverty-Slow Decline Cluster*	*Average Poverty-Fast Decline Cluster*	*Low Poverty-Slow Decline Cluster*	*Low Poverty-Fast Decline Cluster*
INFO	2.316	2.526	1.608	1.793	1.614	1.846	1.711
FINMGM	2.088	1.179	2.754	3.019	3.144	3.787	3.490
PRFSCI	1.942	1.435	1.802	2.088	2.124	2.899	2.411
MFGR	12.146	4.226	17.958	19.545	19.407	23.169	21.572
EDUC	15.525	28.810	8.096	8.647	8.190	9.147	8.175
HLTHSA	12.653	10.207	12.530	12.345	11.651	11.441	11.347
TRSUTL	3.882	2.091	5.306	5.153	5.547	4.981	5.230
CONST	5.490	4.971	6.946	6.458	7.197	6.375	7.110
TRADE	13.587	10.509	14.535	14.678	14.398	14.634	14.503
ADMWST	2.381	1.989	2.093	2.092	1.802	1.952	1.863
LEISUR	12.180	12.814	7.741	7.446	6.803	6.289	6.463
HHSERV	5.340	4.361	5.680	5.679	5.529	5.526	5.372
PUBADM	5.747	8.280	4.713	4.308	4.187	4.274	3.970

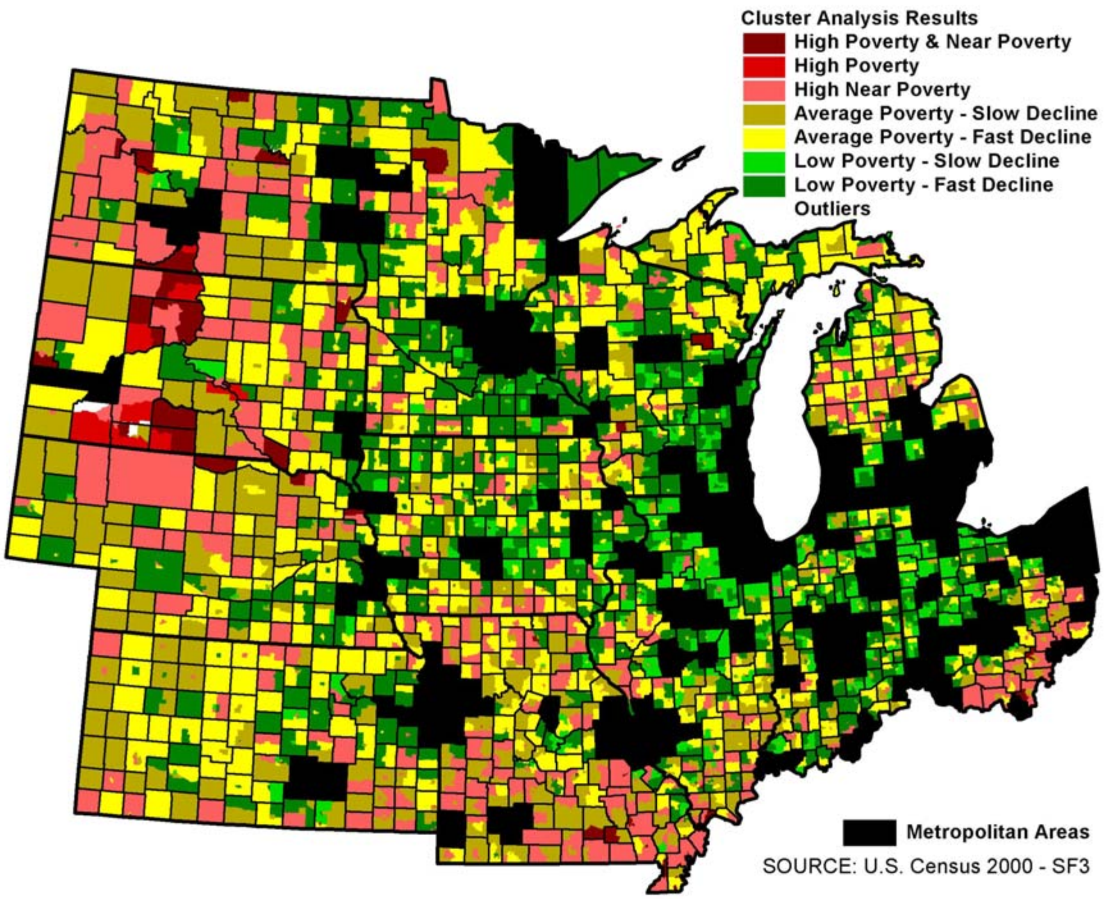
TABLE 16
Cluster Means by Occupation Structure Exogenous Variables

Variable	***High Poverty & Near Poverty Cluster***	***High Poverty Cluster***	***High Near Poverty Cluster***	***Average Poverty-Slow Decline Cluster***	***Average Poverty-Fast Decline Cluster***	***Low Poverty-Slow Decline Cluster***	***Low Poverty-Fast Decline Cluster***
PRFBUS	19.804	24.516	15.602	17.124	16.873	21.941	18.336
ARTENT	1.522	1.796	0.875	1.009	0.890	1.142	0.995
HEALTH	3.316	2.209	4.000	4.198	4.027	4.909	4.266
CONEXT	5.278	5.143	6.413	5.816	6.342	5.337	6.095
MAINRP	3.264	2.101	4.649	4.564	4.838	4.518	4.928
PROD	9.823	3.642	13.256	13.944	13.633	13.917	14.057
TRANS	7.153	5.509	8.996	8.387	8.438	7.444	8.020
HLTPRT	5.343	3.716	4.925	4.600	4.297	3.570	3.807
FOOD	8.469	9.080	5.959	5.736	5.217	4.575	4.869
BLDGRD	4.365	5.096	3.851	3.622	3.315	2.886	3.135
PERSER	3.912	5.288	3.134	2.989	2.900	2.475	2.743
SALEOF	23.663	24.636	21.570	22.387	21.969	24.237	22.882

In summary, cluster analysis is used to identify rural poverty clusters in the north central region by grouping 4,589 nonmetropolitan census tracts based on their similarity along four poverty variables measuring poverty, near poverty, and rates of change. Results of the cluster analysis identifies seven clusters, of which three are termed poverty clusters and four are termed non-poverty clusters. Presented spatially in Figure 35, the three poverty clusters include: the *High Poverty and Near Poverty Cluster*, the *High Poverty Cluster*, and the *High Near Poverty Cluster*; and the four non-poverty clusters include: the *Average Poverty – Slow Decline Cluster*, the *Average Poverty – Fast Decline Cluster*, the *Low Poverty – Slow Decline Cluster*, and the *Low Poverty – Fast Decline Cluster*.

The cluster solution is statistically validated using MANOVA, which found that the clusters are statistically different from each other in terms of their scores on the combined poverty endogenous variables. This supports the assertion that the seven clusters are distinct entities and are not due to chance. Since this condition is supported by the MANOVA results, logistic regression analysis can then be used to predict the odds of cluster membership by taking into account the combination of demographic, agricultural, and economic structure variables as predictors.

FIGURE 35
Cluster Analysis Results by Census Tract



Agriculture and Industry Structure Model

The next two objectives of the analysis are to determine how agricultural structure and postindustrial economic structure affects membership in a poverty cluster. The agriculture and industry structure model is tested using multinomial logistic regression, which is used to predict the odds of poverty and non-poverty cluster membership for 4,589 census tracts in the north central region. The industry structure logistic model is evaluated in terms of model fit, classification accuracy, and the importance of the exogenous variables in prediction. The endogenous variable consists of four nominal categories of poverty clusters, which include Poverty, Near Poverty, Average Poverty, and Low Poverty. In this logistic regression, all results are compared to membership in the Average Poverty Cluster, which is the reference group. The industry structure model includes nine demographic controls, two measures of agriculture structure, and 13 industry structure exogenous variables.

Before beginning, however, one key assumption of logistic regression is meaningful coding of the endogenous variable. The results of the cluster analysis identified seven clusters, which are consolidated into four clusters to make analysis and interpretation understandable. The *Poverty Cluster* consists of 164 tracts and is formed by the merger of the High Poverty / Near Poverty Cluster and the High Poverty Cluster. The *Near Poverty Cluster* is the same as the High Near Poverty Cluster and consists of 695 tracts. The *Average Poverty Cluster* consists of 1,996 tracts and is formed by the merger of the Average

Poverty – Fast Decline Cluster and the Average Poverty – Slow Decline Cluster. The *Low Poverty Cluster* consists of 1,734 tracts and is formed by the merger of the Low Poverty – Fast Decline Cluster and the Low Poverty – Slow Decline Cluster.

Although collapsing the seven clusters into four makes analysis and interpretation easier, doing so essentially discards the change elements in the cluster analysis. This is not deemed overly problematic for two reasons. First, the original clusters comprising the two aggregated clusters (Average Poverty and Low Poverty) are very similar in terms of levels of poverty and near poverty, only the rates of change differ. Second, the rates of change are all in the same direction, but just at different levels. For example, the two original clusters that make up the aggregated Average Poverty Cluster have very similar rates of poverty and near poverty, yet one close in has slow declining rates while the other has more fast declining rates. Even though combining groups in this manner may cause less accurate predictions, it is essential in making the results more understandable.

Additionally, initial multinomial logistic regression runs resulted in errors that prevented the procedure from making sufficient iterations to ascertain model fit, making the results uncertain. This error was attributable to having too many zero value cells in the data matrix, which was caused by too many dichotomous variables. To remedy this effect, the 11 state fixed effect variables were removed from the analysis. Although it is difficult to estimate the effect this has on the final results, initial runs of the model indicated that the state effects variables had limited predictive power. However, due to these errors the initial results are uncertain and should be treated with caution.

The performance of the industry structure logistic regression model is assessed through goodness-of-fit statistics, log likelihood ratio tests (–2LL), and pseudo R-squared measures – all of which estimate how well the covariate model replicates the pattern of observations compared to an alternative model that only includes the intercept. The results of these diagnostics are presented in Table 17. Results of the goodness-of fit tests using a Chi-squared statistic show the industry structure model fits the data well, meaning the model replicates the data better than the intercept-only model. Pearson's Chi-squared test is highly significant ($\chi^2_{(13692)}$ = 203204.54 p>0.000), which indicates the industry structure model fits the data better than the reduced model. The Deviance Chi-squared test also indicates that the covariate model fits the data well, which is indicated by a non-significant finding ($\chi^2_{(13692)}$ = 6192.38 p>1.000). Thus, we can conclude that the distribution of poverty and non-poverty clusters can be better replicated by taking into account demographic, agriculture, and industry structure factors.

The –2LL test evaluates the entire industry structure model, and tests the null hypothesis that all logit coefficients are zero. Analogous to an overall F test in least squares regression, a significant finding indicates that at least one of the exogenous variables contributes in fitting the data better than the intercept-only model. Results of the –2LL test indicate that the industry structure model does fit the data better than the intercept-only model, and we can conclude that at least one of the exogenous variables contributes significantly to model fit ($\chi^2_{(72)}$ = 4222.56 p>0.000). Thus, one or more of the socioeconomic variables in the industry structure model is statistically significant in predicting poverty and non-poverty cluster membership across the four groups.

Another diagnostic in logistic regression is to estimate the strength of association between the endogenous and exogenous variables in the model, which is assessed through pseudo R-squared statistics. Results show that the industry structure model has a high degree of association with the four-category endogenous variable. The Cox and Snell statistic shows a 60 percent association, while Nagelkerke's R-squared shows a high association of 67 percent. It is important to note that these statistics do not measure the percent of variance explained, as in least squares regression, but only the strength of association. Thus, we can conclude that the set of demographic, agriculture, and industry structure variables is highly associated with the two poverty and two non-poverty clusters in the endogenous variable.

TABLE 17
Industry Structure Model – Logistic Regression Diagnostics

	Model Fit Criteria		***Log Likelihood Ratio***	***Chi-Squared***
	AIC	*BIC*		
Goodness-of-Fit				
Pearson	--	--		203204.548 ***
Deviance	--	--		6192.387
Model Fit				
Intercept Model	10420.960	10440.250	10414.955	--
Covariate Model	6342.387	6824.743	6192.387	4222.568 ***
Pseudo R-Squared				
Cox and Snell	0.602			
Nagelkerke	0.671			

NOTE: * Significant at p<0.10. ** Significant at p<0.05. *** Significant at p<0.01.
AIC (Akaike) and BIC (Bayesian) Information Criteria used to compare model iterations.

Since the goodness-of-fit for the industry structure model has been established, the next step is to evaluate the importance of the exogenous variables. The log likelihood ratio test (–2LL) using a Chi-squared distribution is used to assess the significance of the variables in the industry structure model. This test compares the difference in –2LLs for the industry structure model compared to a reduced model that drops a given exogenous variable. If the logit coefficient *b* for the dropped variable can be set to zero without any change in model fit, then the variable contributes nothing to model fit and can be dropped from the covariate model. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are used to compare models, where the step with the lowest AIC or BIC becomes the final model.

Referring to Table 18, nearly all predictors in the industry structure model are significant, indicating that they contribute significantly in fitting the data better than the intercept-only model. The percent employed in real estate, rental, leasing, and other services (HHSERV) exceeds the $p<0.05$ criterion, but is considered a useful predictor since it is still $p<0.10$. However, two variables are not significant, the percent of the total nonmetropolitan population (POP) and the percent of wage workers in agriculture (AGWAGE), although the latter approaches significance. Although the non-significant variables may be dropped from the analysis, their inclusion is strongly supported by previous theory and research. Thus, the variables are kept in the analysis to maintain the assumption of a correctly specified model.

TABLE 18
Industry Structure Model – Exogenous Variable Tests

Variable	*Model Fit Criteria* *AIC*	*BIC*	***Log Likelihood Ratio***	***Chi-Squared***	
Intercept	6351.606	6814.668	6207.606	15.219	***
POP	6339.708	6802.770	6195.708	3.321	
METADJ	6359.697	6822.759	6215.697	23.310	***
MINRTY	6351.219	6814.281	6207.219	14.832	**
DISABL	6358.212	6821.274	6214.212	21.825	***
SHHFAM	6436.242	6899.304	6292.242	99.856	***
HSAA	6401.370	6864.433	6257.370	64.984	***
BAPLUS	6424.264	6887.326	6280.264	87.877	***
UNEMP	6372.210	6835.272	6228.210	35.823	***
POV90	7499.103	7962.165	7355.103	1162.716	***
AGSEMP	6352.824	6815.886	6208.824	16.437	***
AGWAGE	6342.633	6805.695	6198.633	6.246	
INFO	6346.268	6809.330	6202.268	9.881	**
FINMGM	6357.759	6820.821	6213.759	21.373	***
PRFSCI	6347.352	6810.414	6203.352	10.965	**
MFGR	6358.665	6821.727	6214.665	22.278	***
EDUC	6359.208	6822.270	6215.208	22.822	***
HLTHSA	6347.647	6810.709	6203.647	11.261	**
TRSUTL	6348.969	6812.031	6204.969	12.582	***
CONST	6361.142	6824.204	6217.142	24.756	***
TRADE	6350.779	6813.841	6206.779	14.392	***
ADMWST	6344.814	6807.876	6200.814	8.427	**
LEISUR	6354.153	6817.215	6210.153	17.766	***
HHSERV	6343.390	6806.452	6199.390	7.003	**
PUBADM	6348.493	6811.555	6204.493	12.107	***

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
AIC (Akaike) and BIC (Bayesian) Information Criteria used to compare model iterations.

A key feature of multinomial logistic regression is the ability to predict group membership from the covariate logistic model. Comparing predicted membership to the observed membership gives an indication of how accurate the model performed in terms of classification. Results show that the industry structure model correctly predicts cluster membership for over 70 percent of the census tracts. This indicates that one can predict a census tract's cluster membership by knowing its demographic, agriculture, and industry structure. Although this overall accuracy rate is quite high, it varied greatly across clusters.

Referring to Table 19, the industry structure model does a poor job at predicting membership in the Near Poverty Cluster, correctly classifying only 45 percent of all tracts in this cluster. It appears the model does a poor job at discriminating between the Near Poverty Cluster and the Average Poverty Cluster, with in fact more tracts being classified as average poverty rather than as near poverty. However, the model does an above average job in correctly classifying tracts into the Poverty Cluster, with an accuracy rate of nearly 60 percent. Most misclassifications were into the Near Poverty Cluster, which makes sense given that the Poverty Cluster is composed of a subgroup that contains both high poverty and high near poverty tracts. Lastly, the industry structure model performs very well at predicting tract membership into the Average Poverty and Low Poverty clusters, with accuracy rates over 75 percent.

TABLE 19
Industry Structure Model – Classification Results

	Predicted Clusters				
Observed Clusters	*Poverty*	*Near Poverty*	*Average Poverty*	*Low Poverty*	***Percent Correct***
Poverty	95	51	15	3	**57.9%**
Near Poverty	18	309	354	14	**44.5%**
Average Poverty	4	119	1490	383	**74.6%**
Low Poverty	2	6	395	1331	**76.8%**
Overall Percentage	**2.6%**	**10.6%**	**49.1%**	**37.7%**	**70.3%**

Now that the goodness-of-fit, significance of predictors, and accuracy of classification has been established for the industry structure model, the next step is to evaluate the effect of the exogenous variables. This is done by evaluating the logistic regression coefficients *b*, which can be used in prediction equations and are analogous to beta coefficients in least squares regression. Walds statistic is used to test the null hypothesis that the *b* effect is zero, thus a significant Walds test indicates the variable has discriminating power. However, since *b* measures changes in log odds on the endogenous variable it can be difficult to interpret. Logistic coefficients are easier to interpret when they are converted into an odds ratio *exp(b)*, which can be used to measure changes in odds in the endogenous variable and to measure effect size analogous to standardized beta coefficients in least squares regression. Both *b* and *exp(b)* measure the changes in odds on cluster membership compared to membership in the Average Poverty Cluster, which is the reference category.

Comparing census tract membership in the *Poverty Cluster* to the *Average Poverty Cluster*, the logistic regression found eight significant variables, which are listed by strength of effect in Table 20. Larger percentages of employment in the information services industry (INFO) increases the odds of being in a poverty cluster by nearly 37 percent (*exp(b)* = 1.369) per unit increase. Equally strong is the effect of poverty rates a decade ago (POV90), with a one percent increase in poverty in 1990 increasing the odds of poverty cluster membership by almost 36 percent (*exp(b)* = 1.356). Employment in health care and social assistance (HLTHSA) also increases the likelihood of poverty cluster membership, with a one percent increase in employment equating to a 31 percent increase in odds (*exp(b)* = 1.315). Larger percentages of employment in arts, entertainment, recreation, accommodation, and food services (LEISUR) increases the odds of being in a poverty cluster by 28 percent (*exp(b)* = 1.281). Educational services employment (EDUC) also increases the odds of being in a poverty cluster by 26 percent (*exp(b)* = 1.261) per percentage increase.

Other smaller order effects are also significant. Tracts with larger percentages of the population with an employment disability (DISABL) increases the odds of poverty cluster membership by nearly nine percent (*exp(b)* = 1.088), compared to membership in the average poverty cluster. In terms of education, a one percent increase in those with a high school degree, some college, or an associate's degree (HSAA) decreases the odds of being in a poverty cluster by nearly 5 percent (*exp(b)* = 0.954). Lastly, larger minority populations (MINRTY) tends to increase the odds of poverty cluster membership by a little over two percent (*exp(b)* = 1.023) per unit increase.

TABLE 20
Industry Structure Model – Poverty Cluster Logistic Regression Coefficients

Variable	*Logit Coefficient b*	*Standard Error*	*Walds Statistic*		*Odds Ratio exp(b)*
Intercept	(26.221)	11.361	5.326	**	--
POP	(20.795)	15.985	1.692		0.000
METADJ	0.178	0.272	0.429		1.195
MINRTY	0.023	0.011	4.243	**	1.023
DISABL	0.084	0.034	6.156	**	1.088
SHHFAM	0.052	0.040	1.738		1.054
HSAA	(0.047)	0.021	4.903	**	0.954
BAPLUS	(0.016)	0.025	0.423		0.984
UNEMP	0.030	0.038	0.637		1.031
POV90	0.305	0.020	229.982	***	1.356
AGSEMP	0.197	0.123	2.570		1.217
AGWAGE	0.148	0.131	1.272		1.160
INFO	0.314	0.139	5.090	**	1.369
FINMGM	0.117	0.145	0.649		1.124
PRFSCI	0.135	0.162	0.692		1.145
MFGR	0.150	0.113	1.762		1.161
EDUC	0.232	0.118	3.854	**	1.261
HLTHSA	0.274	0.116	5.568	**	1.315
TRSUTL	0.158	0.127	1.546		1.171
CONST	0.162	0.127	1.616		1.176
TRADE	0.184	0.117	2.476		1.202
ADMWST	0.114	0.143	0.628		1.120
LEISUR	0.247	0.115	4.613	**	1.281
HHSERV	0.136	0.127	1.147		1.146
PUBADM	0.168	0.126	1.783		1.183

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.

Next looking at the results for the *Near Poverty Cluster*, many of the variables in the industry structure model are significant in predicting membership compared to the *Average Poverty Cluster*. The results are presented in Table 21 by strength of their *exp(b)* effect. The strongest predictor of near poverty membership is the tract poverty rate in 1990 (POV90), which increases the odds of cluster membership by nearly 30 percent per unit increase (*exp(b)* = 1.296). Larger percentages of employment in professional, scientific, and technical services (PRFSCI) decreases the odds of being in a near poverty cluster by over 14 percent (*exp(b)* = 0.854). The educational services industry (EDUC) also decreases the likelihood of a tract being in near poverty, with an 11 percent (*exp(b)* = 0.887) decrease in odds. Employment in finance, insurance, and management of companies (FINMGM) decreases the odds of being in a near poverty cluster by 10 percent (*exp(b)* = 0.896), per percentage point increase.

It is also found that greater self-employment in agriculture (AGSEMP) decreases the odds of a tract being in near poverty by 10 percent (*exp(b)* = 0.897). Employment in both construction (CONST) and administrative support and waste management services (ADMWST) reduces the odds of near poverty per percentage point increase by 10 percent each (*exp(b)* = 0.903) – although ADMWST was at the $p<0.10$ level. Contrary to what is expected, higher unemployment rates (UNEMP) reduces the chances of a tract being in a near poverty cluster by nearly nine percent (*exp(b)* = 0.912), which seems to indicate that these tracts are characterized by the working poor.

Additionally, a number of variables have a moderate effect at reducing the odds of being in near poverty compared to only average poverty. It is found that greater shares of employment in goods producing industries like manufacturing (MFGR, *exp(b)* = 0.919) and transportation and utilities (TRSUTL, *exp(b)* = 0.919) reduces the odds of near poverty by eight percent. The effect is also similar for several services industries, with percentage point employment increases being associated with a seven to eight percent drop in near poverty odds for: real estate, rental, leasing, and other services (HHSERV, *exp(b)* = 0.919); arts, entertainment, recreation, accommodation, and food services (LEISUR, *exp(b)* = 0.925); and retail and wholesale trade (TRADE, *exp(b)* = 0.928). Further, wage employment in agriculture (AGWAGE) and public administration employment (PUBADM) also reduces the odds of being in near poverty by between six and seven percent per unit increase, respectively (*exp(b)* = 0.930, *exp(b)* = 0.939).

Several smaller order demographic effects are also worth noting. The results find that percentage point increases in the employment disabled population increases the odds of near poverty cluster membership by over three percent (*exp(b)* = 1.034) compared to average poverty membership. Larger minority populations (MINRTY) also tends to increase the odds of near poverty by a little over two percent (*exp(b)* = 1.022). Surprisingly, in terms of educational attainment greater concentrations of people with high school degrees, some college, or an associate's degree (HSAA) increases the odds of near poverty by nearly 3 percent (*exp(b)* = 1.027) per unit increase. Again, this finding seems to indicate the presence of the working poor.

TABLE 21
Industry Structure Model – Near Poverty Cluster Logistic Regression Coefficients

Variable	***Logit Coefficient b***	***Standard Error***	***Walds Statistic***	***Odds Ratio exp(b)***
Intercept	1.426	2.855	0.250	--
POP	(6.374)	7.599	0.703	0.002
METADJ	(0.172)	0.118	2.132	0.842
MINRTY	0.022	0.007	9.140 ***	1.022
DISABL	0.033	0.020	2.754 *	1.034
SHHFAM	(0.035)	0.024	2.195	0.965
HSAA	0.026	0.010	6.300 **	1.027
BAPLUS	(0.008)	0.015	0.249	0.992
UNEMP	(0.092)	0.023	15.997 ***	0.912
POV90	0.259	0.013	389.160 ***	1.296
AGSEMP	(0.109)	0.033	11.213 ***	0.897
AGWAGE	(0.073)	0.037	3.815 **	0.930
INFO	(0.055)	0.056	0.976	0.947
FINMGM	(0.110)	0.049	5.092 **	0.896
PRFSCI	(0.157)	0.061	6.682 ***	0.854
MFGR	(0.085)	0.028	9.218 ***	0.919
EDUC	(0.120)	0.033	13.394 ***	0.887
HLTHSA	(0.029)	0.032	0.841	0.971
TRSUTL	(0.085)	0.038	4.906 **	0.919
CONST	(0.102)	0.036	8.071 ***	0.903
TRADE	(0.074)	0.031	5.669 **	0.928
ADMWST	(0.102)	0.055	3.478 *	0.903
LEISUR	(0.078)	0.032	5.805 **	0.925
HHSERV	(0.085)	0.042	4.000 *	0.919
PUBADM	(0.063)	0.035	3.252 *	0.939

NOTE: * Significant at p<0.10. ** Significant at p<0.05. *** Significant at p<0.01.
Odds compared to membership in the Average Poverty Cluster.

While understanding how the industry structure model predicts membership in poverty and near poverty clusters is the main goal of this analysis, much can be learned from comparing what factors determine membership in the *Low Poverty Cluster* compared to the *Average Poverty Cluster*. The results of the logistic regression on the low poverty cluster are presented in Table 22. Additionally, the logit coefficients and odds ratios for all three clusters are summarized in Table 23 for ease of comparison. One of the strongest predictors in the model is metropolitan adjacency (METADJ), which increases the odds of a tract being in a low poverty cluster by nearly 50 percent compared to being in an average poverty cluster (*exp(b)* = 1.498).

In terms of demographics, higher rates of poverty in 1990 (POV90) and higher percentages of single headed families with children (SHHFAM) both reduce the odds of being in a low poverty cluster by 23 percent (*exp(b)* = 0.775) and 20 percent (*exp(b)* = 0.800), respectively. Greater concentrations of people with bachelor's degrees or higher (BAPLUS) increases the odds of low poverty by 12 percent (*exp(b)* = 1.124). In terms of industry structure, a larger share of employment tends to increase the odds of low poverty membership by: 17 percent in finance, insurance, and management of companies (FINMGM, *exp(b)* = 1.170); 13 percent in construction (CONST, *exp(b)* = 1.132); and by nearly 10 percent in manufacturing (MFGR, *exp(b)* = 1.095).

In terms of more moderate demographic effects, percentage point increases in unemployment rates (UMEMP, *exp(b)* = 0.917) and the employment disabled population (DISABL, *exp(b)* = 0.932) decreases the odds of low poverty cluster membership by eight percent and seven percent, respectively. On the other hand, concentrations of high school graduates and those with some college or an associate's degree (HSAA) increases the odds of low poverty by eight percent (*exp(b)* = 1.083) per percent increase. In addition, larger employment shares in several industries increase the odds of a tract being classified as low poverty per unit increase, with public administration (PUBADM) increasing the odds by eight percent (*exp(b)* = 1.076), transportation and utilities (TRSUTL) increasing the likelihood by seven percent (*exp(b)* = 1.072), and wholesale and retail trade increasing the odds by six percent (*exp(b)* = 1.059), although the latter finding is only at the $p<0.10$ level.

TABLE 22
Industry Structure Model – Low Poverty Cluster Logistic Regression Coefficients

Variable	*Logit Coefficient b*	*Standard Error*	*Walds Statistic*		*Odds Ratio exp(b)*
Intercept	(8.324)	2.881	8.348	***	--
POP	6.591	6.174	1.140		1.760
METADJ	0.404	0.094	18.344	***	1.498
MINRTY	(0.019)	0.010	4.019	*	0.981
DISABL	(0.071)	0.019	13.353	***	0.932
SHHFAM	(0.223)	0.024	86.139	***	0.800
HSAA	0.079	0.011	48.168	***	1.083
BAPLUS	0.117	0.013	77.678	***	1.124
UNEMP	(0.086)	0.023	13.981	***	0.917
POV90	(0.255)	0.015	297.165	***	0.775
AGSEMP	(0.006)	0.033	0.036		0.994
AGWAGE	0.013	0.041	0.104		1.013
INFO	0.045	0.050	0.801		1.046
FINMGM	0.157	0.041	14.402	***	1.170
PRFSCI	0.055	0.050	1.215		1.056
MFGR	0.091	0.028	10.526	***	1.095
EDUC	0.022	0.031	0.505		1.022
HLTHSA	0.036	0.031	1.393		1.037
TRSUTL	0.070	0.035	3.970	*	1.072
CONST	0.124	0.034	13.284	***	1.132
TRADE	0.057	0.031	3.473	*	1.059
ADMWST	0.082	0.053	2.367		1.085
LEISUR	0.049	0.032	2.305		1.050
HHSERV	0.012	0.040	0.085		1.012
PUBADM	0.074	0.033	4.961	**	1.076

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.

TABLE 23
Industry Structure Model – Summary of Logistic Regression Coefficients by Cluster

	Poverty Cluster			***Near Poverty Cluster***			***Low Poverty Cluster***		
Variable	*b*		*exp(b)*	*b*		*exp(b)*	*b*		*exp(b)*
Intercept	(26.221)	**	--	1.426		--	(8.324)	***	--
POP	(20.795)		0.000	(6.374)		0.002	6.591		1.760
METADJ	0.178		1.195	(0.172)		0.842	0.404	***	1.498
MINRTY	0.023	**	1.023	0.022	***	1.022	(0.019)	*	0.981
DISABL	0.084	**	1.088	0.033	*	1.034	(0.071)	***	0.932
SHHFAM	0.052		1.054	(0.035)		0.965	(0.223)	***	0.800
HSAA	(0.047)	**	0.954	0.026	**	1.027	0.079	***	1.083
BAPLUS	(0.016)		0.984	(0.008)		0.992	0.117	***	1.124
UNEMP	0.030		1.031	(0.092)	***	0.912	(0.086)	***	0.917
POV90	0.305	***	1.356	0.259	***	1.296	(0.255)	***	0.775
AGSEMP	0.197		1.217	(0.109)	***	0.897	(0.006)		0.994
AGWAGE	0.148		1.160	(0.073)	**	0.930	0.013		1.013
INFO	0.314	**	1.369	(0.055)		0.947	0.045		1.046
FINMGM	0.117		1.124	(0.110)	**	0.896	0.157	***	1.170
PRFSCI	0.135		1.145	(0.157)	***	0.854	0.055		1.056
MFGR	0.150		1.161	(0.085)	***	0.919	0.091	***	1.095
EDUC	0.232	**	1.261	(0.120)	***	0.887	0.022		1.022
HLTHSA	0.274	**	1.315	(0.029)		0.971	0.036		1.037
TRSUTL	0.158		1.171	(0.085)	**	0.919	0.070	*	1.072
CONST	0.162		1.176	(0.102)	***	0.903	0.124	***	1.132
TRADE	0.184		1.202	(0.074)	**	0.928	0.057	*	1.059
ADMWST	0.114		1.120	(0.102)	*	0.903	0.082		1.085
LEISUR	0.247	**	1.281	(0.078)	**	0.925	0.049		1.050
HHSERV	0.136		1.146	(0.085)	*	0.919	0.012		1.012
PUBADM	0.168		1.183	(0.063)	*	0.939	0.074	**	1.076

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.
Significance tested using Walds Statistic.

Agriculture and Occupation Structure Model

The last objective of the analysis is to determine how agricultural structure and occupational structure affects membership in a poverty cluster. The agriculture and occupation structure model is also tested using multinomial logistic regression, which is used to predict the odds of poverty and non-poverty cluster membership for 4,589 census tracts in the north central region. The occupation structure model includes eight demographic controls, two measures of agriculture structure, and 12 occupation structure exogenous variables. As explained in the previous section, the endogenous poverty cluster variable was condensed from seven to four categories for meaningful analysis. Further, the state fixed effects variables were also dropped due to model errors attributable to zero value cells in the matrix. The occupation structure logistic model is evaluated in terms of model fit, classification accuracy, and the importance of the exogenous variables in prediction.

The performance of the occupation structure logistic regression model is assessed through goodness-of-fit statistics, log likelihood ratio tests (–2LL), and pseudo R-squared measures. The results of these diagnostics are presented in Table 24. Results of the goodness-of fit tests using a Chi-squared statistic show the occupation structure model fits the data well, meaning the model replicates the data better than the intercept-only model. Pearson's Chi-squared test is highly significant ($\chi^2_{(13701)}$ = 28796.33 p>0.000), which indicates the occupation structure model fits the data better than the reduced model. The Deviance Chi-squared test also indicates that the covariate model fits the data well, which is indicated by a non-significant finding ($\chi^2_{(13701)}$ = 6258.53 p>1.000). Thus, we can conclude that the distribution of poverty and non-poverty clusters can be better replicated by taking into account demographic, agriculture, and occupation structure factors.

The –2LL test evaluates the entire occupation structure model, and tests the null hypothesis that all logit coefficients are zero. Results of the –2LL test indicate that the occupation structure model does fit the data better than the intercept-only model, and we can conclude that at least one of the exogenous variables contributes significantly to model fit ($\chi^2_{(63)}$ = 4156.42 p>0.000). Thus, one or more of the socioeconomic variables in the occupation structure model is statistically significant in predicting poverty and non-poverty cluster membership.

Using pseudo R-squared measures, the strength of association between the endogenous and exogenous variables in the model is estimated. Results show that the occupation structure model has a high degree of association with the four-category endogenous variable. The Cox and Snell statistic shows a 60 percent association, while Nagelkerke's R-squared shows a high association of 66 percent. Again, it is important to note that these measures do not measure the percent of variance explained, but only the strength of association. Thus, we can conclude that the set of demographic, agriculture, and occupation structure variables is highly associated with the two poverty and two non-poverty clusters in the endogenous variable.

TABLE 24
Occupation Structure Model – Logistic Regression Diagnostics

	Model Fit Criteria		***Log Likelihood Ratio***	***Chi-Squared***	
	AIC	*BIC*			
Goodness-of-Fit					
Pearson	--	--		28796.332	***
Deviance	--	--		6258.535	
Model Fit					
Intercept Model	10420.960	10440.250	10414.955	--	
Covariate Model	6390.535	6815.009	6258.535	4156.420	***
Pseudo R-Squared					
Cox and Snell	0.596				
Nagelkerke	0.664				

NOTE: * Significant at p<0.10. ** Significant at p<0.05. *** Significant at p<0.01.
AIC (Akaike) and BIC (Bayesian) Information Criteria used to compare model iterations.

Since the goodness-of-fit for the occupation structure model has been established, the next step is to evaluate the importance of the exogenous variables. The log likelihood ratio test (–2LL) using a Chi-squared distribution is used to assess the significance of the variables in the occupation structure model. Referring to Table 25, results find that all demographic predictors are significant, while only a handful of occupation structure variables reached significance. Most of the occupation structure variables that are significant exceed the p<0.05 criterion including: farmers and farm managers (FARMER); transportation and materials moving jobs (TRANS); healthcare support and protective service occupations (HLTPRT); and arts, design, entertainment, sports, and media jobs (ARTENT). However, these variables are still considered useful predictors since the significance values are still $p<0.10$.

Although the non-significant variables may be dropped from the analysis, their inclusion is strongly supported by previous theory and research. Thus, the variables are kept in the analysis to maintain the assumption of a correctly specified model. In short, results of the –2LL tests indicate that demographic controls contribute significantly in fitting the data better than the intercept-only model, while most occupational structure measures do not.

TABLE 25
Occupation Structure Model – Exogenous Variable Tests

Variable	Model Fit Criteria *AIC*	*BIC*	*Log Likelihood Ratio*	*Chi-Squared*	
Intercept	6395.571	6800.750	11.036	11.036	**
POP	6387.535	6792.714	6261.535	2.999	
METADJ	6416.821	6822.001	6290.821	32.286	***
MINRTY	6404.698	6809.877	6278.698	20.163	***
DISABL	6414.546	6819.725	6288.546	30.011	***
SHHFAM	6484.326	6889.506	6358.326	99.791	***
HSAA	6432.093	6837.272	6306.093	47.558	***
UNEMP	6433.567	6838.747	6307.567	49.032	***
POV90	7696.213	8101.392	7570.213	1311.678	***
FARMER	6391.206	6796.385	6265.206	6.671	*
PRFBUS	6394.628	6799.807	6268.628	10.093	**
ARTENT	6392.061	6797.240	6266.061	7.526	*
HEALTH	6394.598	6799.778	6268.598	10.063	**
CONEXT	6385.675	6790.854	6259.675	1.140	
MAINRP	6390.015	6795.194	6264.015	5.480	
PROD	6387.898	6793.077	6261.898	3.363	
TRANS	6391.409	6796.589	6265.409	6.874	*
HLTPRT	6391.698	6796.877	6265.698	7.163	*
FOOD	6387.810	6792.989	6261.810	3.275	
BLDGRD	6389.171	6794.350	6263.171	4.636	
PERSER	6397.030	6802.210	6271.030	12.495	***
SALEOF	6387.220	6792.399	6261.220	2.685	

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
AIC (Akaike) and BIC (Bayesian) Information Criteria used to compare model iterations.

In terms of how well the occupation structure logistic model predicts cluster membership, results show that the model correctly sorts 70 percent of the census tracts into the observed clusters. This indicates that one can predict a census tract's poverty cluster membership by knowing its demographic, agriculture, and occupation structure. Although this overall accuracy rate is quite high, it varied greatly within clusters. The classification accuracy of the occupation structure model mirrors the results found for the industry structure model, indicating that both models predict equally well.

Referring to Table 26, the occupation structure model does a poor job at predicting membership in the Near Poverty Cluster, correctly classifying only 44 percent of all tracts in this cluster. It appears the model does a poor job at discriminating between the Near Poverty Cluster and the Average Poverty Cluster, with in fact more tracts being classified as average poverty rather than as near poverty. However, the model does an above average job in correctly classifying tracts into the Poverty Cluster, with an accuracy rate of 57 percent. Most misclassifications were into the Near Poverty Cluster. Lastly, the occupation structure model performs very well at predicting tract membership in the Average Poverty and Low Poverty clusters, with accuracy rates at or near 75 percent.

TABLE 26
Occupation Structure Model – Classification Results

	Predicted Clusters				
Observed Clusters	*Poverty*	*Near Poverty*	*Average Poverty*	*Low Poverty*	***Percent Correct***
Poverty	94	50	18	2	**57.3%**
Near Poverty	22	303	358	12	**43.6%**
Average Poverty	3	121	1477	395	**74.0%**
Low Poverty	2	5	388	1339	**77.2%**
Overall Percentage	**2.6%**	**10.4%**	**48.8%**	**38.1%**	**70.0%**

Now that the goodness-of-fit, significance of predictors, and accuracy of classification has been established for the occupation structure model, the next step is to evaluate the effect of the exogenous variables. This is done by evaluating the logistic regression coefficients *b* and the odds ratios *exp(b)*. Both *b* and *exp(b)* measure the changes in odds on cluster membership compared to membership in the Average Poverty Cluster, which is the reference category.

Comparing census tract membership in the *Poverty Cluster* to the *Average Poverty Cluster*, the logistic regression found eight significant variables, which are listed by strength of effect in Table 27. Larger percentages of employment in arts, design, entertainment, sports, and media occupations (ARTENT) increases the odds of being in a poverty cluster by a stunning 48 percent (*exp(b)* = 1.478), per unit increase. Poverty rates a decade ago (POV90) also has a strong effect, with a one percent increase in 1990 poverty increasing the odds of poverty cluster membership by 36 percent (*exp(b)* = 1.362). Employment in personal care and services occupations (PERSER) also increases the likelihood of being in a poverty cluster by 27 percent (*exp(b)* = 1.315). However, larger shares of installation, maintenance and repair occupations reduces the odds by 16 percent (*exp(b)* = 0.839) per percentage increase, although this finding is only significant at $p<0.10$.

Other more moderate demographic effects are also significant in determining poverty cluster membership, compared to membership in the average poverty cluster. Tracts with larger percentages of the population with an employment disability (DISABL) increases the odds of membership by nearly 11 percent (*exp(b)* = 1.107). Families with children headed by single persons (SHHFAM) also tends to increase a tract's likelihood of being in a poverty cluster, with a one percent increase increasing the odds by seven percent (*exp(b)* = 1.069), although this finding is only significant at $p<0.10$. In terms of education, a one percent increase in those with a high school degree, some college, or an associate's degree (HSAA) decreases the odds of being in a poverty cluster by nearly 5 percent (*exp(b)* = 0.954). Although the effect is small, larger minority populations (MINRTY) tends to increase the odds of membership by a little over two percent (*exp(b)* = 1.024) per unit increase.

TABLE 27
Occupation Structure Model – Poverty Cluster Logistic Regression Coefficients

Variable	*Logit Coefficient b*	*Standard Error*	*Walds Statistic*	*Odds Ratio exp(b)*
Intercept	(8.507)	6.314	1.815	--
POP	(15.191)	15.083	1.014	0.000
METADJ	0.081	0.268	0.092	1.085
MINRTY	0.024	0.010	5.762 **	1.024
DISABL	0.102	0.042	5.837 **	1.107
SHHFAM	0.067	0.038	3.162 *	1.069
HSAA	(0.046)	0.017	7.421 ***	0.955
UNEMP	0.019	0.035	0.299	1.019
POV90	0.309	0.019	261.624 ***	1.362
FARMER	0.004	0.084	0.002	1.004
PRFBUS	(0.024)	0.066	0.135	0.976
ARTENT	0.391	0.150	6.780 ***	1.478
HEALTH	(0.009)	0.088	0.010	0.991
CONEXT	(0.004)	0.081	0.002	0.996
MAINRP	(0.176)	0.101	3.009 *	0.839
PROD	(0.057)	0.066	0.756	0.944
TRANS	0.049	0.077	0.412	1.051
HLTPRT	0.013	0.082	0.025	1.013
FOOD	0.036	0.074	0.240	1.037
BLDGRD	0.028	0.098	0.080	1.028
PERSER	0.236	0.103	5.268 **	1.267
SALEOF	0.022	0.066	0.107	1.022

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.

Next looking at how the occupation structure model predicts membership in the *Near Poverty Cluster*, compared to the *Average Poverty Cluster*, we find that two demographic controls and several occupational types exert the strongest effects. The results are presented in Table 28 by strength of their *exp(b)* effects. A census tract's poverty rate in 1990 is a strong predictor of near poverty, with a one percent increase in 1990 poverty increasing the odds of membership by 29 percent (*exp(b)* = 1.290). Conversely, metropolitan adjacency (METADJ) decreases the odds of a tract being in a near poverty by nearly 20 percent (*exp(b)* = 0.796), compared to being in an average poverty cluster.

In terms of occupational structure, several types of jobs are significant in predicting near poverty membership. Results indicate that larger shares of personal care and services occupations (PERSER) increases the odds of near poverty by 11 percent (*exp(b)* = 1.112) per percentage point increase. Likewise, employment in building, grounds and maintenance occupations (BLDGRD) increases the odds of membership also by 11 percent (*exp(b)* = 1.107); and employment in transportation and materials moving occupations (TRANS) increases the odds by 10 percent (*exp(b)* = 1.092), compared to the average poverty cluster. Surprisingly, percentage point increases in healthcare practitioners and related technical health occupations (HEALTH) also increases the likelihood of being in a near poverty cluster by 10 percent (*exp(b)* = 1.097).

Further, several smaller order demographic effects are worth noting. As is the case in the industry structure model, higher rates of unemployment (UNEMP) reduces the odds of being in near poverty by over nine percent (*exp(b)* = 0.909). Again, this indicates that near poverty is associated with the working poor. Larger shares of the population with an employment disability (DISABL) increases the odds of cluster membership by about four percent (*exp(b)* = 1.036), although the effect is only significant at $p<0.10$. Lastly, larger concentrations of high school graduates or those with some college or an associate's degree (HSAA) and larger minority populations (MINRTY) tends to increase the odds of being in a near poverty tract by a little over two percent each (*exp(b)* = 1.024 and *exp(b)* = 1.022, respectively).

TABLE 28
Occupation Structure Model – Near Poverty Cluster Logistic Regression Coefficients

Variable	*Logit Coefficient b*	*Standard Error*	*Walds Statistic*	*Odds Ratio exp(b)*
Intercept	(9.900)	3.265	9.195 ***	--
POP	(9.945)	7.515	1.751	0.000
METADJ	(0.228)	0.117	3.828 **	0.796
MINRTY	0.022	0.007	10.970 ***	1.022
DISABL	0.036	0.020	3.089 *	1.036
SHHFAM	(0.029)	0.023	1.591	0.971
HSAA	0.024	0.010	5.997 **	1.024
UNEMP	(0.096)	0.023	18.071 ***	0.909
POV90	0.254	0.013	396.814 ***	1.290
FARMER	0.020	0.041	0.240	1.020
PRFBUS	0.004	0.035	0.016	1.004
ARTENT	0.041	0.087	0.218	1.042
HEALTH	0.092	0.043	4.643 **	1.097
CONEXT	0.030	0.040	0.577	1.031
MAINRP	0.036	0.046	0.600	1.036
PROD	0.019	0.033	0.343	1.019
TRANS	0.088	0.039	5.040 **	1.092
HLTPRT	0.050	0.039	1.648	1.051
FOOD	0.036	0.041	0.754	1.036
BLDGRD	0.102	0.050	4.221 **	1.107
PERSER	0.106	0.053	4.028 **	1.112
SALEOF	0.016	0.033	0.241	1.016

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.

Looking at the results from a different perspective, it is useful to understand how the occupation structure model predicts membership in the *Low Poverty Cluster* compared to the *Average Poverty Cluster*. The results of the logistic regression on the low poverty cluster are presented in Table 29, with the results for all three clusters summarized in Table 30 for comparison. One of the strongest predictors in the occupation model is metropolitan adjacency (METADJ), which increases the odds of a tract being in a low poverty cluster by nearly 59 percent (*exp(b)* = 1.586), compared to being in an average poverty cluster. In terms of demographics, higher rates of poverty in 1990 (POV90) and higher percentages of single headed families with children (SHHFAM) both reduce the odds of being in a low poverty cluster by 24 percent (*exp(b)* = 0.759) and 20 percent (*exp(b)* = 0.804), respectively. These findings mirror those found for the industry structure model.

More moderate demographic effects are also found, with percentage point increases in unemployment rates (UMEMP, *exp(b)* = 0.896) and the employment disabled population (DISABL, *exp(b)* = 0.821) decreasing the odds of low poverty cluster membership by 10 percent and eight percent, respectively. On the other hand, concentrations of high school graduates and those with some college or an associate's degree (HSAA) increases the odds of low poverty by five percent (*exp(b)* = 1.052), per unit increase. For agricultural structure, the results indicate that greater concentrations of farmers and farm managers (FARMER) reduces the odds of low poverty by seven percent (*exp(b)* = 0.935).

Looking at significant occupational predictors, we find that larger employment shares in healthcare practitioner and related technical occupations (HEALTH) increases the odds of low poverty cluster membership by eight percent (*exp(b)* = 1.078), per percentage point increase. Management, business, and other professional occupations (PRFBUS) also increases the odds of membership by eight percent (*exp(b)* = 1.075), compared to the average poverty cluster. The percent of people working in sales and office occupations (SALEOF) increases the likelihood of low poverty by about four percent (*exp(b)* = 1.035), per unit increase.

Conversely, several occupations tend to reduce the likelihood of being in a low poverty cluster. Large concentrations of workers employed in personal care and services (PERSER) reduces the odds of cluster membership by seven percent (*exp(b)* = 0.928), compared to the average poverty cluster. Health care support and protective service occupations (HLHPRT) also reduce the likelihood of low poverty by six percent (*exp(b)* = 0.937), per percentage point increase.

TABLE 29
Occupation Structure Model – Low Poverty Cluster Logistic Regression Coefficients

Variable	***Logit Coefficient b***	***Standard Error***	***Walds Statistic***		***Odds Ratio exp(b)***
Intercept	0.067	1.684	0.002		--
POP	4.649	6.060	0.589		1.501
METADJ	0.461	0.092	25.124	***	1.586
MINRTY	(0.021)	0.009	6.076	**	0.979
DISABL	(0.083)	0.019	19.451	***	0.921
SHHFAM	(0.218)	0.024	85.823	***	0.804
HSAA	0.051	0.010	27.574	***	1.052
UNEMP	(0.110)	0.022	24.895	***	0.896
POV90	(0.276)	0.014	375.155	***	0.759
FARMER	(0.067)	0.025	7.304	***	0.935
PRFBUS	0.073	0.020	13.525	***	1.075
ARTENT	0.027	0.069	0.147		1.027
HEALTH	0.075	0.031	5.775	**	1.078
CONEXT	0.021	0.028	0.531		1.021
MAINRP	0.032	0.033	0.968		1.033
PROD	0.028	0.019	2.095		1.029
TRANS	(0.029)	0.027	1.187		0.971
HLTPRT	(0.065)	0.030	4.820	**	0.937
FOOD	(0.047)	0.032	2.222		0.954
BLDGRD	(0.009)	0.041	0.052		0.991
PERSER	(0.075)	0.040	3.484	*	0.928
SALEOF	0.034	0.020	2.778	*	1.035

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.

TABLE 30
Occupation Structure Model – Summary of Logistic Regression Coefficients by Cluster

	Poverty Cluster			*Near Poverty Cluster*			*Low Poverty Cluster*		
Variable	*b*		*exp(b)*	*b*		*exp(b)*	*b*		*exp(b)*
Intercept	(8.507)		--	(9.900)	***	--	0.067		--
POP	(15.191)		0.000	(9.945)		0.000	4.649		1.501
METADJ	0.081		1.085	(0.228)	**	0.796	0.461	***	1.586
MINRTY	0.024	**	1.024	0.022	***	1.022	(0.021)	**	0.979
DISABL	0.102	**	1.107	0.036	*	1.036	(0.083)	***	0.921
SHHFAM	0.067	*	1.069	(0.029)		0.971	(0.218)	***	0.804
HSAA	(0.046)	***	0.955	0.024	**	1.024	0.051	***	1.052
UNEMP	0.019		1.019	(0.096)	***	0.909	(0.110)	***	0.896
POV90	0.309	***	1.362	0.254	***	1.290	(0.276)	***	0.759
FARMER	0.004		1.004	0.020		1.020	(0.067)	***	0.935
PRFBUS	(0.024)		0.976	0.004		1.004	0.073	***	1.075
ARTENT	0.391	***	1.478	0.041		1.042	0.027		1.027
HEALTH	(0.009)		0.991	0.092	**	1.097	0.075	**	1.078
CONEXT	(0.004)		0.996	0.030		1.031	0.021		1.021
MAINRP	(0.176)	*	0.839	0.036		1.036	0.032		1.033
PROD	(0.057)		0.944	0.019		1.019	0.028		1.029
TRANS	0.049		1.051	0.088	**	1.092	(0.029)		0.971
HLTPRT	0.013		1.013	0.050		1.051	(0.065)	**	0.937
FOOD	0.036		1.037	0.036		1.036	(0.047)		0.954
BLDGRD	0.028		1.028	0.102	**	1.107	(0.009)		0.991
PERSER	0.236	**	1.267	0.106	**	1.112	(0.075)	*	0.928
SALEOF	0.022		1.022	0.016		1.016	0.034	*	1.035

NOTE: * Significant at $p<0.10$. ** Significant at $p<0.05$. *** Significant at $p<0.01$.
Odds compared to membership in the Average Poverty Cluster.
Significance tested using Walds Statistic.

CHAPTER EIGHT

DISCUSSION AND CONCLUSION

Throughout this dissertation, it has been argued that the labor market perspective is the most comprehensive approach to understanding poverty in communities. This approach merges both individual or person-based explanations of poverty with structural or place-based approaches within a spatial context. At its core, the labor market perspective argues that local socioeconomic structure determines the level of poverty within an area, with individual characteristics providing the means by which that poverty is distributed within the community. This dissertation has further argued that different economic structures produce different levels of poverty, according to the types of industries and the types of jobs within the area. Drawing on the postindustrial restructuring literature, the transition from an industrial to postindustrial economy has caused a shift in what constitutes the core segments of the economy, which has also resulted in a new class structure. Why this matters is that previous research has found that different types of industries and occupations produce different socioeconomic outcomes within communities, especially in terms of poverty and economic well being.

This dissertation merges two major strands of theory to better define how structure impacts poverty, within the context of the labor market perspective.

The segmented economy literature argues that communities concentrated in core or basic industries (export-oriented industries dependent on factors external to the local economy) are more developed socioeconomically than those composed of periphery or non-basic industries (local-oriented industries dependent on the local economy), because it is the core that powers the wider economy by bringing money into the community. However, it is important not to omit the impact of the agriculture sector on socioeconomic well being. Drawing on the sociology of agriculture literature, it is also argued that communities composed mainly of moderate sized owner-operated farms are more socioeconomically developed than those with large scale absentee-owned farms that employ wage workers.

Economic restructuring over the past several decades has shifted the core away from production of material goods to the production of symbolic goods, or in other words a shift away from manufacturing to more advanced services. In turn, this has created a new class structure where most workers are now employed in services occupations, ranging from highly skilled professionals to lower skilled service workers. This has implications for the labor market perspective as conceptualizations of structure need to be revisited. First, there is a need to evaluate the labor market perspective using industry classifications that better reflect the postindustrial economy, especially in terms of advanced services. Second, in the postindustrial economy what workers do is becoming more important than where they work. As production of symbols and information permeates almost all economic sectors, a more diverse workforce is needed across all industries. Thus, an economy can be better described by the occupational structure of the labor force, rather than the industries in which they work. Lastly, the farm and non-farm sectors need to be considered together when talking about structure. Although previous research has linked these two segments together, they have done so in the context of an industrial economy, not a postindustrial one.

To test the relationships between individual and structural determinants of poverty in the north central region, tract-level socioeconomic data are analyzed to achieve two ends. First, to identify rural poverty clusters in the region; and second to determine how agriculture and postindustrial economic structure determines membership in these clusters. The first objective of this dissertation is to identify **rural poverty clusters** in the north central region using statistically appropriate methods. This objective is met in the analysis, where statistical cluster analysis is used to identify poverty clusters in the north central region by grouping 4,589 nonmetropolitan census tracts based on their similarity along four poverty status variables, which include: poverty, near poverty, and their rates of change from one decade ago.

Results of the cluster analysis – which is validated using multivariate analysis of variance – identify seven clusters of which three are termed poverty clusters and four are termed non-poverty clusters. The three poverty clusters include: the *High Poverty and Near Poverty Cluster* consisting of 130 tracts encompassing nearly 500,000 people; the *High Poverty Cluster* consisting of 34 tracts including under 80,000 people; and the *High Near Poverty Cluster* consisting of 695 tracts containing over 2.3 million people. The poverty clusters account for only a small percentage of all tracts and people within the north central region, covering only 19 percent of all census tracts containing only 16 percent of the region's population – with the Near Poverty Cluster containing the most tracts and people. Spatially, most of the poverty clusters are located on or adjacent to Native American Indian reservations in the Dakotas and northern Minnesota and Wisconsin; in the public forest areas of southern Missouri, southern Ohio, and portions of Michigan; and in less populated farming areas particularly in Missouri and the Dakotas, and to a lesser extent in Nebraska and Kansas.

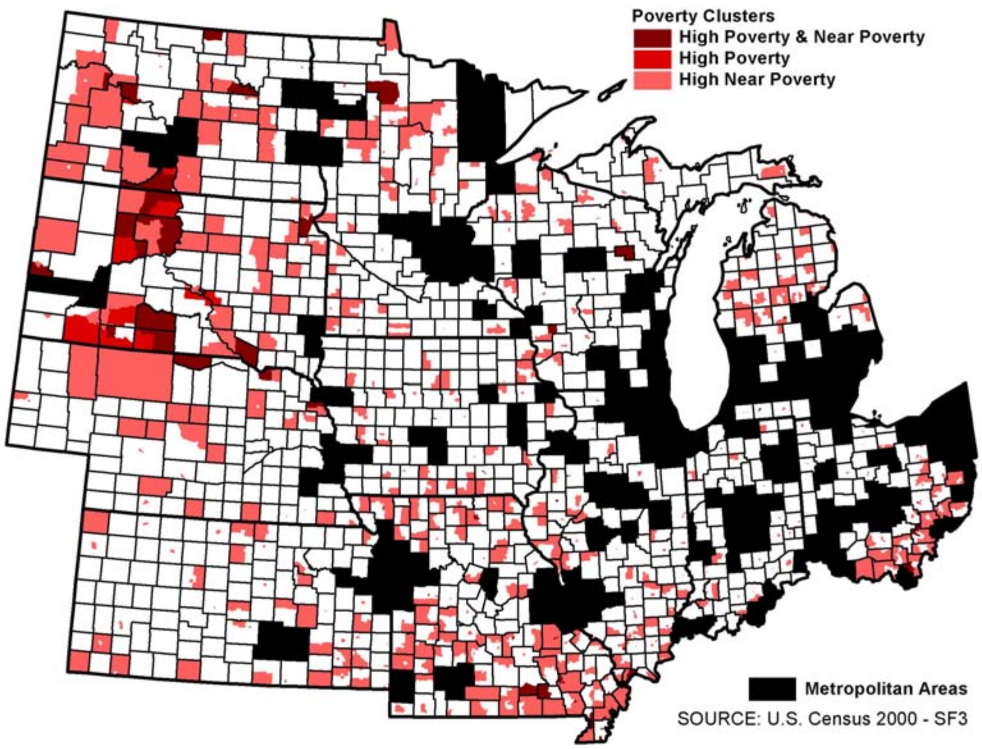
The four non-poverty clusters include: the *Average Poverty – Slow Decline Cluster* which covers 962 census tracts and encompasses over 3.5 million people; the *Average Poverty – Fast Decline Cluster* including 1,034 tracts and also containing over 3.5 million people; the *Low Poverty – Slow Decline Cluster* consisting of 607 tracts that include over 2.6 million people; and lastly the *Low Poverty – Slow Decline Cluster* that covers 1,127 tracts containing well over 4.0 million people. The non-poverty clusters account for the majority of the census tracts and population within the north central region. The average poverty group contains over 43 percent of all tracts and population within the region; and the low poverty group covers 38 percent of all tracts containing 40 percent of the population. Spatially, the non-poverty clusters and found in the eastern and northern states of the study area, especially in Minnesota, Indiana, Wisconsin, Iowa and Illinois.

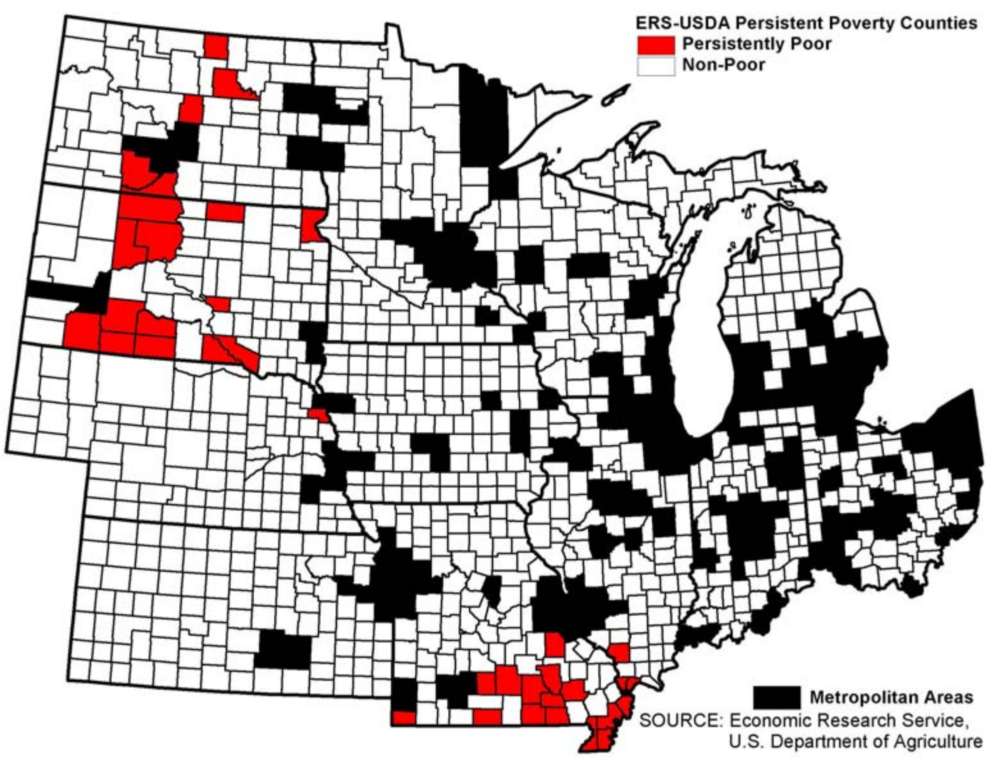
Achieving this objective addresses a need in the literature to identify poverty clusters using more statistically appropriate methods and using more localized units of analysis. The most commonly used typology of poverty is from the U.S. Department of Agriculture's Economic Research Service (ERS), which defines persistent poverty counties as those with a poverty rate of 20 percent or more each year in 1970, 1980, 1990 and 2000 (Cook and Mizer 1994). Although this definition is consistent with the Census Bureau practice of identifying poverty areas, it is limited in terms of the methods used. Instead of relying in a single threshold to determine poverty, this analysis uses a statistical procedure termed cluster analysis to group census tracts into homogenous clusters according to their similarity in poverty rates and change from a decade ago. Therefore, this analysis identifies high poverty areas using more rigorous methods that should be used in other typologies.

Figure 36 compares the poverty clusters identified in this analysis with the ERS persistent poverty counties. Although differences should be expected since the methods differ, comparison of the two groupings yields some interesting observations. To begin, there is a fairly high degree of overlap between the poverty clusters and the persistent poverty clusters in the western states of the study area, especially in the Great Plains. This is likely attributable to the concentrated nature of poverty in these states on Native American Indian reservations, and to the fact that tracts in these states are quite large.

However, the comparison also shows that the ERS method missed highly localized pockets of poverty, which has several implications for policy analysis. First, the poverty cluster method identified high poverty areas that were not identified using the ERS definition. Specifically, these areas include Native American Indian reservations in northern Minnesota and Wisconsin, portions of southern Ohio, and areas in northern Missouri. Although some of these discrepancies are due to method differences, a closer look at the data reveals that this may not be true for all cases. Missouri's poverty clusters provide a good example of this. In Figure 37, we find highly localized pockets of poverty in Kirksville to north, Maryville to the northwest, and Rolla to the south central. None of these areas are in a persistent poverty county. One explanation for this may be that the effect of high poverty tracts is mediated by low poverty ones at the county level – in effect the high poverty tract statistically vanishes due to averaging at the county level.

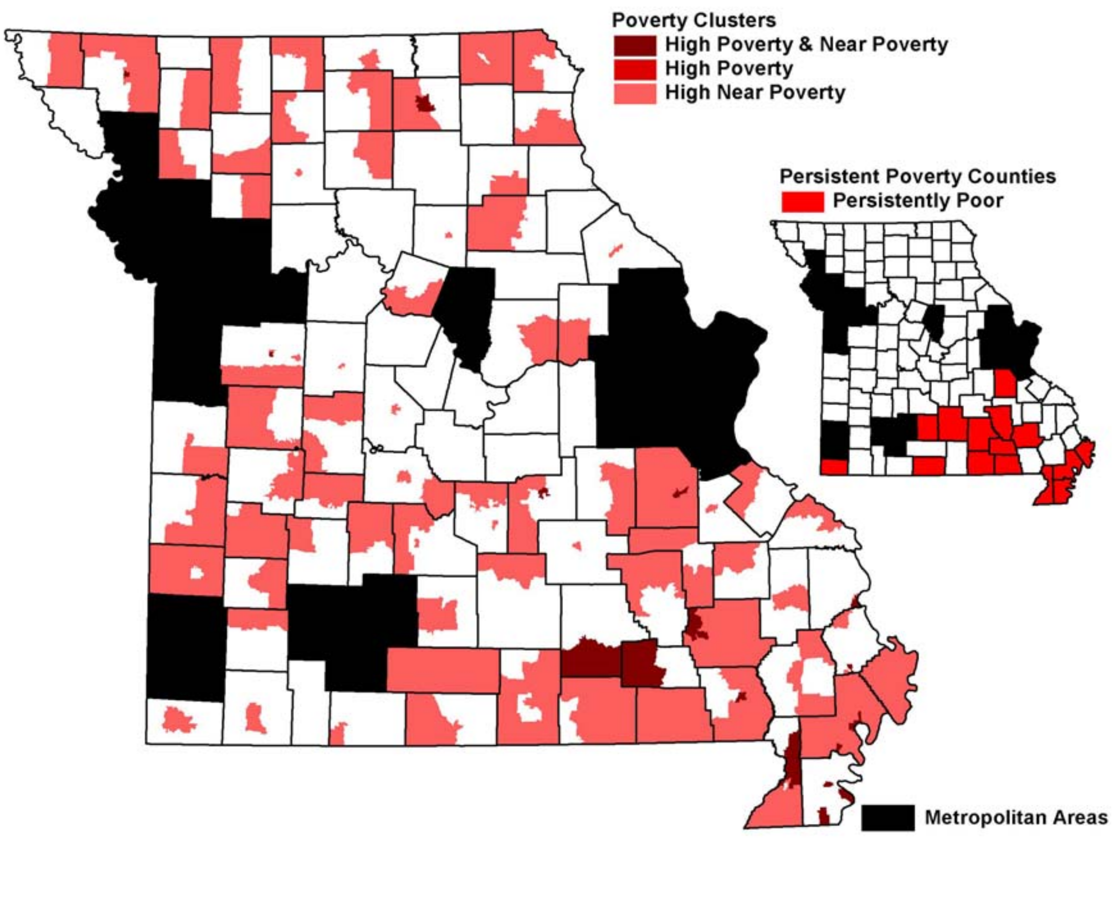
FIGURE 36
Comparison of Poverty Clusters with Persistent Poverty Counties





The second implication is that entire counties are identified as persistently poor, when in fact only a small portion of the county is actually in poverty. Again, Missouri provides a good illustration of this assertion. Referring to Figure 36, in southeast Missouri we find that only small portions of counties are in poverty, yet these tracts contain enough population where the entire county is classified as persistently poor. Examples of this include Washington County (city of Potosi) adjacent to the St. Louis metropolitan area, Pemiscot County (cities of Caruthersville and Hayti) in the Bootheel, and Wayne County (city of Piedmont) and Butler County (city of Poplar Bluff) in extreme southeast Missouri.

FIGURE 37
Missouri Comparison of Poverty Clusters with Persistent Poverty Counties



Evaluation of Hypotheses

The following section evaluates and discusses the hypotheses that were formulated in the theory and methods chapters. The hypotheses are tested by examining the results of the industry structure and occupation structure logistic models. Summary tables of the significant results by each hypothesis are provided for each model, with the industry structure model summary presented in Table 31 and the occupation structure model presented in Table 32. The second objective of this dissertation is to determine how **agriculture structure** affects membership in a rural poverty cluster. Here the structure of agriculture is defined in terms of the organization of labor relationships. The following hypotheses are drawn from the sociology of agriculture literature, and tests whether communities characterized by family farm agriculture are more developed socioeconomically than those characterized by industrial agriculture.

The *first hypothesis* posits that a greater concentration of farmers or workers self-employed in agriculture reduces the odds of a census tract being in a poverty cluster. The findings provide limited support for the hypothesis. Results indicate that a larger concentration of self-employed workers in agriculture reduces the odds of near poverty by 10 percent, yet are not significant in reducing the odds of being in a poverty cluster. This indicates that agriculture self-employment is associated with average poverty cluster membership. In terms of occupation, greater numbers of farmers and farm managers do not reduce the odds of being in poverty or near poverty, but in fact reduce the odds of being in a low poverty cluster – a finding contrary to what is hypothesized. Again, this indicates that farmers are associated with average poverty.

The *second hypothesis* posits that greater concentrations of agricultural workers employed as wage laborers increases the odds of a census tract being in a poverty cluster. The findings do not support this hypothesis, and provide evidence to the contrary. It is found that larger shares of workers employed as wage laborers in agriculture tend to reduce the odds of being in a near poverty cluster by seven percent, and have no effect in sorting tracts into poverty. Mirroring the results for farm self-employment, it appears that agricultural wage workers are also associated with membership in the average poverty cluster.

In short, the findings show that agriculture structure has no impact on reducing the odds of poverty. Neither self-employment nor wage-work in agriculture reduces the chances of being in a poverty cluster. However, results indicate that both self-employment and wage-work in agriculture does reduce the chances of being in near poverty. Further, agriculture self-employment does not seem to produce any unique benefit in reducing poverty over wage employment, as posited by previous theory and research. In fact, the findings indicate that agricultural wage workers benefit communities by reducing the chances of near poverty by almost the same effect as agricultural self-employment. Therefore, the results support the assertion that agricultural employment reduces near poverty but not poverty; and that agricultural structure or labor relations has no discriminating effect on poverty status. Thus, the findings support the conclusion that the agricultural sector – both self-employed and wage-employed – is associated with membership in the average poverty cluster.

The third objective is to determine how postindustrial **industry structure** affects membership in a rural poverty cluster. The following hypotheses are drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by postindustrial core industries are more developed socioeconomically than those characterized by postindustrial periphery industries. Analogous to the concepts of basic and non-basic industries in economics, the former are generally export-oriented and dependent on external factors, while the latter is mostly dependent on local markets and conditions. Semi-basic industries sell to both export and local markets, and thus are both basic or non-basic. The postindustrial core consists of a set of information and communication networks centered around reflexive producers selling symbolic-intensive products and services to reflexive consumers. Industries that drive this new core include information, publishing, telecommunications, advanced producer services, professional services, and manufacturing (Lash and Urry 1994).

The *third hypothesis* posits that greater concentrations of workers employed in postindustrial core industries reduces the odds of a census tract being in a poverty cluster. Referring to Table 31, the findings provide limited support for the hypothesis. To begin with, no core industries reduced the odds of being in a poverty cluster, contrary to what is hypothesized. However, most core industries did reduce the odds of near poverty while also increasing the odds of low poverty, relative to average poverty membership. Results indicate that employment in finance, insurance, and management of companies reduces the odds of near poverty by 10 percent, while also increasing the odds of low poverty by 17 percent. Manufacturing also has a similar effect, reducing the odds of near poverty cluster membership by eight percent, while at the same time increasing the odds of low poverty membership by 10 percent. Employment in professional, technical, and scientific services also reduces the chances of near poverty by 15 percent, but has no effect at increasing the chances of low poverty.

However, one surprising finding is that employment in the information services industry has an effect contrary to what is hypothesized, increasing the odds of poverty by a stunning 37 percent. It is unclear why information services increases the chances of poverty to such a great degree while the other core industries have the opposite effect. The information industry is generally characterized by having good paying jobs in publishing, telecommunications, internet service providers, and related activities – at least before the information technology economic downturn after 2000.

One plausible explanation may have to do with the composition of the industry, where one sub-sector of information deals with motion picture exhibition (i.e. movie theaters). It may be that information employment in certain tracts may be entirely made up of the cinema sub-sector, or that in most tracts this sub-sector constitutes a large portion of the industry. In that case, information services in the study area may more reflect the entertainment industry rather than the information technology industry, in which case the finding of higher poverty would be consistent with segmented economy theory. In other words, the composition of the information industry in the north central region may be more periphery/non-basic rather than core/basic.

Therefore, the findings support the conclusion that core industries engaged in advanced services and manufacturing tend to reduce the chances of near poverty, while at the same time increasing the changes of being in low poverty. Thus, these core industries are associated with average and low poverty cluster membership. It is further concluded that the information industry contains high shares of entertainment-related sub-sectors, thus producing effects similar to periphery industries. This results in the information industry being associated with poverty cluster membership.

The *fourth hypothesis* posits that greater concentrations of workers employed in postindustrial semi-core industries reduces the odds of a census tract being in a poverty cluster. The findings provide very limited support for this hypothesis, with many providing evidence to the contrary (refer to Table 31). Supporting the hypothesis, the analysis found that employment in transportation and utilities reduces the odds of near poverty by eight percent while increasing low poverty odds by seven percent, relative to average poverty. This means transportation is associated with average and low poverty cluster membership.

However, the findings for the other two semi-core industries provided almost no support. Contradictory, it seems that employment in educational services both increases the odds of being in a poverty cluster by 26 percent, while at the same time reducing the chances of being in near poverty by 11 percent. Wholly refuting the hypothesis, the health care and social assistance industry does not reduce poverty or near poverty, but in fact increases the odds of poverty by 32 percent. These findings indicate that the education and health care sectors are associated with poverty cluster membership, with education also being associated with average poverty membership.

One reason why transportation and utilities tends to reduce poverty is that these goods-producing industries are well established in rural areas, being characterized as mostly unionized and having more equality in pay across workers. By contrast, education, health care, and social assistance are services-based industries that are relatively new to rural areas and have grown quite fast over the past decade. Mostly publicly-supported and non-unionized, these industries are characterized by having large pay inequalities among workers, with a small number of well paid and highly educated professionals contrasted with a large number of low paid and lower skilled support staff.

In addition, the effect for health care and social assistance may also have to do with the distribution of employment in that industry between health care and social assistance. It may be that in many highly poor rural areas employment in this industry is skewed in favor of social assistance employment, as various agencies locate there to serve poor persons. Because of this effect, it is likely that social assistance employment is associated with poverty as an effect of that poverty, not as a cause. Also, most above average education employment is due to higher education and thus associated with large non-institutional student populations that tend to increase the rates of poverty. Thus, it may not be the education sector itself that causes poverty, but the student populations who are in temporary “poverty” while enrolled in school.

Therefore, the findings support the assertion that postindustrial semi-core industries engaged in transportation and utilities are associated with low and average poverty cluster membership, by reducing near poverty odds while increasing low poverty odds relative to the average poverty cluster. This is attributable to a history of well established firms and pay equality in this industry. However, it is also concluded that education and health care services is associated with poverty cluster membership. The explanation for this is that social assistance employment is an effect of serving poor people; and education employment is associated with large student populations who are temporarily poor.

The *fifth hypothesis* posits that greater concentrations of workers employed in postindustrial periphery industries increases the odds of a census tract being in a poverty cluster. Referring to Table 31, the findings provide very little support for the hypothesis, and in fact most provide evidence to the contrary. Results indicate that only one industry provides limited support for the hypothesis. Employment in leisure services (arts, entertainment, recreation, accommodation, and food services) has a contradictory effect, both increasing the odds of being in a poverty cluster by a stunning 28 percent, yet also reducing the chances of near poverty by eight percent at the same time – both relative to average poverty membership. Given the temporary, lower skilled, and lower paid nature of the work, it is clear why the leisure industry increases poverty.

However, it is less clear why the majority of periphery industries do not increase poverty or near poverty. In fact, these industries actually reduce near poverty, which is contrary to what is hypothesized. Several periphery industries are associated with average and low poverty cluster membership, including construction, trade, and public administration. These industries tend to reduce the odds of near poverty while increasing low poverty odds, relative to average poverty. One explanation for this effect is that both the construction and public administration industries tend to pay above average wages, usually provide benefits, require skilled labor, and often have union or trade representation. This would account for why these industries are associated with average and low poverty membership. The finding for the trade industry can be explained in terms of sub-sector mix between retail and wholesale. Whereas retail trade jobs are part-time and low paid, most wholesale trade jobs are more highly skilled and better paid. Thus, it is likely that the wholesale share of the overall trade sector balances out the negative effects of the retail share.

While most jobs in any sector tend to reduce the chances of near poverty relative to average poverty, not all sectors increase the odds of low poverty. Periphery industries associated with average poverty membership include administrative support services and household services (real estate, rental, leasing, and other services). The explanation for why these industries are not associated with low poverty are that they employ less skilled labor, are often part-time or temporary, offer fewer benefits, and generally are not well paid.

Therefore, the findings support the conclusion that postindustrial periphery industries engaged in the leisure sector is associated with being in a poverty cluster. However, the findings also suggest that many periphery industries do not produce a strong deleterious effect on communities in terms of poverty or near poverty. It seems that industries employing more skilled labor, such as in construction and public administration, are associated with average and low poverty cluster membership. These industries also tend to pay above average wages, provide benefits, and have a history or union or trade representation. In other words, these periphery industries also provide a strong benefit in terms of promoting low poverty. On the other hand, lower skilled periphery industries are also associated with average poverty, yet do not increase the chances of low poverty. Thus, it is concluded that most periphery industries do not result in poverty or near poverty, but tend to result in average poverty cluster membership.

TABLE 31
Industry Structure Model Summary – Percent Odds of Cluster Membership

			Poverty Cluster	
Hypothesis	***Variable***	*Poverty*	*Near Poverty*	*Low Poverty*
H1 Agriculture Self-Employment Reduces Poverty Odds				
	AGSEMP	--	↓10%**	--
H2 Agriculture Wage Workers Increases Poverty Odds				
	AGWAGE	--	↓ 7%**	--
H3 Postindustrial Core/Basic Employment Reduces Poverty Odds				
	INFO	↑37%**	--	--
	FINMGM	--	↓10%**	↑17%**
	PRFSCI	--	↓15%**	--
	MFGR	--	↓ 8%**	↑10%**
H4 Postindustrial Semi-Core/Semi-Basic Employment Reduces Poverty Odds				
	EDUC	↑26%**	↓11%**	--
	HLTHSA	↑32%**	--	--
	TRSUTL	--	↓ 8%**	↑ 7%**
H5 Postindustrial Periphery/Non-Basic Employment Increases Poverty Odds				
	CONST	--	↓10%**	↑13%**
	TRADE	--	↓ 7%**	↑ 6%*
	ADMWST	--	↓10%*	--
	LEISUR	↑28%**	↓ 8%**	--
	HHSERV	--	↓ 8%**	--
	PUBADM	--	↓ 6%*	↑ 8%**
Control Variables				
	POP	--	--	--
	METADJ	--	--	↑50%**
	MINRTY	↑ 2%**	↑ 2%**	↓ 2%**
	DISABL	↑ 9%**	↑ 3%*	↓ 7%**
	SHHFAM	--	--	↓20%**
	HSAA	↓ 5%**	↑ 3%**	↑ 8%**
	BAPLUS	--	--	↑12%**
	UMEMP	--	↓ 9%**	↓ 8%**
	POV90	↑37%**	↑30%**	↓23%**

NOTE: ↑ or ↓ denotes increased/decreased odds of membership compared to Average Poverty Cluster. -- denotes non-significance. * Significant at $p< 0.10$. ** Significant at $p< 0.05$.

The fourth objective is to look at economic structure in a different manner, by describing local economies according to what workers do rather than the industries in which they work. This objective seeks to determine how **occupation structure** affects membership in a rural poverty cluster. The following hypotheses are also drawn from the segmented economy and postindustrial literatures, and tests whether communities characterized by the new postindustrial professional-managerial class are more developed socioeconomically than those characterized by the new postindustrial lower services class. It is assumed that occupational structure reflects class structure.

The ascendancy of postindustrial capitalism and the shift from a primarily goods-producing to a services-producing economy has led to a new stratification order that is radically different from what existed under industrial capitalism. This new class structure is dominated by two large services classes, which include the professional-managerial class that produces and consumes postindustrial symbols, and a lower services class that services the professional-managerial class. In addition, remnants of the industrial working class also exists, albeit much diminished.

The *sixth hypothesis* posits that greater concentrations of workers employed in postindustrial professional-managerial class occupations reduce the odds of a census tract being in a poverty cluster, relative to average poverty membership. The findings do not support this hypothesis. However, the findings indicate that the impact of this occupational group is multifaceted. Referring to

Table 32, the results indicate that although employment in management, business, and other professional occupations do not reduce the chances of poverty or near poverty, they do seem to increase the odds of being in a low poverty cluster. Given the higher levels of skill and compensation, it is surprising that employment in this occupation does not reduce poverty or near poverty. One explanation is that this group includes education and teaching occupations, and previous findings from the industry structure model found that higher education employment increases poverty due to large student populations. Coupled with the fact that education occupations often constitute a large percentage of this group in many census tracts, the higher education effect seems plausible.

Wholly contrary to what is hypothesized, employment in arts, design, entertainment, sports, and media occupations increases the odds of being in a poverty cluster by a stunning 48 percent. One explanation for this is that the majority of jobs in this occupational group are most likely in the entertainment sub-group. This effect may be caused by a skewed distribution in the aggregate variable, where entertainment occupations account for nearly all jobs in the north central region, thus reducing the effect of the other design and media occupations. Given this assumption, it seems reasonable to expect that entertainment jobs, which are generally characterized by part-time seasonal work that often pays below average wages, would tend to increase the chances of being in a poverty cluster. In fact, this sub-group more closely resembles the lower services class in terms of function, skill, and pay.

One mixed finding is that employment in health practitioner and related health technical occupations increases the odds of near poverty by 10 percent, while at the same time increasing the odds of low poverty also by 10 percent. Although this dual finding is difficult to reconcile, the explanation is likely due to the diverse nature of this occupational group and by the spatial distribution of its employment. It is reasoned that the low poverty effect occurs when areas are dominated by large health care facilities, where the occupational employment is likely skewed in favor of health practitioners (i.e. medical doctors, dentists, registered nurses, etc.). When this occurs, the occupation will represent highly skilled and generally well paid health care jobs, thus leading to low poverty. By contrast, it is also reasoned that in many areas health care is dominated by small clinics and offices that primarily employ health technicians (i.e. medical technicians, dental hygienists, licensed practical nurses, records clerks, etc.). When this is the case, the occupation will represent lower skilled and lower paid health care jobs, which leads to near poverty.

Therefore, the findings support the conclusion that professional, managerial, and health practitioner sub-group occupations are associated with low poverty cluster membership. This lends support to the assertion that postindustrial “knowledge workers” are associated with socioeconomic well-being. However, it is also concluded that not all health care jobs have this effect.

This finding shows that the health technician sub-group is associated with near poverty cluster membership, since many of these jobs are similar to the lower services class. Lastly, the findings allow us to conclude that in the study area the arts, design, entertainment, sports, and media occupation is primarily composed of entertainment jobs and very little else. Being more similar to lower services class jobs, it is clear why employment in the occupation is associated with poverty cluster membership.

The *seventh hypothesis* posits that greater concentrations of workers employed in postindustrial working class occupations reduces the odds of a census tract being in a poverty cluster. The findings provide some limited support for this assertion (refer to Table 32). Results find that employment in installation, maintenance, and repair occupations reduces the odds of being in a poverty cluster by 16 percent, relative to average poverty. However, employment in transportation and materials moving occupations increases the chances of being in near poverty by nine percent. Further, none of the other working class occupational variables are significant in reducing either poverty or near poverty.

It is somewhat surprising that only one working class occupation is significant in reducing poverty, given that these occupations have a history of paying above average wages with benefits, mostly due to the effect of unionization. It is unclear what characteristics installation, maintenance, and repair occupations have that make them effective at reducing poverty compared to other occupations in this class. One reason may be that the occupation is more prevalent in rural areas than other working class occupations – like production jobs – which have seen large declines during the past decade.

However, by all accounts both construction and production jobs are skilled, well paid, and usually have union or trade representation. Although production jobs have declined, they still constitute a large segment of the rural labor market. Further, building boomed during the 1990s, so there should have been no declines in construction occupations. Taken together, the findings may indicate that both construction and production jobs are associated with the average poverty cluster, since they are not significant in sorting tracts into the other three groups.

By contrast, transportation and materials moving occupations are found to increase near poverty relative to average poverty. One reason for this may be that many of these occupations are relatively lower paid and offer fewer benefits compared to other working class occupations. Some examples of lower skilled transportation jobs include warehouse workers, laborers, and parking lot attendants. Further, these lower-skill transportation jobs probably account for a large percent of total employment in this occupation, and the effect is probably more pronounced in rural areas because they lack specialized transportation sectors, like major airports. For example, large shares of lower skilled and paid jobs will mask the impact of higher ones like pilots or rail workers. In addition, many of these transportation jobs offer few benefits, are prone to changes in the business cycle, and often require long period away from home.

Therefore, the findings support the conclusion that most working class occupations are associated with membership in the average poverty cluster. Further, installation and repair occupations are found to actually reduce poverty, yet it is unclear why other working class occupations have no effect at reducing either poverty or near poverty. The findings also allow us to conclude that transportation occupations are associated with near poverty cluster membership. This is most likely attributable to a low skill and low pay sub-group within this occupation that accounts for most of the employment, especially in more remote areas.

Lastly, the *eighth hypothesis* posits that greater concentrations of workers employed in postindustrial lower services class occupations increases the odds of a census tract being in a poverty cluster. In general, the findings provide broad support for this hypothesis, as evidenced in Table 32. Personal care and service occupations have the strongest deleterious effects, increasing the odds of being in a poverty cluster by 27 percent, increasing the odds of near poverty by 11 percent, and reducing the odds of low poverty by seven percent. While occupations related to building, grounds, and maintenance do not increase poverty, they are found to increase the odds of near poverty by 11 percent. In general, these occupations are part-time and seasonal in nature, require few skills, pay below average wages, and offer few benefits. Further, these occupations are highly dependent upon local economic conditions which causes uncertainty in employment.

However, health care support, protective services, sales, and office occupations are not found to increase either poverty or near poverty, but instead seem to reduce the odds of being in a low poverty cluster. This indicates that these occupations are associated with the average poverty cluster. Although it is somewhat surprising that not more lower service class occupations are significant at increasing poverty or near poverty, most of these other occupations are generally higher skilled. For example, health care and protective service occupations require unique and specialized skill sets, and are often better paid than other lower service class jobs. Even though health care service jobs (such as aides and assistants) pay lower wages than protective service jobs (firefighters and police officers), they are still more skilled and better paid that other personal service jobs. Thus, these occupations tend to pay enough to prevent them from being associated with poverty or near poverty, yet they do not pay well enough so that they are significant at increasing low poverty – thus they are associated with average poverty.

Surprisingly, sales and office occupations tend to increase the odds of low poverty relative to average poverty. Again, it is unclear why this occupation does not increase the odds of poverty or near poverty – or even average poverty – as the literature suggests. One explanation for this contrary effect may have to do with the diverse nature of this occupational group. One the face of it, one would expect these jobs to be lower skilled and lower paid due to the function they serve (i.e. retail sales clerks, administrative assistants, office clerks, etc.).

Although these lower skill jobs do constitute a sizable segment of this occupational group, there also exists more highly skilled sub-groups. For example, this group also contains high skill (usually college educated) sales representatives that often earn well above average wages selling insurance, financial services, advertising, electronics, pharmaceuticals, and other wholesale manufactured goods. Although the actual employment base may be small, the income of this sales representative sub-group is likely high enough to offset the negative effect of the low skill and low income sales and office worker sub-group.

Therefore, the findings support a two-fold conclusion for lower services class jobs based on skill levels. First, the results find that lower skill occupations in this class are associated with membership in the poverty and near poverty clusters. These lower skill occupations include jobs in personal services, building maintenance, and grounds keeping. Second, the results also indicate that more highly skilled occupations engaged in health services, protective services, sales, and office support are associated with average poverty and low poverty cluster membership. Healthcare and protective services jobs, being better skilled and paid than personal services jobs, are associated with average poverty. Further, sales and office jobs are associated with low poverty membership, although this effect is likely due to the small number of high earning sales representatives that mask the negative effects of low earning sales and office clerks.

TABLE 32
Occupation Structure Model Summary – Percent Odds of Cluster Membership

		Poverty Cluster		
Hypothesis	***Variable***	*Poverty*	*Near Poverty*	*Low Poverty*
H1 Agriculture Self-Employment Reduces Poverty Odds				
	FARMER	--	--	↓ 7%**
H2 Agriculture Wage Workers Increases Poverty Odds				
	NA	--	--	--
H6 Professional-Managerial Class Employment Reduces Poverty Odds				
	PRFBUS	--	--	↑ 8%**
	ARTENT	↑48%**	--	--
	HEALTH	--	↑10%**	↑ 8%**
H7 Working Class Employment Reduces Poverty Odds				
	CONEXT	--	--	--
	MAINRP	↓16%*	--	--
	PROD	--	--	--
	TRANS	--	↑ 9%**	--
H8 Lower Services Class Employment Increases Poverty Odds				
	HLTPRT	--	--	↓ 6%**
	FOOD	--	--	--
	BLDGRD	--	↑11%**	--
	PERSER	↑27%**	↑11%**	↓ 7%*
	SALEOF	--	--	↑ 4%*
Control Variables				
	POP	--	--	--
	METADJ	--	↓20%**	↑59%**
	MINRTY	↑ 2%**	↑ 2%**	↓ 2%**
	DISABL	↑11%**	↑ 4%*	↓ 8%**
	SHHFAM	↑ 7%*	--	↓20%**
	HSAA	↓ 5%**	↑ 2%**	↑ 5%**
	UMEMP	--	↓ 9%**	↓10%**
	POV90	↑36%**	↑29%**	↓24%**

NOTE: ↑ or ↓ denotes increased/decreased odds of membership compared to Average Poverty Cluster. -- denotes non-significance. * Significant at $p< 0.10$. ** Significant at $p<0.05$.

The preceding hypotheses are tested while controlling for a series of geographic, demographic and economic factors. Further, these controls are also some of the strongest predictors of poverty cluster odds. In terms of geography, the results find that being adjacent to a metropolitan area greatly increases a census tract's odds of being in a low poverty cluster, relative to being in an average poverty cluster. This indicates that being closer to metropolitan labor markets promotes lower poverty rates due to a greater diversity of employment and training opportunities. Population was not found to be significant in predicting cluster membership.

In terms of demographic controls, the findings show that larger concentrations of single headed families with children greatly reduce the odds of being in a low poverty cluster relative to average poverty. More moderate effects include the employment disabled population and the minority population, both which tend to increase the odds of poverty and near poverty while reducing the chances of low poverty. All of these findings concur with previous poverty research and are of the expected direction.

The verdict on education is mixed. Numbers of high school graduates and those with some college reduces the odds of poverty and increases the odds of low poverty, but at the same time also increases the odds of being in near poverty. This latter finding is puzzling and may indicate the presence of the working poor. Results from the cluster analysis indicate that near poor areas generally have lower unemployment rates, higher rates of full-time and full-year employment, and more high school graduates. This suggests that in many rural areas a high school education may prevent poverty and joblessness, but may also lead to lower paid employment causing near poverty.

In terms of economic controls, the strongest predictor of poverty odds is the poverty rate one decade ago. As expected, higher poverty rates in 1990 greatly increases a census tract's odds of being both in a poverty cluster and a near poverty cluster, while at the same time reducing the odds of low poverty. This indicates that most poor areas have historically high poverty rates. The consensus on unemployment rates is mixed, with higher unemployment associated with reduced chances of low poverty, yet surprisingly it also reduces the odds of near poverty. Again, this may be attributable to the near poverty cluster containing many of the working poor, as discussed above.

Conclusion

In conclusion, the literature used to ground this analysis needs to be reinterpreted in light of these findings. The results of the analysis have important implications for the labor market poverty perspective, the sociology of agriculture, and the segmented economy literatures. In this dissertation the theoretical approach to understanding poverty is based on the labor market perspective. This analysis shows that this approach is still relevant in understanding poverty in a postindustrial economy, and that the perspective is still relevant at more localized units of analysis like census tracts. The findings indicated that person-based factors had a weaker effect on predicting poverty clusters than place-based factors. Consistent with previous research, traditional person-based correlates of poverty were found to be significant. Single household families and minority populations tended to increase poverty odds, while most educational attainment factors reduced poverty odds. However, high school education had the usual effect of increasing near poverty odds while at the same time reducing poverty odds. This means that in rural areas high school education prevents poverty, yet does not prevent near poverty – which is an indicator of the working poor.

Place-based factors had a stronger effect on predicting poverty cluster membership. This indicates that rural poverty is likely a function of rural places rather than rural people. In this analysis, place or structure was conceptualized in terms of both agriculture structure and economic structure. The results found that both the farm and non-farm sectors were important in understanding rural poverty. Economic structure was further delineated in terms of industry or occupation structure. In general, the findings show that the combination of agriculture and economic structure – both by industry and occupation – is still relevant in understanding poverty within a postindustrial economy, and that the relationships hold at more localized units of analysis. A discussion of how specific structure literatures are impacted by the results of this analysis is presented below.

In terms of the sociology of agriculture literature, the findings show that the agricultural sector is still important in understanding rural poverty, but that structure makes no difference. Both agricultural self-employment and wage employment had the same effect at reducing the odds of near poverty, regardless of the structure of labor relations. The findings indicate that agriculture is still relevant in a postindustrial economy in understanding socioeconomic well being, but that the ownership structure argument does not hold in the rural north central region. This suggests that structure may no longer matter in production agriculture, as originally conceptualized. If the sociology of agriculture literature is to remain relevant in terms of understanding well being, it must be reformulated to reconcile the contradictory findings of this and other studies.

In terms of the segmented economy literature, the analysis found limited support for the core-periphery distinction. The findings suggest three major flaws with using this literature to classify industries into core and periphery using secondary data. First, industry aggregations do not account for the different types of firms within a single industry at the local level, nor do they indicate if firms are oriented to local or external markets. For example, secondary data does not tell us if the entertainment sector serves a local market (i.e. non-basic) or whether it is a tourism destination that brings money into the local economy (i.e. basic). Second, industry aggregations are not precise enough to measure sub-sector industry effects. For example, it is of little use knowing the employment level in non-durable goods manufacturing without knowing if this means producing pharmaceuticals or textile products. Third, industry averages do not capture the differences in labor or skill within an industry that may lead to aggregation error. For example, the health care sector includes a small number of highly paid professionals and a large number of low paid support staff, which leads to an above average wage rate that really reflects no one working in the industry. Because of the pitfalls of using secondary data, the utility of the segmented economy approach can be called into question.

In general, the findings indicated that most core industries reduced poverty and near poverty odds, which is consistent with the literature. This finding was especially true for postindustrial core industries engaged in finance and professional services. However, the information industry had the opposite effect of increasing poverty odds, contrary to what is purported in the literature. This is likely attributable to the industry aggregation not being precise enough to identify relevant sub-sectors. In the study area, it is likely that most information services employment is composed of the movie exhibition sub-sector, thus behaving more like a local-oriented periphery industry.

Next, the findings for the semi-core industries produced contradictory support that they reduce poverty and near poverty. It was found that transportation and utilities reduced near poverty and increase low poverty odds. However, it was also found that education services and health care and social assistance actually increased poverty odds. More strangely, education also seems to reduce near poverty at the same time. There are three explanations for these effects, all having to do with aggregation errors in the data. First, industry aggregations do not capture the differences in labor and skill, and these industries have a wide diversity of occupations and income. Second, industry data does not account for the different types of firms or their market orientation. In the case of education, it is impossible to tell if employment is in K-12 education that serves a local market, or a large doctoral research university that serves an external market. Third, industry aggregations are not precise enough to identify sub-sectors. In the case of health care and social assistance, if is likely the social assistance employment is an effect of high poverty, not a cause of it.

Lastly, the findings also provide limited support for the assertion that periphery industries increase poverty. The results show that employment in the leisure and entertainment industries substantially increases poverty. However, all other periphery industries actually reduced near poverty, including the leisure industry, and many increased the odds of low poverty as well. These findings call into question the notions of core-periphery, and provide evidence that many periphery industries are not associated with poor socioeconomic well being. This suggests that the concept of “periphery” industries does not hold under postindustrialism, and that former periphery industries no longer result in poor socioeconomic conditions. One explanation for this, rooted in economic restructuring, is that tourism and personal services are becoming more important to consumers and they become more self-reflexive and individuated. Along this line of argument, these industries may be increasingly “export” dependent as consumers travel to these certain communities for tourism, entertainment and recreation.

As stated above, one major flaw in using industry aggregations is that they do not capture differences in labor and skill within an industry, which leads to aggregation errors and heterogeneity. To address this problem, occupation structure is used in place of industry structure to test the segmented economy and postindustrial literatures. However, using occupations makes notions of core and periphery meaningless. Drawing on the postindustrial literature, occupation structure was delineated in terms of the new class structure that has resulted as the economy has transitioned from goods-production to services-production.

In general, the analysis found limited support for assertion that different postindustrial classes affect socioeconomic well being. In the occupation structure model, the results show that person-based and control predictors exerted a stronger effect on poverty cluster membership than the occupational factors. This indicates that an occupation-based concept of the economy is less informative in understanding poverty than an industry-based one, although both the industry structure and occupation structure models performed equally well in terms of model fit and accuracy. However, one major flaw in the occupation structure model is that occupational aggregations are not precise enough to measure job-specific effects within the occupational group. For example, sales workers include both high skill and high paid sales representative, as well as low skill and low paid sales clerks.

The findings indicated that professional-managerial class occupations did not reduce poverty and near poverty, as was suggested by the literature. None of these occupations was significant at reducing poverty odds. However, the findings indicated that professional, business and health occupations promoted low poverty, although the latter also increased near poverty at the same time. This contradictory finding for health care occupations is attributable to aggregation errors, that includes both high paid health practitioners and low paid health technicians. Thus, we can conclude that these types of professional-managerial jobs tend to be associated with low poverty areas, and are generally absent from poverty and near poverty areas. This finding calls into question whether the professional-managerial class actually ameliorates poverty and near poverty. The results suggest that this class tends to promote localized pockets of low poverty, rather than reducing poverty.

Contrary to what the literature suggests, the arts, entertainment and media occupational group substantially increased poverty odds over average poverty membership. The explanation for this effect is likely due to aggregation error, where entertainment workers constitute a large share of employment in this occupation, with arts and design workers comprising a small share. However, this finding also calls into question whether workers engaged in the production of cultural products really are part of this new postindustrial upper class, as is theorized in the literature. This suggests that there may be a distinction between the production of cognitive or information produces, and the production of aesthetic or cultural products. The postindustrial literature should begin to address this issue of why occupations producing aesthetic goods tend to promote poverty, while those producing cognitive goods tend to promote low poverty.

Only limited support was provided to the thesis that industrial working class occupations reduce poverty. It was found that most working class occupations were associated with average poverty cluster membership. Only installation, maintenance and repair occupations had any effect at reducing poverty. Conversely, transportation occupations tended to increase near poverty odds. This finding suggests that in a postindustrial economy most working class occupations do not have sizable effect on poverty or near poverty in local areas. Although consistent with the postindustrial literature, this finding represents a significant challenge to previous poverty research, which has linked working class jobs to better socioeconomic outcomes.

Lastly, the findings supported the assertion that lower services class occupations were associated with increased odds of poverty and near poverty membership. Results found that many lower skilled services occupations (like personal services, building maintenance, and grounds keeping) are associated with poverty and near poverty cluster membership. Given the low skill, pay and function of these occupations, these results concur with the poverty and postindustrial literatures. However, it was also found that more skilled occupations in this class were associated with average poverty (healthcare support and protective services jobs) and low poverty (sales and office jobs). The former finding indicates that these jobs may more closely resemble working class occupations in terms of pay, skill and function. The latter finding can be attributable to aggregation errors in the sales and office variable, with a small number of highly skilled and paid sales representatives countering the negative effects of a large number of lower skilled and paid sales clerks.

In conclusion, it is hoped that the results of this dissertation can be used in the north central region to inform collective action within communities and public policy across various units of government. The findings show that poverty and near poverty are highly concentrated in the region, and are affected by both individual and structural factors. In terms of individual factors, reducing the negative impacts of employment disabilities and single headed families with children is key to reducing poverty and near poverty. In addition, improvement in human capital, through investment in education and job training, can reduce poverty and near poverty by increasing skills and earnings.

In terms of structural factors, communities and government can reduce poverty and near poverty by targeting rural development efforts at particular types of industries and occupations. The leisure services industry is particularly prone to creating poverty. Education and health care services, mostly likely associated with university centers and student populations, also tends to increase poverty – albeit the “temporary” poverty of students. However, many traditional rural industries are still effective at reducing both poverty and near poverty, especially in manufacturing, transportation, and agriculture. In short, poverty and near poverty can be ameliorated in the region so long as attention is given simultaneously to individual and structures issues. As the results strongly show, any efforts to reduce poverty today have a large impact at reducing poverty in the future.

APPENDIX

Pearson Correlation Matrix – Industry Structure Model

	POP	METADJ	MINRTY	DISABL	SHHFAM	HSAA	BAPLUS	UNEMP
POP	1	.236(**)	-.045(**)	-.045(**)	.066(**)	-.135(**)	.130(**)	-.045(**)
METADJ	.236(**)	1	-.098(**)	0.012	0.017	.111(**)	-.079(**)	-.092(**)
MINRTY	-.045(**)	-.098(**)	1	.129(**)	.600(**)	-.255(**)	-0.018	.446(**)
DISABL	-.045(**)	0.012	.129(**)	1	.310(**)	-0.023	-.391(**)	.215(**)
SHHFAM	.066(**)	0.017	.600(**)	.310(**)	1	-.112(**)	-.189(**)	.454(**)
HSAA	-.135(**)	.111(**)	-.255(**)	-0.023	-.112(**)	1	-.545(**)	-.221(**)
BAPLUS	.130(**)	-.079(**)	-0.018	-.391(**)	-.189(**)	-.545(**)	1	-.078(**)
UNEMP	-.045(**)	-.092(**)	.446(**)	.215(**)	.454(**)	-.221(**)	-.078(**)	1
POV90	-.178(**)	-.199(**)	.486(**)	.238(**)	.411(**)	-.312(**)	-.104(**)	.566(**)
AGSEMP	-.374(**)	-.188(**)	-.097(**)	-.157(**)	-.341(**)	.192(**)	-.123(**)	-.235(**)
AGWAGE	-.279(**)	-.189(**)	-0.026	-.072(**)	-.235(**)	.107(**)	-.104(**)	-.148(**)
INFO	.071(**)	-0.002	.045(**)	-.077(**)	.075(**)	-.132(**)	.242(**)	0.029
FINMGM	.043(**)	.042(**)	-.173(**)	-.230(**)	-.183(**)	.065(**)	.179(**)	-.232(**)
PRFSCI	.167(**)	.077(**)	-.101(**)	-.197(**)	-.120(**)	-.187(**)	.459(**)	-.128(**)
MFGR	.226(**)	.329(**)	-.129(**)	.220(**)	.094(**)	.191(**)	-.348(**)	-.143(**)
EDUC	.038(**)	-.103(**)	.229(**)	-.234(**)	0.010	-.430(**)	.611(**)	.240(**)
HLTHSA	-.048(**)	-.138(**)	.049(**)	-0.010	.139(**)	-.107(**)	.061(**)	.083(**)
TRSUTL	-.087(**)	-.030(*)	-.140(**)	0.025	-.140(**)	.216(**)	-.231(**)	-.101(**)
CONST	-0.018	.039(**)	-.151(**)	.140(**)	-.109(**)	.191(**)	-.253(**)	0.017
TRADE	.108(**)	-.069(**)	-.153(**)	-0.007	0.016	-0.007	.053(**)	-0.029
ADMWST	.100(**)	.075(**)	.075(**)	.123(**)	.180(**)	-.078(**)	-0.002	.139(**)
LEISUR	.062(**)	-.077(**)	.263(**)	.091(**)	.292(**)	-.210(**)	.175(**)	.409(**)
HHSERV	0.023	-.075(**)	-0.001	.036(*)	0.020	-.072(**)	.043(**)	0.026
PUBADM	-.063(**)	-.056(**)	.323(**)	-.046(**)	.181(**)	-.032(*)	0.026	.163(**)
IL	-.031(*)	.030(*)	0.005	-.038(*)	0.018	0.000	-.044(**)	.079(**)
IN	.085(**)	.178(**)	-.038(*)	.153(**)	0.023	0.022	-.101(**)	-.043(**)
IA	-.053(**)	-.037(*)	-.081(**)	-.104(**)	-.083(**)	.094(**)	.066(**)	-.112(**)
KS	-0.021	-.112(**)	.099(**)	-0.001	-0.025	-.029(*)	.103(**)	-.076(**)
MI	-0.024	-.086(**)	-0.025	.030(*)	.062(**)	.041(**)	0.008	.202(**)
MN	-0.020	-.059(**)	-0.029	-.075(**)	-.060(**)	0.009	.051(**)	-0.022
MO	.077(**)	-.083(**)	-0.003	.121(**)	.052(**)	-.197(**)	-.072(**)	0.024
NB	-.071(**)	-.141(**)	0.008	-.077(**)	-.062(**)	.059(**)	.046(**)	-.133(**)
ND	-.187(**)	-.102(**)	.070(**)	-.065(**)	-.041(**)	-.081(**)	.034(*)	0.007
OH	.159(**)	.255(**)	-.049(**)	.093(**)	.062(**)	.045(**)	-.092(**)	0.002
SD	-.107(**)	-.138(**)	.237(**)	-0.029	.104(**)	-.074(**)	.046(**)	.069(**)
WI	.062(**)	.152(**)	-.064(**)	-.062(**)	-.055(**)	.060(**)	0.015	-0.028

	POV90	AGSEMP	AGWAGE	INFO	FINMGM	PRFSCI	MFGR	EDUC
POP	-.178(**)	-.374(**)	-.279(**)	.071(**)	.043(**)	.167(**)	.226(**)	.038(**)
METADJ	-.199(**)	-.188(**)	-.189(**)	-0.002	.042(**)	.077(**)	.329(**)	-.103(**)
MINRTY	.486(**)	-.097(**)	-0.026	.045(**)	-.173(**)	-.101(**)	-.129(**)	.229(**)
DISABL	.238(**)	-.157(**)	-.072(**)	-.077(**)	-.230(**)	-.197(**)	.220(**)	-.234(**)
SHHFAM	.411(**)	-.341(**)	-.235(**)	.075(**)	-.183(**)	-.120(**)	.094(**)	0.010
HSAA	-.312(**)	.192(**)	.107(**)	-.132(**)	.065(**)	-.187(**)	.191(**)	-.430(**)
BAPLUS	-.104(**)	-.123(**)	-.104(**)	.242(**)	.179(**)	.459(**)	-.348(**)	.611(**)
UNEMP	.566(**)	-.235(**)	-.148(**)	0.029	-.232(**)	-.128(**)	-.143(**)	.240(**)
POV90	1	.066(**)	.043(**)	.035(*)	-.270(**)	-.229(**)	-.276(**)	.300(**)
AGSEMP	.066(**)	1	.640(**)	-.163(**)	.037(*)	-.222(**)	-.331(**)	-.048(**)
AGWAGE	.043(**)	.640(**)	1	-.138(**)	-0.007	-.182(**)	-.259(**)	-.055(**)
INFO	.035(*)	-.163(**)	-.138(**)	1	.047(**)	.143(**)	-.114(**)	.181(**)
FINMGM	-.270(**)	.037(*)	-0.007	.047(**)	1	.188(**)	-.187(**)	-.035(*)
PRFSCI	-.229(**)	-.222(**)	-.182(**)	.143(**)	.188(**)	1	-.143(**)	.150(**)
MFGR	-.276(**)	-.331(**)	-.259(**)	-.114(**)	-.187(**)	-.143(**)	1	-.399(**)
EDUC	.300(**)	-.048(**)	-.055(**)	.181(**)	-.035(*)	.150(**)	-.399(**)	1
HLTHSA	.043(**)	-.146(**)	-.138(**)	.042(**)	.069(**)	.043(**)	-.315(**)	-0.020
TRSUTL	-.079(**)	.175(**)	.194(**)	-.124(**)	.056(**)	-.111(**)	-.157(**)	-.178(**)
CONST	-0.028	-0.002	-0.005	-.121(**)	-.060(**)	-0.023	-.085(**)	-.236(**)
TRADE	-.091(**)	-.269(**)	-.213(**)	.035(*)	.120(**)	.121(**)	-.154(**)	-.139(**)
ADMWST	.095(**)	-.250(**)	-.226(**)	.095(**)	-.045(**)	.074(**)	-0.011	-.042(**)
LEISUR	.305(**)	-.327(**)	-.263(**)	.100(**)	-.174(**)	.057(**)	-.224(**)	.151(**)
HHSERV	0.025	-.181(**)	-.146(**)	.034(*)	0.025	.077(**)	-.163(**)	-0.028
PUBADM	.134(**)	-.085(**)	-.092(**)	-0.009	0.010	0.002	-.322(**)	.041(**)
IL	0.012	-.095(**)	-.081(**)	.032(*)	.113(**)	-0.010	-.055(**)	0.023
IN	-.136(**)	-.149(**)	-.124(**)	-.051(**)	-.112(**)	-.047(**)	.334(**)	-.086(**)
IA	-.090(**)	.074(**)	.032(*)	.060(**)	.100(**)	.045(**)	-0.002	.032(*)
KS	-0.014	.070(**)	.107(**)	0.016	.030(*)	0.027	-.147(**)	.113(**)
MI	.043(**)	-.176(**)	-.112(**)	-.053(**)	-.106(**)	.052(**)	0.013	0.002
MN	-0.019	.050(**)	0.024	0.006	0.009	.044(**)	-.052(**)	-0.006
MO	.180(**)	-.039(**)	-0.005	-0.015	-.037(*)	-.062(**)	-.057(**)	-0.019
NB	-.036(*)	.209(**)	.268(**)	-0.003	.088(**)	-0.015	-.162(**)	-0.028
ND	.068(**)	.257(**)	.080(**)	.040(**)	.043(**)	-.053(**)	-.252(**)	.060(**)
OH	-0.018	-.175(**)	-.158(**)	0.020	-.100(**)	0.016	.248(**)	-.049(**)
SD	.205(**)	.259(**)	.135(**)	-0.018	0.019	-.067(**)	-.226(**)	.119(**)
WI	-.111(**)	-0.014	0.007	-0.027	-0.004	0.024	.122(**)	-.090(**)

	HLTHSA	TRSUTL	CONST	TRADE	ADMWST	LEISUR	HHSERV	PUBADM
POP	-.048(**)	-.087(**)	-0.018	.108(**)	.100(**)	.062(**)	0.023	-.063(**)
METADJ	-.138(**)	-.030(*)	.039(**)	-.069(**)	.075(**)	-.077(**)	-.075(**)	-.056(**)
MINRTY	.049(**)	-.140(**)	-.151(**)	-.153(**)	.075(**)	.263(**)	-0.001	.323(**)
DISABL	-0.010	0.025	.140(**)	-0.007	.123(**)	.091(**)	.036(*)	-.046(**)
SHHFAM	.139(**)	-.140(**)	-.109(**)	0.016	.180(**)	.292(**)	0.020	.181(**)
HSAA	-.107(**)	.216(**)	.191(**)	-0.007	-.078(**)	-.210(**)	-.072(**)	-.032(*)
BAPLUS	.061(**)	-.231(**)	-.253(**)	.053(**)	-0.002	.175(**)	.043(**)	0.026
UNEMP	.083(**)	-.101(**)	0.017	-0.029	.139(**)	.409(**)	0.026	.163(**)
POV90	.043(**)	-.079(**)	-0.028	-.091(**)	.095(**)	.305(**)	0.025	.134(**)
AGSEMP	-.146(**)	.175(**)	-0.002	-.269(**)	-.250(**)	-.327(**)	-.181(**)	-.085(**)
AGWAGE	-.138(**)	.194(**)	-0.005	-.213(**)	-.226(**)	-.263(**)	-.146(**)	-.092(**)
INFO	.042(**)	-.124(**)	-.121(**)	.035(*)	.095(**)	.100(**)	.034(*)	-0.009
FINMGM	.069(**)	.056(**)	-.060(**)	.120(**)	-.045(**)	-.174(**)	0.025	0.010
PRFSCI	.043(**)	-.111(**)	-0.023	.121(**)	.074(**)	.057(**)	.077(**)	0.002
MFGR	-.315(**)	-.157(**)	-.085(**)	-.154(**)	-0.011	-.224(**)	-.163(**)	-.322(**)
EDUC	-0.020	-.178(**)	-.236(**)	-.139(**)	-.042(**)	.151(**)	-0.028	.041(**)
HLTHSA	1	-.050(**)	-.112(**)	.118(**)	0.028	-0.020	.083(**)	.130(**)
TRSUTL	-.050(**)	1	.098(**)	-0.026	-.073(**)	-.233(**)	-.038(**)	-.073(**)
CONST	-.112(**)	.098(**)	1	-0.022	0.003	0.003	0.024	-0.010
TRADE	.118(**)	-0.026	-0.022	1	.120(**)	.065(**)	.145(**)	-.120(**)
ADMWST	0.028	-.073(**)	0.003	.120(**)	1	.171(**)	.057(**)	-.032(*)
LEISUR	-0.020	-.233(**)	0.003	.065(**)	.171(**)	1	.103(**)	.082(**)
HHSERV	.083(**)	-.038(**)	0.024	.145(**)	.057(**)	.103(**)	1	-0.003
PUBADM	.130(**)	-.073(**)	-0.010	-.120(**)	-.032(*)	.082(**)	-0.003	1
IL	.081(**)	.139(**)	-.086(**)	.062(**)	.073(**)	-.044(**)	.050(**)	.068(**)
IN	-.156(**)	-.058(**)	-0.012	-.045(**)	.034(*)	-.071(**)	-0.008	-.079(**)
IA	0.026	-0.018	-.045(**)	.055(**)	0.018	-.120(**)	-.055(**)	-.106(**)
KS	.040(**)	.082(**)	-0.015	-.038(*)	-.059(**)	-.040(**)	0.018	0.012
MI	-0.005	-.161(**)	.114(**)	.053(**)	-0.005	.206(**)	.101(**)	.034(*)
MN	.101(**)	-.051(**)	0.017	0.002	-0.013	.043(**)	0.018	-.063(**)
MO	0.019	.033(*)	.119(**)	0.028	-.035(*)	-0.026	.066(**)	.153(**)
NB	0.014	.137(**)	-.040(**)	0.029	-.040(**)	-.059(**)	-0.010	-.046(**)
ND	.083(**)	.046(**)	-.071(**)	-0.029	.056(**)	-0.017	-0.001	.053(**)
OH	-.080(**)	0.012	-0.019	-.063(**)	.048(**)	-0.013	-.041(**)	-.051(**)
SD	0.002	-.044(**)	-.056(**)	-.099(**)	-.032(*)	.031(*)	-0.012	.119(**)
WI	-.088(**)	-.081(**)	.040(**)	-0.009	-.060(**)	.092(**)	-.137(**)	-.048(**)

	IL	IN	IA	KS	MI	MN	MO	NB
POP	-.031(*)	.085(**)	-.053(**)	-0.021	-0.024	-0.020	.077(**)	-.071(**)
METADJ	.030(*)	.178(**)	-.037(*)	-.112(**)	-.086(**)	-.059(**)	-.083(**)	-.141(**)
MINRTY	0.005	-.038(*)	-.081(**)	.099(**)	-0.025	-0.029	-0.003	0.008
DISABL	-.038(*)	.153(**)	-.104(**)	-0.001	.030(*)	-.075(**)	.121(**)	-.077(**)
SHHFAM	0.018	0.023	-.083(**)	-0.025	.062(**)	-.060(**)	.052(**)	-.062(**)
HSAA	0.000	0.022	.094(**)	-.029(*)	.041(**)	0.009	-.197(**)	.059(**)
BAPLUS	-.044(**)	-.101(**)	.066(**)	.103(**)	0.008	.051(**)	-.072(**)	.046(**)
UNEMP	.079(**)	-.043(**)	-.112(**)	-.076(**)	.202(**)	-0.022	0.024	-.133(**)
POV90	0.012	-.136(**)	-.090(**)	-0.014	.043(**)	-0.019	.180(**)	-.036(*)
AGSEMP	-.095(**)	-.149(**)	.074(**)	.070(**)	-.176(**)	.050(**)	-.039(**)	.209(**)
AGWAGE	-.081(**)	-.124(**)	.032(*)	.107(**)	-.112(**)	0.024	-0.005	.268(**)
INFO	.032(*)	-.051(**)	.060(**)	0.016	-.053(**)	0.006	-0.015	-0.003
FINMGM	.113(**)	-.112(**)	.100(**)	.030(*)	-.106(**)	0.009	-.037(*)	.088(**)
PRFSCI	-0.010	-.047(**)	.045(**)	0.027	.052(**)	.044(**)	-.062(**)	-0.015
MFGR	-.055(**)	.334(**)	-0.002	-.147(**)	0.013	-.052(**)	-.057(**)	-.162(**)
EDUC	0.023	-.086(**)	.032(*)	.113(**)	0.002	-0.006	-0.019	-0.028
HLTHSA	.081(**)	-.156(**)	0.026	.040(**)	-0.005	.101(**)	0.019	0.014
TRSUTL	.139(**)	-.058(**)	-0.018	.082(**)	-.161(**)	-.051(**)	.033(*)	.137(**)
CONST	-.086(**)	-0.012	-.045(**)	-0.015	.114(**)	0.017	.119(**)	-.040(**)
TRADE	.062(**)	-.045(**)	.055(**)	-.038(*)	.053(**)	0.002	0.028	0.029
ADMWST	.073(**)	.034(*)	0.018	-.059(**)	-0.005	-0.013	-.035(*)	-.040(**)
LEISUR	-.044(**)	-.071(**)	-.120(**)	-.040(**)	.206(**)	.043(**)	-0.026	-.059(**)
HHSERV	.050(**)	-0.008	-.055(**)	0.018	.101(**)	0.018	.066(**)	-0.010
PUBADM	.068(**)	-.079(**)	-.106(**)	0.012	.034(*)	-.063(**)	.153(**)	-.046(**)
IL	1	-.114(**)	-.121(**)	-.100(**)	-.125(**)	-.112(**)	-.119(**)	-.086(**)
IN	-.114(**)	1	-.106(**)	-.087(**)	-.110(**)	-.098(**)	-.104(**)	-.076(**)
IA	-.121(**)	-.106(**)	1	-.093(**)	-.116(**)	-.104(**)	-.110(**)	-.080(**)
KS	-.100(**)	-.087(**)	-.093(**)	1	-.096(**)	-.086(**)	-.091(**)	-.066(**)
MI	-.125(**)	-.110(**)	-.116(**)	-.096(**)	1	-.108(**)	-.114(**)	-.083(**)
MN	-.112(**)	-.098(**)	-.104(**)	-.086(**)	-.108(**)	1	-.102(**)	-.075(**)
MO	-.119(**)	-.104(**)	-.110(**)	-.091(**)	-.114(**)	-.102(**)	1	-.079(**)
NB	-.086(**)	-.076(**)	-.080(**)	-.066(**)	-.083(**)	-.075(**)	-.079(**)	1
ND	-.068(**)	-.060(**)	-.063(**)	-.052(**)	-.066(**)	-.059(**)	-.062(**)	-.045(**)
OH	-.125(**)	-.110(**)	-.116(**)	-.096(**)	-.121(**)	-.108(**)	-.114(**)	-.083(**)
SD	-.071(**)	-.062(**)	-.066(**)	-.054(**)	-.068(**)	-.061(**)	-.065(**)	-.047(**)
WI	-.117(**)	-.102(**)	-.109(**)	-.090(**)	-.113(**)	-.101(**)	-.107(**)	-.078(**)

	ND	OH	SD	WI
POP	-.187(**)	.159(**)	-.107(**)	.062(**)
METADJ	-.102(**)	.255(**)	-.138(**)	.152(**)
MINRTY	.070(**)	-.049(**)	.237(**)	-.064(**)
DISABL	-.065(**)	.093(**)	-0.029	-.062(**)
SHHFAM	-.041(**)	.062(**)	.104(**)	-.055(**)
HSAA	-.081(**)	.045(**)	-.074(**)	.060(**)
BAPLUS	.034(*)	-.092(**)	.046(**)	0.015
UNEMP	0.007	0.002	.069(**)	-0.028
POV90	.068(**)	-0.018	.205(**)	-.111(**)
AGSEMP	.257(**)	-.175(**)	.259(**)	-0.014
AGWAGE	.080(**)	-.158(**)	.135(**)	0.007
INFO	.040(**)	0.020	-0.018	-0.027
FINMGM	.043(**)	-.100(**)	0.019	-0.004
PRFSCI	-.053(**)	0.016	-.067(**)	0.024
MFGR	-.252(**)	.248(**)	-.226(**)	.122(**)
EDUC	.060(**)	-.049(**)	.119(**)	-.090(**)
HLTHSA	.083(**)	-.080(**)	0.002	-.088(**)
TRSUTL	.046(**)	0.012	-.044(**)	-.081(**)
CONST	-.071(**)	-0.019	-.056(**)	.040(**)
TRADE	-0.029	-.063(**)	-.099(**)	-0.009
ADMWST	.056(**)	.048(**)	-.032(*)	-.060(**)
LEISUR	-0.017	-0.013	.031(*)	.092(**)
HHSERV	-0.001	-.041(**)	-0.012	-.137(**)
PUBADM	.053(**)	-.051(**)	.119(**)	-.048(**)
IL	-.068(**)	-.125(**)	-.071(**)	-.117(**)
IN	-.060(**)	-.110(**)	-.062(**)	-.102(**)
IA	-.063(**)	-.116(**)	-.066(**)	-.109(**)
KS	-.052(**)	-.096(**)	-.054(**)	-.090(**)
MI	-.066(**)	-.121(**)	-.068(**)	-.113(**)
MN	-.059(**)	-.108(**)	-.061(**)	-.101(**)
MO	-.062(**)	-.114(**)	-.065(**)	-.107(**)
NB	-.045(**)	-.083(**)	-.047(**)	-.078(**)
ND	1	-.066(**)	-.037(*)	-.061(**)
OH	-.066(**)	1	-.068(**)	-.113(**)
SD	-.037(*)	-.068(**)	1	-.064(**)
WI	-.061(**)	-.113(**)	-.064(**)	1

NOTE: ** Significant at *p*<0.01. * Significant at *p*<0.05.

APPENDIX

Pearson Correlation Matrix – Occupation Structure Model

	POP	METADJ	MINRTY	DISABL	SHHFAM	HSAA	BAPLUS	UNEMP
POP	1	.236(**)	-.045(**)	-.045(**)	.066(**)	-.135(**)	.130(**)	-.045(**)
METADJ	.236(**)	1	-.098(**)	0.012	0.017	.111(**)	-.079(**)	-.092(**)
MINRTY	-.045(**)	-.098(**)	1	.129(**)	.600(**)	-.255(**)	-0.018	.446(**)
DISABL	-.045(**)	0.012	.129(**)	1	.310(**)	-0.023	-.391(**)	.215(**)
SHHFAM	.066(**)	0.017	.600(**)	.310(**)	1	-.112(**)	-.189(**)	.454(**)
HSAA	-.135(**)	.111(**)	-.255(**)	-0.023	-.112(**)	1	-.545(**)	-.221(**)
BAPLUS	.130(**)	-.079(**)	-0.018	-.391(**)	-.189(**)	-.545(**)	1	-.078(**)
UNEMP	-.045(**)	-.092(**)	.446(**)	.215(**)	.454(**)	-.221(**)	-.078(**)	1
POV90	-.178(**)	-.199(**)	.486(**)	.238(**)	.411(**)	-.312(**)	-.104(**)	.566(**)
FARMER	-.369(**)	-.185(**)	-.091(**)	-.157(**)	-.337(**)	.189(**)	-.120(**)	-.240(**)
AGRFOR	-.301(**)	-.188(**)	-0.021	-.070(**)	-.232(**)	.117(**)	-.123(**)	-.132(**)
PRFBUS	.156(**)	-.032(*)	.099(**)	-.315(**)	-.047(**)	-.400(**)	.761(**)	-0.009
ARTENT	.139(**)	-0.002	0.000	-.169(**)	-0.028	-.270(**)	.444(**)	.105(**)
HEALTH	.065(**)	-.035(*)	-.112(**)	-.142(**)	-.097(**)	-.103(**)	.256(**)	-.069(**)
CONEXT	-.055(**)	.038(*)	-.082(**)	.182(**)	-.050(**)	.184(**)	-.327(**)	.070(**)
MAINRP	-.032(*)	0.028	-.128(**)	.046(**)	-.122(**)	.255(**)	-.249(**)	-.105(**)
PROD	.187(**)	.293(**)	-.096(**)	.313(**)	.153(**)	.176(**)	-.442(**)	-.080(**)
TRANS	0.002	.098(**)	-.078(**)	.315(**)	.091(**)	.234(**)	-.532(**)	-0.010
HLTPRT	-.057(**)	-.041(**)	.166(**)	.058(**)	.215(**)	-.053(**)	-.133(**)	.230(**)
FOOD	0.019	-.091(**)	.192(**)	.082(**)	.264(**)	-.192(**)	.081(**)	.375(**)
BLDGRD	-.056(**)	-.075(**)	.259(**)	.206(**)	.306(**)	-.081(**)	-.142(**)	.287(**)
PERSER	-.050(**)	-.104(**)	.200(**)	-.037(*)	.178(**)	-.049(**)	.044(**)	.191(**)
SALEOF	.187(**)	-0.023	0.016	-.171(**)	.057(**)	-.100(**)	.330(**)	.073(**)
IL	-.031(*)	.030(*)	0.005	-.038(*)	0.018	0.000	-.044(**)	.079(**)
IN	.085(**)	.178(**)	-.038(*)	.153(**)	0.023	0.022	-.101(**)	-.043(**)
IA	-.053(**)	-.037(*)	-.081(**)	-.104(**)	-.083(**)	.094(**)	.066(**)	-.112(**)
KS	-0.021	-.112(**)	.099(**)	-0.001	-0.025	-.029(*)	.103(**)	-.076(**)
MI	-0.024	-.086(**)	-0.025	.030(*)	.062(**)	.041(**)	0.008	.202(**)
MN	-0.020	-.059(**)	-0.029	-.075(**)	-.060(**)	0.009	.051(**)	-0.022
MO	.077(**)	-.083(**)	-0.003	.121(**)	.052(**)	-.197(**)	-.072(**)	0.024
NB	-.071(**)	-.141(**)	0.008	-.077(**)	-.062(**)	.059(**)	.046(**)	-.133(**)
ND	-.187(**)	-.102(**)	.070(**)	-.065(**)	-.041(**)	-.081(**)	.034(*)	0.007
OH	.159(**)	.255(**)	-.049(**)	.093(**)	.062(**)	.045(**)	-.092(**)	0.002
SD	-.107(**)	-.138(**)	.237(**)	-0.029	.104(**)	-.074(**)	.046(**)	.069(**)
WI	.062(**)	.152(**)	-.064(**)	-.062(**)	-.055(**)	.060(**)	0.015	-0.028

	POV90	FARMER	AGRFOR	PRFBUS	ARTENT	HEALTH	CONEXT	MAINRP
POP	-.178(**)	-.369(**)	-.301(**)	.156(**)	.139(**)	.065(**)	-.055(**)	-.032(*)
METADJ	-.199(**)	-.185(**)	-.188(**)	-.032(*)	-0.002	-.035(*)	.038(*)	0.028
MINRTY	.486(**)	-.091(**)	-0.021	.099(**)	0.000	-.112(**)	-.082(**)	-.128(**)
DISABL	.238(**)	-.157(**)	-.070(**)	-.315(**)	-.169(**)	-.142(**)	.182(**)	.046(**)
SHHFAM	.411(**)	-.337(**)	-.232(**)	-.047(**)	-0.028	-.097(**)	-.050(**)	-.122(**)
HSAA	-.312(**)	.189(**)	.117(**)	-.400(**)	-.270(**)	-.103(**)	.184(**)	.255(**)
BAPLUS	-.104(**)	-.120(**)	-.123(**)	.761(**)	.444(**)	.256(**)	-.327(**)	-.249(**)
UNEMP	.566(**)	-.240(**)	-.132(**)	-0.009	.105(**)	-.069(**)	.070(**)	-.105(**)
POV90	1	.057(**)	.102(**)	-.108(**)	.044(**)	-.183(**)	.055(**)	-.119(**)
FARMER	.057(**)	1	.689(**)	-.245(**)	-.200(**)	-.117(**)	-0.025	0.012
AGRFOR	.102(**)	.689(**)	1	-.245(**)	-.182(**)	-.154(**)	.034(*)	0.013
PRFBUS	-.108(**)	-.245(**)	-.245(**)	1	.326(**)	.240(**)	-.276(**)	-.283(**)
ARTENT	.044(**)	-.200(**)	-.182(**)	.326(**)	1	.040(**)	-.142(**)	-.170(**)
HEALTH	-.183(**)	-.117(**)	-.154(**)	.240(**)	.040(**)	1	-.096(**)	-.073(**)
CONEXT	.055(**)	-0.025	.034(*)	-.276(**)	-.142(**)	-.096(**)	1	.148(**)
MAINRP	-.119(**)	0.012	0.013	-.283(**)	-.170(**)	-.073(**)	.148(**)	1
PROD	-.170(**)	-.309(**)	-.258(**)	-.407(**)	-.179(**)	-.264(**)	-0.023	.053(**)
TRANS	0.018	-.061(**)	-0.015	-.511(**)	-.285(**)	-.196(**)	.095(**)	.117(**)
HLTPRT	.204(**)	-.138(**)	-.126(**)	-.106(**)	-.075(**)	.177(**)	-0.027	-.045(**)
FOOD	.372(**)	-.258(**)	-.195(**)	-0.023	.226(**)	-.125(**)	-.051(**)	-.168(**)
BLDGRD	.261(**)	-.163(**)	-.103(**)	-.136(**)	0.014	-.098(**)	.091(**)	-.035(*)
PERSER	.201(**)	-.104(**)	.039(**)	0.025	.077(**)	-.047(**)	-0.016	-.117(**)
SALEOF	-.074(**)	-.386(**)	-.384(**)	.298(**)	.226(**)	.120(**)	-.179(**)	-.159(**)
IL	0.012	-.089(**)	-.114(**)	-0.005	-0.023	.100(**)	-.039(**)	0.000
IN	-.136(**)	-.147(**)	-.145(**)	-.064(**)	-.040(**)	-.068(**)	0.021	.048(**)
IA	-.090(**)	.083(**)	0.001	0.024	0.027	-0.021	-.081(**)	-.046(**)
KS	-0.014	.075(**)	.078(**)	.052(**)	-0.007	0.016	0.009	.034(*)
MI	.043(**)	-.185(**)	-.101(**)	.033(*)	.039(**)	0.017	.094(**)	0.017
MN	-0.019	.048(**)	0.018	.062(**)	.053(**)	.031(*)	-0.017	-.038(*)
MO	.180(**)	-.040(**)	0.002	-.065(**)	-0.016	0.013	.116(**)	.040(**)
NB	-.036(*)	.216(**)	.247(**)	-.045(**)	-0.026	-0.007	-.048(**)	0.023
ND	.068(**)	.245(**)	.128(**)	0.021	-.054(**)	-0.014	-.034(*)	0.011
OH	-0.018	-.174(**)	-.161(**)	-.040(**)	-0.020	0.021	-0.009	0.012
SD	.205(**)	.263(**)	.194(**)	.064(**)	-0.024	-.042(**)	-.058(**)	-.082(**)
WI	-.111(**)	-0.025	.058(**)	-0.010	.056(**)	-.078(**)	0.001	-.037(*)

	PROD	TRANS	HLTPRT	FOOD	BLDGRD	PERSER	SALEOF	IL
POP	.187(**)	0.002	-.057(**)	0.019	-.056(**)	-.050(**)	.187(**)	-.031(*)
METADJ	.293(**)	.098(**)	-.041(**)	-.091(**)	-.075(**)	-.104(**)	-0.023	.030(*)
MINRTY	-.096(**)	-.078(**)	.166(**)	.192(**)	.259(**)	.200(**)	0.016	0.005
DISABL	.313(**)	.315(**)	.058(**)	.082(**)	.206(**)	-.037(*)	-.171(**)	-.038(*)
SHHFAM	.153(**)	.091(**)	.215(**)	.264(**)	.306(**)	.178(**)	.057(**)	0.018
HSAA	.176(**)	.234(**)	-.053(**)	-.192(**)	-.081(**)	-.049(**)	-.100(**)	0.000
BAPLUS	-.442(**)	-.532(**)	-.133(**)	.081(**)	-.142(**)	.044(**)	.330(**)	-.044(**)
UNEMP	-.080(**)	-0.010	.230(**)	.375(**)	.287(**)	.191(**)	.073(**)	.079(**)
POV90	-.170(**)	0.018	.204(**)	.372(**)	.261(**)	.201(**)	-.074(**)	0.012
FARMER	-.309(**)	-.061(**)	-.138(**)	-.258(**)	-.163(**)	-.104(**)	-.386(**)	-.089(**)
AGRFOR	-.258(**)	-0.015	-.126(**)	-.195(**)	-.103(**)	.039(**)	-.384(**)	-.114(**)
PRFBUS	-.407(**)	-.511(**)	-.106(**)	-0.023	-.136(**)	0.025	.298(**)	-0.005
ARTENT	-.179(**)	-.285(**)	-.075(**)	.226(**)	0.014	.077(**)	.226(**)	-0.023
HEALTH	-.264(**)	-.196(**)	.177(**)	-.125(**)	-.098(**)	-.047(**)	.120(**)	.100(**)
CONEXT	-0.023	.095(**)	-0.027	-.051(**)	.091(**)	-0.016	-.179(**)	-.039(**)
MAINRP	.053(**)	.117(**)	-.045(**)	-.168(**)	-.035(*)	-.117(**)	-.159(**)	0.000
PROD	1	.367(**)	-.154(**)	-.133(**)	-.065(**)	-.197(**)	-.312(**)	-.044(**)
TRANS	.367(**)	1	-0.028	-.099(**)	0.009	-.167(**)	-.281(**)	.091(**)
HLTPRT	-.154(**)	-0.028	1	.145(**)	.129(**)	.088(**)	-0.025	.130(**)
FOOD	-.133(**)	-.099(**)	.145(**)	1	.259(**)	.189(**)	.117(**)	.030(*)
BLDGRD	-.065(**)	0.009	.129(**)	.259(**)	1	.125(**)	-0.026	.058(**)
PERSER	-.197(**)	-.167(**)	.088(**)	.189(**)	.125(**)	1	.044(**)	0.005
SALEOF	-.312(**)	-.281(**)	-0.025	.117(**)	-0.026	.044(**)	1	.067(**)
IL	-.044(**)	.091(**)	.130(**)	.030(*)	.058(**)	0.005	.067(**)	1
IN	.315(**)	.087(**)	-.108(**)	-.061(**)	-0.017	-.097(**)	-.065(**)	-.114(**)
IA	-0.021	0.020	-.050(**)	-.063(**)	-.086(**)	.049(**)	0.024	-.121(**)
KS	-.132(**)	-.064(**)	0.002	-0.014	.033(*)	0.024	-0.001	-.100(**)
MI	0.029	-.154(**)	.049(**)	.120(**)	.080(**)	.086(**)	.063(**)	-.125(**)
MN	-.076(**)	-.054(**)	-.033(*)	-0.017	0.008	.045(**)	0.012	-.112(**)
MO	-0.015	.072(**)	.046(**)	-.032(*)	0.020	0.007	0.011	-.119(**)
NB	-.146(**)	-.061(**)	-.060(**)	-0.025	-.036(*)	0.017	-0.005	-.086(**)
ND	-.223(**)	-.096(**)	0.025	0.000	-0.027	.124(**)	-0.017	-.068(**)
OH	.218(**)	.203(**)	0.006	0.006	-.053(**)	-.144(**)	-.052(**)	-.125(**)
SD	-.210(**)	-.158(**)	-0.012	0.023	0.022	.052(**)	-0.027	-.071(**)
WI	.091(**)	-0.012	-0.022	0.024	-0.014	-.095(**)	-.036(*)	-.117(**)

	IN	IA	KS	MI	MN	MO	NB	ND
POP	.085(**)	-.053(**)	-0.021	-0.024	-0.020	.077(**)	-.071(**)	-.187(**)
METADJ	.178(**)	-.037(*)	-.112(**)	-.086(**)	-.059(**)	-.083(**)	-.141(**)	-.102(**)
MINRTY	-.038(*)	-.081(**)	.099(**)	-0.025	-0.029	-0.003	0.008	.070(**)
DISABL	.153(**)	-.104(**)	-0.001	.030(*)	-.075(**)	.121(**)	-.077(**)	-.065(**)
SHHFAM	0.023	-.083(**)	-0.025	.062(**)	-.060(**)	.052(**)	-.062(**)	-.041(**)
HSAA	0.022	.094(**)	-.029(*)	.041(**)	0.009	-.197(**)	.059(**)	-.081(**)
BAPLUS	-.101(**)	.066(**)	.103(**)	0.008	.051(**)	-.072(**)	.046(**)	.034(*)
UNEMP	-.043(**)	-.112(**)	-.076(**)	.202(**)	-0.022	0.024	-.133(**)	0.007
POV90	-.136(**)	-.090(**)	-0.014	.043(**)	-0.019	.180(**)	-.036(*)	.068(**)
FARMER	-.147(**)	.083(**)	.075(**)	-.185(**)	.048(**)	-.040(**)	.216(**)	.245(**)
AGRFOR	-.145(**)	0.001	.078(**)	-.101(**)	0.018	0.002	.247(**)	.128(**)
PRFBUS	-.064(**)	0.024	.052(**)	.033(*)	.062(**)	-.065(**)	-.045(**)	0.021
ARTENT	-.040(**)	0.027	-0.007	.039(**)	.053(**)	-0.016	-0.026	-.054(**)
HEALTH	-.068(**)	-0.021	0.016	0.017	.031(*)	0.013	-0.007	-0.014
CONEXT	0.021	-.081(**)	0.009	.094(**)	-0.017	.116(**)	-.048(**)	-.034(*)
MAINRP	.048(**)	-.046(**)	.034(*)	0.017	-.038(*)	.040(**)	0.023	0.011
PROD	.315(**)	-0.021	-.132(**)	0.029	-.076(**)	-0.015	-.146(**)	-.223(**)
TRANS	.087(**)	0.020	-.064(**)	-.154(**)	-.054(**)	.072(**)	-.061(**)	-.096(**)
HLTPRT	-.108(**)	-.050(**)	0.002	.049(**)	-.033(*)	.046(**)	-.060(**)	0.025
FOOD	-.061(**)	-.063(**)	-0.014	.120(**)	-0.017	-.032(*)	-0.025	0.000
BLDGRD	-0.017	-.086(**)	.033(*)	.080(**)	0.008	0.020	-.036(*)	-0.027
PERSER	-.097(**)	.049(**)	0.024	.086(**)	.045(**)	0.007	0.017	.124(**)
SALEOF	-.065(**)	0.024	-0.001	.063(**)	0.012	0.011	-0.005	-0.017
IL	-.114(**)	-.121(**)	-.100(**)	-.125(**)	-.112(**)	-.119(**)	-.086(**)	-.068(**)
IN	1	-.106(**)	-.087(**)	-.110(**)	-.098(**)	-.104(**)	-.076(**)	-.060(**)
IA	-.106(**)	1	-.093(**)	-.116(**)	-.104(**)	-.110(**)	-.080(**)	-.063(**)
KS	-.087(**)	-.093(**)	1	-.096(**)	-.086(**)	-.091(**)	-.066(**)	-.052(**)
MI	-.110(**)	-.116(**)	-.096(**)	1	-.108(**)	-.114(**)	-.083(**)	-.066(**)
MN	-.098(**)	-.104(**)	-.086(**)	-.108(**)	1	-.102(**)	-.075(**)	-.059(**)
MO	-.104(**)	-.110(**)	-.091(**)	-.114(**)	-.102(**)	1	-.079(**)	-.062(**)
NB	-.076(**)	-.080(**)	-.066(**)	-.083(**)	-.075(**)	-.079(**)	1	-.045(**)
ND	-.060(**)	-.063(**)	-.052(**)	-.066(**)	-.059(**)	-.062(**)	-.045(**)	1
OH	-.110(**)	-.116(**)	-.096(**)	-.121(**)	-.108(**)	-.114(**)	-.083(**)	-.066(**)
SD	-.062(**)	-.066(**)	-.054(**)	-.068(**)	-.061(**)	-.065(**)	-.047(**)	-.037(*)
WI	-.102(**)	-.109(**)	-.090(**)	-.113(**)	-.101(**)	-.107(**)	-.078(**)	-.061(**)

	OH	SD	WI
POP	.159(**)	-.107(**)	.062(**)
METADJ	.255(**)	-.138(**)	.152(**)
MINRTY	-.049(**)	.237(**)	-.064(**)
DISABL	.093(**)	-0.029	-.062(**)
SHHFAM	.062(**)	.104(**)	-.055(**)
HSAA	.045(**)	-.074(**)	.060(**)
BAPLUS	-.092(**)	.046(**)	0.015
UNEMP	0.002	.069(**)	-0.028
POV90	-0.018	.205(**)	-.111(**)
FARMER	-.174(**)	.263(**)	-0.025
AGRFOR	-.161(**)	.194(**)	.058(**)
PRFBUS	-.040(**)	.064(**)	-0.010
ARTENT	-0.020	-0.024	.056(**)
HEALTH	0.021	-.042(**)	-.078(**)
CONEXT	-0.009	-.058(**)	0.001
MAINRP	0.012	-.082(**)	-.037(*)
PROD	.218(**)	-.210(**)	.091(**)
TRANS	.203(**)	-.158(**)	-0.012
HLTPRT	0.006	-0.012	-0.022
FOOD	0.006	0.023	0.024
BLDGRD	-.053(**)	0.022	-0.014
PERSER	-.144(**)	.052(**)	-.095(**)
SALEOF	-.052(**)	-0.027	-.036(*)
IL	-.125(**)	-.071(**)	-.117(**)
IN	-.110(**)	-.062(**)	-.102(**)
IA	-.116(**)	-.066(**)	-.109(**)
KS	-.096(**)	-.054(**)	-.090(**)
MI	-.121(**)	-.068(**)	-.113(**)
MN	-.108(**)	-.061(**)	-.101(**)
MO	-.114(**)	-.065(**)	-.107(**)
NB	-.083(**)	-.047(**)	-.078(**)
ND	-.066(**)	-.037(*)	-.061(**)
OH	1	-.068(**)	-.113(**)
SD	-.068(**)	1	-.064(**)
WI	-.113(**)	-.064(**)	1

NOTE: ** Significant at $p<0.01$. * Significant at $p<0.05$.

APPENDIX

MANOVA Post-Hoc Tests – Scheffe and LSD

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
POV	Scheffee	1	2	-8.5952051(*)	0.209
			3	-1.7661402(*)	0.189
			4	-8.9728907(*)	0.195
			5	-26.1905170(*)	0.363
			6	-3.7499315(*)	0.192
			7	-52.8443118(*)	0.663
		2	1	8.5952051(*)	0.209
			3	6.8290649(*)	0.181
			4	(0.378)	0.187
			5	-17.5953119(*)	0.359
			6	4.8452736(*)	0.184
			7	-44.2491067(*)	0.660
		3	1	1.7661402(*)	0.189
			2	-6.8290649(*)	0.181
			4	-7.2067505(*)	0.165
			5	-24.4243769(*)	0.348
			6	-1.9837913(*)	0.162
			7	-51.0781716(*)	0.654
		4	1	8.9728907(*)	0.195
			2	0.378	0.187
			3	7.2067505(*)	0.165
			5	-17.2176264(*)	0.351
			6	5.2229592(*)	0.168
			7	-43.8714211(*)	0.656
		5	1	26.1905170(*)	0.363
			2	17.5953119(*)	0.359
			3	24.4243769(*)	0.348
			4	17.2176264(*)	0.351
			6	22.4405856(*)	0.350
			7	-26.6537948(*)	0.724
		6	1	3.7499315(*)	0.192
			2	-4.8452736(*)	0.184
			3	1.9837913(*)	0.162
			4	-5.2229592(*)	0.168
			5	-22.4405856(*)	0.350
			7	-49.0943803(*)	0.655
		7	1	52.8443118(*)	0.663
			2	44.2491067(*)	0.660
			3	51.0781716(*)	0.654
			4	43.8714211(*)	0.656
			5	26.6537948(*)	0.724
			6	49.0943803(*)	0.655

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
	LSD	1	2	-8.5952051(*)	0.209
			3	-1.7661402(*)	0.189
			4	-8.9728907(*)	0.195
			5	-26.1905170(*)	0.363
			6	-3.7499315(*)	0.192
			7	-52.8443118(*)	0.663
		2	1	8.5952051(*)	0.209
			3	6.8290649(*)	0.181
			4	-.3776855(*)	0.187
			5	-17.5953119(*)	0.359
			6	4.8452736(*)	0.184
			7	-44.2491067(*)	0.660
		3	1	1.7661402(*)	0.189
			2	-6.8290649(*)	0.181
			4	-7.2067505(*)	0.165
			5	-24.4243769(*)	0.348
			6	-1.9837913(*)	0.162
			7	-51.0781716(*)	0.654
		4	1	8.9728907(*)	0.195
			2	.3776855(*)	0.187
			3	7.2067505(*)	0.165
			5	-17.2176264(*)	0.351
			6	5.2229592(*)	0.168
			7	-43.8714211(*)	0.656
		5	1	26.1905170(*)	0.363
			2	17.5953119(*)	0.359
			3	24.4243769(*)	0.348
			4	17.2176264(*)	0.351
			6	22.4405856(*)	0.350
			7	-26.6537948(*)	0.724
		6	1	3.7499315(*)	0.192
			2	-4.8452736(*)	0.184
			3	1.9837913(*)	0.162
			4	-5.2229592(*)	0.168
			5	-22.4405856(*)	0.350
			7	-49.0943803(*)	0.655
		7	1	52.8443118(*)	0.663
			2	44.2491067(*)	0.660
			3	51.0781716(*)	0.654
			4	43.8714211(*)	0.656
			5	26.6537948(*)	0.724
			6	49.0943803(*)	0.655
NPOV	Scheffe	1	2	-13.2963877(*)	0.208
			3	-1.6672782(*)	0.188
			4	-8.0600978(*)	0.194

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
			5	-11.2107019(*)	0.362
			6	-7.8248220(*)	0.191
			7	-5.9620656(*)	0.659
		2	1	13.2963877(*)	0.208
			3	11.6291095(*)	0.180
			4	5.2362899(*)	0.186
			5	2.0856857(*)	0.357
			6	5.4715656(*)	0.183
			7	7.3343221(*)	0.657
		3	1	1.6672782(*)	0.188
			2	-11.6291095(*)	0.180
			4	-6.3928196(*)	0.164
			5	-9.5434237(*)	0.347
			6	-6.1575438(*)	0.161
			7	-4.2947874(*)	0.651
		4	1	8.0600978(*)	0.194
			2	-5.2362899(*)	0.186
			3	6.3928196(*)	0.164
			5	-3.1506041(*)	0.350
			6	0.235	0.168
			7	2.098	0.653
		5	1	11.2107019(*)	0.362
			2	-2.0856857(*)	0.357
			3	9.5434237(*)	0.347
			4	3.1506041(*)	0.350
			6	3.3858799(*)	0.348
			7	5.2486363(*)	0.721
		6	1	7.8248220(*)	0.191
			2	-5.4715656(*)	0.183
			3	6.1575438(*)	0.161
			4	(0.235)	0.168
			5	-3.3858799(*)	0.348
			7	1.863	0.652
		7	1	5.9620656(*)	0.659
			2	-7.3343221(*)	0.657
			3	4.2947874(*)	0.651
			4	(2.098)	0.653
			5	-5.2486363(*)	0.721
			6	(1.863)	0.652
	LSD	1	2	-13.2963877(*)	0.208
			3	-1.6672782(*)	0.188
			4	-8.0600978(*)	0.194
			5	-11.2107019(*)	0.362
			6	-7.8248220(*)	0.191
			7	-5.9620656(*)	0.659

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
		2	1	13.2963877(*)	0.208
			3	11.6291095(*)	0.180
			4	5.2362899(*)	0.186
			5	2.0856857(*)	0.357
			6	5.4715656(*)	0.183
			7	7.3343221(*)	0.657
		3	1	1.6672782(*)	0.188
			2	-11.6291095(*)	0.180
			4	-6.3928196(*)	0.164
			5	-9.5434237(*)	0.347
			6	-6.1575438(*)	0.161
			7	-4.2947874(*)	0.651
		4	1	8.0600978(*)	0.194
			2	-5.2362899(*)	0.186
			3	6.3928196(*)	0.164
			5	-3.1506041(*)	0.350
			6	0.235	0.168
			7	2.0980322(*)	0.653
		5	1	11.2107019(*)	0.362
			2	-2.0856857(*)	0.357
			3	9.5434237(*)	0.347
			4	3.1506041(*)	0.350
			6	3.3858799(*)	0.348
			7	5.2486363(*)	0.721
		6	1	7.8248220(*)	0.191
			2	-5.4715656(*)	0.183
			3	6.1575438(*)	0.161
			4	(0.235)	0.168
			5	-3.3858799(*)	0.348
			7	1.8627565(*)	0.652
		7	1	5.9620656(*)	0.659
			2	-7.3343221(*)	0.657
			3	4.2947874(*)	0.651
			4	-2.0980322(*)	0.653
			5	-5.2486363(*)	0.721
			6	-1.8627565(*)	0.652
DPOV	Scheffe	1	2	5.6924703(*)	0.214
			3	.7320970(*)	0.194
			4	-1.7800830(*)	0.200
			5	0.573	0.373
			6	2.8799038(*)	0.197
			7	-10.3518915(*)	0.679
		2	1	-5.6924703(*)	0.214
			3	-4.9603733(*)	0.186
			4	-7.4725533(*)	0.192

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
			5	-5.1193168(*)	0.368
			6	-2.8125665(*)	0.189
			7	-16.0443618(*)	0.677
		3	1	-.7320970(*)	0.194
			2	4.9603733(*)	0.186
			4	-2.5121800(*)	0.169
			5	(0.159)	0.357
			6	2.1478068(*)	0.166
			7	-11.0839885(*)	0.671
		4	1	1.7800830(*)	0.200
			2	7.4725533(*)	0.192
			3	2.5121800(*)	0.169
			5	2.3532365(*)	0.360
			6	4.6599868(*)	0.173
			7	-8.5718085(*)	0.673
		5	1	(0.573)	0.373
			2	5.1193168(*)	0.368
			3	0.159	0.357
			4	-2.3532365(*)	0.360
			6	2.3067502(*)	0.359
			7	-10.9250451(*)	0.743
		6	1	-2.8799038(*)	0.197
			2	2.8125665(*)	0.189
			3	-2.1478068(*)	0.166
			4	-4.6599868(*)	0.173
			5	-2.3067502(*)	0.359
			7	-13.2317953(*)	0.672
		7	1	10.3518915(*)	0.679
			2	16.0443618(*)	0.677
			3	11.0839885(*)	0.671
			4	8.5718085(*)	0.673
			5	10.9250451(*)	0.743
			6	13.2317953(*)	0.672
	LSD	1	2	5.6924703(*)	0.214
			3	.7320970(*)	0.194
			4	-1.7800830(*)	0.200
			5	0.573	0.373
			6	2.8799038(*)	0.197
			7	-10.3518915(*)	0.679
		2	1	-5.6924703(*)	0.214
			3	-4.9603733(*)	0.186
			4	-7.4725533(*)	0.192
			5	-5.1193168(*)	0.368
			6	-2.8125665(*)	0.189
			7	-16.0443618(*)	0.677

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
		3	1	-.7320970(*)	0.194
			2	4.9603733(*)	0.186
			4	-2.5121800(*)	0.169
			5	(0.159)	0.357
			6	2.1478068(*)	0.166
			7	-11.0839885(*)	0.671
		4	1	1.7800830(*)	0.200
			2	7.4725533(*)	0.192
			3	2.5121800(*)	0.169
			5	2.3532365(*)	0.360
			6	4.6599868(*)	0.173
			7	-8.5718085(*)	0.673
		5	1	(0.573)	0.373
			2	5.1193168(*)	0.368
			3	0.159	0.357
			4	-2.3532365(*)	0.360
			6	2.3067502(*)	0.359
			7	-10.9250451(*)	0.743
		6	1	-2.8799038(*)	0.197
			2	2.8125665(*)	0.189
			3	-2.1478068(*)	0.166
			4	-4.6599868(*)	0.173
			5	-2.3067502(*)	0.359
			7	-13.2317953(*)	0.672
		7	1	10.3518915(*)	0.679
			2	16.0443618(*)	0.677
			3	11.0839885(*)	0.671
			4	8.5718085(*)	0.673
			5	10.9250451(*)	0.743
			6	13.2317953(*)	0.672
DNPOV	Scheffe	1	2	-2.6238043(*)	0.241
			3	6.7400426(*)	0.218
			4	1.9198162(*)	0.225
			5	-2.1717264(*)	0.419
			6	2.6373149(*)	0.222
			7	(0.067)	0.764
		2	1	2.6238043(*)	0.241
			3	9.3638469(*)	0.209
			4	4.5436205(*)	0.216
			5	0.452	0.414
			6	5.2611192(*)	0.213
			7	2.557	0.761
		3	1	-6.7400426(*)	0.218
			2	-9.3638469(*)	0.209
			4	-4.8202263(*)	0.190

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
			5	-8.9117690(*)	0.401
			6	-4.1027276(*)	0.187
			7	-6.8071561(*)	0.754
		4	1	-1.9198162(*)	0.225
			2	-4.5436205(*)	0.216
			3	4.8202263(*)	0.190
			5	-4.0915427(*)	0.405
			6	.7174987(*)	0.194
			7	(1.987)	0.756
		5	1	2.1717264(*)	0.419
			2	(0.452)	0.414
			3	8.9117690(*)	0.401
			4	4.0915427(*)	0.405
			6	4.8090414(*)	0.403
			7	2.105	0.835
		6	1	-2.6373149(*)	0.222
			2	-5.2611192(*)	0.213
			3	4.1027276(*)	0.187
			4	-.7174987(*)	0.194
			5	-4.8090414(*)	0.403
			7	-2.7044285(*)	0.755
		7	1	0.067	0.764
			2	(2.557)	0.761
			3	6.8071561(*)	0.754
			4	1.987	0.756
			5	(2.105)	0.835
			6	2.7044285(*)	0.755
	LSD	1	2	-2.6238043(*)	0.241
			3	6.7400426(*)	0.218
			4	1.9198162(*)	0.225
			5	-2.1717264(*)	0.419
			6	2.6373149(*)	0.222
			7	(0.067)	0.764
		2	1	2.6238043(*)	0.241
			3	9.3638469(*)	0.209
			4	4.5436205(*)	0.216
			5	0.452	0.414
			6	5.2611192(*)	0.213
			7	2.5566908(*)	0.761
		3	1	-6.7400426(*)	0.218
			2	-9.3638469(*)	0.209
			4	-4.8202263(*)	0.190
			5	-8.9117690(*)	0.401
			6	-4.1027276(*)	0.187
			7	-6.8071561(*)	0.754

VARIABLE	TEST	CLUSTER I	CLUSTER J	MEAN DIFFERENCE	STD ERROR
		4	1	-1.9198162(*)	0.225
			2	-4.5436205(*)	0.216
			3	4.8202263(*)	0.190
			5	-4.0915427(*)	0.405
			6	.7174987(*)	0.194
			7	-1.9869298(*)	0.756
		5	1	2.1717264(*)	0.419
			2	(0.452)	0.414
			3	8.9117690(*)	0.401
			4	4.0915427(*)	0.405
			6	4.8090414(*)	0.403
			7	2.1046129(*)	0.835
		6	1	-2.6373149(*)	0.222
			2	-5.2611192(*)	0.213
			3	4.1027276(*)	0.187
			4	-.7174987(*)	0.194
			5	-4.8090414(*)	0.403
			7	-2.7044285(*)	0.755
		7	1	0.067	0.764
			2	-2.5566908(*)	0.761
			3	6.8071561(*)	0.754
			4	1.9869298(*)	0.756
			5	-2.1046129(*)	0.835
			6	2.7044285(*)	0.755

NOTE: * Significant at $p<0.05$.

REFERENCES

Adamchak, D.J., L.E. Bloomquist, K. Bausman and R. Qureshi. 1999. "Consequences of Population Change for Retail/Wholesale Sector Employment in the Nonmetropolitan Great Plains: 1950-1996." *Rural Sociology* 64: 92-112.

Agiletta, M. 1979. *A Theory of Capitalist Regulation*. London UK: Verso Press.

Albrecht, D.E. 1998. "The Industrial Transformation of Farm Communities: Implications for Family Structure and Socioeconomic Conditions." *Rural Sociology* 63: 51-64.

Albrecht, D.E., C.M. Albrecht and S.L. Albrecht. 2000. "Poverty in Nonmetropolitan America: Impacts of Industrial, Employment and Family Structure Variables." *Rural Sociology* 65: 87-103.

Aldenderfer, M.S. and R.K. Blashfield. 1984. *Cluster Analysis*. Sage University Paper Series: Quantitative Applications in the Social Sciences No. 07-044. Beverly Hills CA: Sage Publications.

Antonio, R.J. and A. Bonanno. 1996. "Post-Fordism I the United States: The Poverty of Market Centered Democracy." *Current Perspectives in Social Theory* 16: 3-32.

Barnes, D.A. and A. Blevins. 1993. “Farm Structure and the Economic Well Being of Nonmetropolitan Counties.” *Rural Sociology*: 333-346.

Bartik, T.J. 1985. “Business Location Decisions in the United States: Estimates of the Effects of Unionization, Taxes and Other Effects of Characteristics of States.” *Journal of Economics and Business Statistics* 3: 14-22.

Bartik, T. and R. Eberts. 1999. "Examining the Effect of Industry Trends and Structure on Welfare Caseloads." In *Economic Conditions and Welfare Reform*, edited by S. Danziger. Kalamazoo MI: W.E. Upjohn Institute for Employment Research.

Beale, C.L. and K.M. Johnson. 1998. "The Identification of Recreational Counties in Nonmetropolitan Areas of the USA." *Population and Research Policy Review* 17: 37-53.

Beck, U. 1992. *Risk Society: Towards a New Modernity*. London UK: Sage Publications.

Beck, U. A. Giddens and S. Lash. 1994. *Reflexive Modernization: Politics, Tradition and Aesthetics in the Modern Social World*. Stanford CA: Stanford University Press.

Beckley, T.M. and N.T. Krogman. 2002. "Social Consequences of Employee/Management Buyouts: Two Canadian Examples From the Forest Sector." *Rural Sociology* 67: 183-207.

Beeghley, L. 1988. "Individual and Structural Explanations of Poverty." *Population Research and Policy Review* 7: 201-222.

Beeghley, L. 1983. *Living Poorly in America*. New York NY: Praeger Press.

Bell, D. 1979. *The Cultural Contradictions of Capitalism*. London UK: Heinemann.

Bell, D. 1976. *The Coming of Post-Industrial Society*. New York NY: Basic Books.

Bell, D. 1960. *The End of Ideology*. New York NY: The Free Press.

Bender, L.D., B. Green, T.A. Hady, J.A. Kuehn, M.K. Nelson, L.B. Perkinson and P. Ross. 1985. *The Diverse Social and Economic Structure of Nonmetropolitan America*. RD-49, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Bergman, E.M. 1998. "Industrial Trade Clusters in Action: Seeing Regional Economies as a Whole." In *Clusters and Regional Specialisation*, edited by M. Steiner. London UK: Pion Limited.

Bernstein, J., H. Boushey, E.C. McNichol and R. Zahradnik. 2002. *Pulling Apart: A State by State Analysis of Income Trends*. Washington DC: Economic Policy Institute.

Besser, T.L. 2003. “New Economy Businesses in Rural, Urban, and Metropolitan Locations.” *Rural Sociology* 68: 531-553.

Blank, B. 2004. *Poverty, Policy and Place: How Poverty and Policies to Alleviate Poverty Are Shaped by Local Characteristics.* RPRC 04-02, RUPRI Rural Poverty Research Center. Columbia MO: Rural Policy Research Institute.

Blashfield, R.K. and M.S. Aldenderfer. 1978. “The Literature on Cluster Analysis.” *Multivariate Behavioral Research* 13: 271-295.

Bloomquist, L.E. 1988. "Performance in the Rural Manufacturing Sector." In *Rural Economic Development in the 1980s: Prospects for the Future*, edited by D.L. Brown et al. RD-69, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Bloomquist, L.E., C. Gringeri, D. Tomaskovic-Devey and C. Truelove. 1993. "Local Labor Market Characteristics and the Occupational Concentration of Different Socio-Economic Groups." *Rural Sociology* 55: 199-213.

Bluestone, B. and B. Harrison. 2000. *Growing Prosperity: The Battle for Growth with Equity in the 21st Century*. Boston MA: Houghton Mifflin.

Bonanno, A. and D. Constance. 1996. *Caught in the Net: The Global Tuna Industry, Environmentalism and the State*. Lawrence KS: University Press of Kansas.

Bourdieu, P. 1984. *Distinction: A Social Critique of the Judgment of Taste*. Cambridge MA: Harvard University Press.

Borjas, G.J. and V.A. Ramey. 1994. "Rising Wage Inequality in the United States - Causes and Consequences: Time Series Evidence on the Sources of Trends in Wage Inequality." *American Economic Review* 84: 10-16.

Brown, D.L. and M.A. Lee. 1999. "Persisting Inequality Between Metropolitan and Nonmetropolitan America: Implications for Theory and Practice." In *A Nation Divided: Diversity, Inequality and Community in American Society*, edited by P. Moen, D. Dempster-McClain and H.A. Walker. Ithaca NY: Cornell University Press.

Brown, B.B., X. Xu and J.F. Toth. 1988. "Lifestyle Options and Economic Strategies: Subsistence Activities in the Mississippi Delta." *Rural Sociology* 63: 599-623.

Busch, L., W.B. Lacy, J. Burkhardt and L. Lacy. 1991. *Plants, Power and Profit*. Oxford UK: Blackwell Press.

Buttel, F.H., M. Lancelle and D.R. Lee. 1988. "Farm Structure and Rural Communities in the Northeast." In *Agriculture and Community Change in the U.S.: The Congressional Research Reports*, edited by L.E. Swanson. Boulder CO: Westview Press.

Buttel, F.H. and H. Newby. 1980. *The Rural Sociology of Advanced Societies*. Montclair NJ: Allenheld Osmun.

Carlino, G.R. and E.S. Mills. 1987. “The Determinants of County Growth.” *Journal of Regional Science* 27: 39-54.

Carlino, G.R. and R. Voight. 1992. “Accounting for Differences in Aggregate State Productivity.” *Regional Science and Urban Economics* 22: 597-617.

Chevan, A. and R. Stokes. 2000. "Growth in Family Income Inequality, 1970-1990: Industrial Restructuring and Demographic Change." *Demography* 36: 365-380.

Cook, P.J. and K.L. Mizer. 1994. *The Revised ERS County Typology: An Overview*. RDRP 89, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Cotter, D.A. 2002. "Poor People in Poor Places: Local Opportunity Structures and Household Poverty." *Rural Sociology* 67: 534-555.

Crandall, M.S. and B.A. Weber. 2004. “Local Social and Economic Conditions, Spatial Concentrations of Poverty, and Poverty Dynamics.” *American Journal of Agricultural Economics* 86: 1276-1281.

Cromartie, J.B. and M. Nord. 1996. *Migration and Economic Restructuring in Nonmetropolitan Areas, 1989-94*. AGES-9615, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Davis, E.E., L.S. Connolly and B.A. Weber. 2003. “Local Labor Market Conditions and the Jobless Poor: How Much Does Local Job Growth Help in Rural Areas?” *Journal of Agricultural and Resource Economics* 28: 503-518.

Dore, R. 1983. “Goodwill and the Spirit of Capitalism.” *British Journal of Sociology* 34: 459-482.

Duncan, C.M. 1999. *Worlds Apart: Why Poverty Persists in Rural America*. New Haven CT: Yale University Press.

Duncan, G. and J. Brooks-Gunn. 1997. *The Consequences of Growing Up Poor*. New York NY: Russell Sage Foundation.

Drabenstott, M. and T. Smith. 1996. *Economic Forces Shaping the Rural Heartland*. Kansas City MO: Federal Reserve Bank of Kansas City.

Durkheim, E. 1893. [1984]. *The Division of Labor in Society*. New York NY: The Free Press.

Edwards, R. 1979. *Contested Terrain: The Transformation of the Workplace in the Twentieth Century*. New York NY: Basic Books.

Eggertsson, T. 1990. *Economic Behavior and Institutions*. Cambridge UK: Cambridge University Press.

Ellwood, D. 2000. "Anti-Poverty Policy for Families in the Next Century." *The Journal of Economic Perspectives* 14: 187-198.

Everitt, B. 1980. *Cluster Analysis*. New York NY: Halsted Press.

Feser, E.J. 1998. "Old and New Theories of Industry Clusters." In *Clusters and Regional Specialisation*, edited by M. Steiner. London UK: Pion Limited.

Findes J. and L. Jensen. 1998. "Employment Opportunities in Rural Areas: Implications for Poverty in a Changing Policy Environment." *American Journal of Agricultural Economics* 80: 1000-1008.

Fitchen, J.M. 1995. "Spatial Redistribution of Poverty Through Migration of Poor People to Depressed Rural Communities." *Rural Sociology* 60:181-201.

Fitchen, J.M. 1981. *Poverty in Rural America: A Case Study*. Boulder CO: Westview Press.

Flora, C.B. and J.L. Flora. 1993. “Entrepreneurial Social Infrastructure: A Necessary Ingredient.” *Annals, AAPS* 529: 48-58.

Flora, J.L., G.P. Green, E.A. Gale, F.E. Schmidt and C.B. Flora. 1992. “Self-Development: A Viable Rural Development Option?” *Policy Studies Journal* 20: 276-288.

Fox, W.F. and M.N. Murray. 1990. “Local Public Policies and Interregional Business Development.” *Southern Economic Journal* 57:413-427.

Friedland, W.H., L. Busch, F.H. Buttel and A. Rudy. 1991. *Towards a New Political Economy of Agriculture*. Boulder CO: Westview Press.

Friedmann, H. and P. McMichael. 1989. "Agriculture and the State System." *Sociologia Ruralis* 29: 93-117.

Fulton, J.A., G.V. Fuguitt and R.M. Gibson. 1997. "Recent Changes in Metropolitan - Non Metropolitan Migration Streams." *Rural Sociology* 62: 363-384.

Galston, W.A. and H.J. Baehler. 1995. *Rural Development in the United States: Connecting Theory, Practice and Probabilities*. Washington DC: Island Press.

Garkovich, L. J. Bokemeier and B. Foote. 1995. *Harvest of Hope: Family Farming / Farming Families*. Lexington KY: University of Kentucky Press.

Giddens, A. 2000. *How Globalization is Reshaping Our Lives*. New York NY: Routledge.

Giddens, A. 1990. *The Consequences of Modernity*. Stanford CA: Stanford University Press.

Giddens, A. 1984. *The Constitution of Society*. Cambridge UK: Polity Press.

Gilens, M. 1999. *Why American Hate Welfare: Race, Media and the Politics of Anti-Poverty Policy*. Chicago IL: University of Chicago Press.

Gilles, J.L. and M. Dalecki. 1988. "Rural Well-Being and Agricultural Change in Two Farming Regions." *Rural Sociology* 53: 40-55.

Glickman, N.J. 2000. "Prosperity and Inequality Among America's Cities and Regions." In *Back to Shared Prosperity*, edited by R. Marshall. Armonk NY: Sharpe Press.

Goe, W.R. 2002. "Factors Associated with the Development of Nonmetropolitan Growth Nodes in Producer Service Industries, 1980-1990." *Rural Sociology* 67: 416-441.

Goldschmidt, W. 1978. *As You Sow: Three Studies in the Social Consequences of Agribusiness*. Monclair CA: Allanheld, Osmun and Company.

Gordon, D., R. Edwards and M. Reich. 1982. *Segmented Work, Divided Workers: The Historical Transformation of Labor in the United States*. Cambridge UK: Cambridge University Press.

Green, G.P. 1985. "Large Scale Farming and the Quality of Life in Rural Communities: Further Specification of the Goldschmidt Hypothesis." *Rural Sociology* 50: 262-274.

Green, G.P., J.L. Flora, C. Flora and F.E. Schmidt. 1990. "Local Self-Development Strategies: National Survey Results." *Journal of the Community Development Society* 21: 56-73.

Gujarati, D.N. 1995. *Basic Econometrics*. New York NY: McGraw-Hill, Inc.

Gunderson, M., J. Sack, J. McCartney, D. Wakely and J. Eaton. 1995. "Employee Buyouts in Canada." *British Journal of Industrial Relations* 33: 417-422.

Habermas, J. 1975. *Legitimation Crisis*. Boston MA: Beacon Press.

Harrison, B. and B. Bluestone. 1988. *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. New York NY: Basic Books.

Harvey, D. 1990. *The Condition of Postmodernity*. Oxford UK: Blackwell Press.

Hayes, M.N. and A.L. Olmstead. 1984. "Farm Size and Community Quality: Arvin and Dinuba Revisited." *American Journal of Agricultural Economics* 56: 534-542.

Heady, E.O. and S.T. Sonka. 1974. "Farm Side, Rural Community Income and Consumer Welfare." *American Journal of Agricultural Economics* 56: 534-542.

Heffernan, W.D. 2000. "Concentration of Ownership and Control in Agriculture." In *Hungry for Profit: The Agribusiness Threat to Farmers, Food and the Environment*, edited by F. Magdoff, J.B. Foster and F.H. Buttel. New York NY: Monthly Review Press.

Heffernan, W.D. 1982. "Structure of Agriculture and Quality of Life in Rural Communities." In *Rural Society in the U.S.: Issues for the 1980s*, edited by D.A. Dillman and D.J. Hobbs. Boulder CO: Westview Press.

Heffernan, W.D. 1972. "Sociological Dimensions of Agricultural Structures in the United States." *Sociologia Ruralis* 12: 481-499.

Heffernan, W.D. and P. Lasley. 1978. "Agricultural Structure and Interaction in the Local Community: A Case Study." *Rural Sociology* 43: 348-361.

Hirsch, P., S. Michaels, and R. Friedman. 1990. “Clean Models vs. Dirty Hands.” In *Structures of Capital*, edited by S. Zukin and P. DiMaggio. Cambridge UK: Cambridge University Press.

Hodson, R. 1984. "Companies, Industries and the Measurement of Economic Segmentation." *American Sociological Review* 49: 335-348.

Honadle, B.W. and J.N. Reid. 1987. *National Rural Entrepreneurship Symposium*. SRDC Report Series #97, Southern Rural Development Center. Mississippi State MS: Mississippi State University.

Horan, P.M. and C.M. Tolbert. 1984. *The Organization of Work in Rural and Urban Labor Markets.* Boulder CO: Westview Press.

Humphrey, C.R. and K.P. Wilkenson. 1993. “Growth Promotion Activities in Rural Areas: Do They Make a Difference?” *Rural Sociology* 58:175-189.

Irwin, M., C. Tolbert and T. Lyson. 1999. “There’s No Place Like Home: Non-Migration and Civic Engagement.” *Environment and Planning A* 31: 223-238.

Jaffe, D.J. 1991. *Working with the Ones You Love: Strategies for a Successful Family Business*. Berkeley CA: Conari Press.

Jameson, F. 1991. *Postmodernism, or, The Cultural Logic of Late Capitalism*. Durham NC: Duke University Press.

John, D., S.S. Batie and K. Norris. 1988. *A Brighter Future for Rural America?* Center for Policy Research. Washington DC: National Governors Association.

Jones, J. 1992. *The Dispossessed: America's Underclasses from the Civil War to the Present*. New York NY: Basic Books.

Jones, A.F. and D.H. Weinberg. 2000. *The Changing Shape of the Nation's Incomes Distribution*. P60-204, U.S. Census Bureau. Washington DC: U.S. Department of Commerce.

Katz, M.B. 1989. *The Undeserving Poor: From the War on Poverty to the War on Welfare*. New York NY: Pantheon Press.

Kenney, M., L.M. Lobao, J. Curry and R. Coe. 1989. "Midwest Agriculture and U.S. Fordism." *Sociologia Ruralis* 29: 131-148.

Kim, J-O and C.W. Mueller. 1978. *Factor Analysis: Statistical Methods and Practical Issues*. Sage University Paper Series: Quantitative Applications in the Social Sciences No. 07-014. Beverly Hills CA: Sage Publications.

Kuehn, J.A., C. Braschler and J.S. Shonkwiler. 1979. "Rural Industrialization and Community Action: New Plant Locations Among Missouri's Small Towns." *Journal of the Community Development Society* 10: 95-107.

Kusmin, L.D. 1994. *Factors Associated with the Growth of Local and Regional Economies: A Review of Selected Empirical Literature*. AGES 9405, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Kusmin, L.D., J.M. Redman and D.W. Sears. 1996. *Factors Associated with Rural Economic Growth: Lessons from the 1980s*. TB 1850, Economic Research Service. Washington DC: U.S. Department of Agriculture.

Lance, G. and W. Williams. 1967. "A General Theory of Classification Sorting Strategies." *Computer Journal* 9: 373-380.

Lash, S. and J. Urry. 1994. *Economies of Signs and Space*. Thousand Oaks CA: Sage Publications.

Lash, S. and J. Urry. 1987. *The End of Organized Capitalism*. Madison WI: University of Wisconsin Press.

Leontief, W. 1982. "Letters: Academic Economies." *Science* 217, 4555: 106-107.

Leontief, W. 1971. "Theoretical Assumptions and Nonobserved Facts." *American Economic Review* 61: 1-7.

Levernier, W., M.D. Partridge and D.S. Rickman. 2000. “The Causes of Regional Variations in U.S. Poverty; People or Place Based?”. *Journal of Regional Science* 40: 473-497.

Lichter, D.T. and D.K. McLaughlin. 1995. “Changing Economic Opportunities, Family Structure, and Poverty in Rural Areas.” *Rural Sociology* 60: 688-706.

Lipietz, A. 1992. *Towards a New Economic Order: Post-Fordism, Ecology and Democracy*. New York NY: Oxford University Press.

Lipietz, A. 1987. *Mirages and Miracles*. London UK: New Left Books.

Lobao, L.M. 1990. *Locality and Inequality: Farm and Industry Structure and Socioeconomic Conditions*. Albany NY: State University Press of New York.

Lobao, L. and K. Meyer. 2001. “The Great Agricultural Transition: Crisis, Change, and Social Consequences of Twentieth Century U.S. Farming.” *Annual Review of Sociology* 27: 103-124.

Lobao, L.M., J. Rulli and L.A. Brown. 1999. "Macro-Level Theory and Local-Level Inequality: Industrial Structure, Institutional Arrangements and the Political Economy of Redistribution, 1970 to 1990." *Annals of the Association of American Geographers* 89: 571-601.

Lobao, L.M. and R. Saenz. 2002. “Spatial Inequality and Diversity as an Emerging Research Area.” *Rural Sociology* 67: 497-511.

Lobao, L.M. and M.D. Schulman. 1991. “Farming Patterns, Rural Restructuring and Poverty: A Comparative Regional Analysis.” *Rural Sociology* 56: 565-602.

Lobao, L.M., M.D. Schulman and L.E. Swanson. 1993. “Still Going: Recent Debates on the Goldschmidt Hypothesis.” *Rural Sociology* 58: 277-288.

Loehlin, J.C. 1992. *Latent Variables Models: An Introduction to Factor, Path and Structural Analysis*. London UK: Lawrence Earlbaum Associates Publishers.

Luloff, A.E. and W.H. Chittenden. 1984. “Rural Industrialization: A Logit Analysis.” *Rural Sociology* 49: 67-88.

Lyson, T.A., R.J. Torres and R. Welsh. 2001. “Scale of Agricultural Production, Civic Engagement, and Community Welfare.” *Social Forces* 80: 311-327.

MacConnell, D. 1988. “Industrial Agriculture and Rural Community Degradation.” In *Agriculture and Community Change in the U.S.: The Congressional Research Reports*, edited by L.E. Swanson. Boulder CO: Westview Press.

Marcuse, H. 1964. *One Dimensional Man*. Boston MA: Beacon Press.

Marousek, G. 1979. "Farm Size and Rural Communities: Some Economic Relationships." *Southern Journal of Agricultural Economics* 11: 57-61.

Martinson, O.B., E.A. Wilkening and R.D. Rodefeld. 1976. "Feelings of Powerlessness and Social Isolation Among Large-Scale Farm Personnel." *Rural Sociology* 41: 452-472.

Marx, K. 1867. [1990]. *Capital: A Critique of Political Economy*. London UK: Penguin Classics.

Marx, K. 1859. [1970]. *A Contribution to the Critique of Political Economy*. New York NY: International Publishers.

Marx, K. 1858. [1993]. *Grundrisse: Foundations of the Critique of Political Economy*. London UK: Penguin Classics.

McCall, L. 2001. "Source of Racial Wage Inequality in Metropolitan Labor Markets: Racial, Ethnic and Gender Differences." *American Sociological Review* 66: 520-541.

McGranahan, D.A. 1999. *Natural Amenities Drive Rural Population Change*. AE-781, Economic Research Service. Washington DC: U.S. Department of Agriculture.

McLaughlin, D.K. 2002. "Changing Income Inequality in Nonmetropolitan Counties, 1980 to 1990." *Rural Sociology* 67: 512-533.

McMichael, P. 1996. *Development and Social Change: A Global Perspective*. Thousand Oaks CA: Pine Forge Press.

McNamara, K.T., W.P. Kriesel and B.J. Deaton. 1988. “Manufacturing Location: The Impact of Human Capital Stocks and Flows.” *Review of Regional Studies* 18: 42-48.

Merton, R.K. 1968. *Social Theory and Social Structure*. New York NY: The Free Press.

Milligan, G.W. and M.C. Cooper. 1985. “An Examination of Procedures for Detecting the Number of Clusters in a Dataset.” *Psychometrika* 50: 159-179.

Mingione, E. 1991. *Fragmented Societies*. Oxford UK: Basil Blackwell Press.

Mojena, R. 1977. “Hierarchical Grouping Methods and Stopping Rules - An Evaluation.” *Computer Journal* 20: 359-363.

Morris, M. and B. Western. 1999. "Inequality in Earnings at the Close of the Twentieth Century." *Annual Review of Sociology* 25: 623-657.

Murphy, K. and F. Welch. 1993. "Industrial Change and the Rising Importance of Skill." In *Uneven Tides: Rising Inequality in America*, edited by S. Danziger and P. Gottschalk. New York NY: Russell Sage Foundation.

Nielsen, F. and A.S. Alderson. 1997. "Income Inequality in U.S. Counties, 1970 to 1990." *Annual Sociological Review* 62: 12-33.

Nord, M. 1997. "Overcoming Persistent Poverty - And Sinking Into It: Income Trends in Persistent Poverty and Other High Poverty Rural Counties." *Rural Development Perspectives* 12(3): 2-30.

Nord, M., A.E. Luloff and L. Jensen. 1995. "Migration and the Spatial Concentration of Poverty." *Rural Sociology* 60: 399-415.

North, D. 1990. *Institutions, Institutional Change and Economic Performance*. Cambridge UK: Cambridge University Press.

O'Conner, J. 1973. *The Fiscal Crisis of the State*. New York NY: St. Martins Press.

Osterman, P. 1999. *Securing Prosperity: The American Labor Market: How It Has Changed and What to Do About It*. Princeton NJ: Princeton University Press Press.

Partridge, M.D. and D.S. Rickman. 2005. *Persistent Pockets of Extreme American Poverty: People or Placed Based?* RPRC 05-01, RUPRI Rural Poverty Research Center. Columbia MO: Rural Policy Research Institute.

Piore, M.J. and C.F. Sabel. 1984. *The Second Industrial Divide: Possibilities for Prosperity*. New York NY: Basic Books.

Poole, D.L. 1981. "Farm Scale, Family Life and Community Participation." *Rural Sociology* 46: 112-127.

Proctor, B.D. and J. Dalaker. 2003. *Poverty in the United States: 2002*. P60-222, U.S. Census Bureau. Washington DC: U.S. Department of Commerce.

Pugliese, E. 1991. Agriculture and the New Division of Labor." In *Towards a New Political Economy of Agriculture*, edited by W. Friedland, L. Busch, F. Buttel and A. Rudy. Boulder CO: Westview Press.

Quan, N.T. and J.H. Beck. 1987. "Public Educational Expenditures and State Economic Growth: Northeast and Sunbelt Regions." *Southern Economic Journal* 46: 361-376.

Reich, R. 1991. *The Work of Nations*. New York NY: Alfred A. Knopf Press.

Rhodes, V.J. 1995. "The Industrialization of Hog Production." *Review of Agricultural Economics* 17: 107-118.

Ritzer, G. 1997. *Postmodern Social Theory*. New York NY: McGraw-Hill.

Ritzer, G. 1994. *The McDonaldization of Society*. Thousand Oaks CA: Pine Forge Press.

Sahlins, M. 1976. *Culture and Practical Reason*. Chicago IL: University of Chicago Press.

Salamon, S. 1992. *Prairie Patrimony: Family, Farming and Community in the Midwest*. Chapel Hill NC: University of North Carolina Press.

Schumpeter, J. 1926. [1961]. *The Theory of Economic Development*. New York NY: Oxford University Press.

Smelser, N.J. and R. Swedberg. 1994. "The Sociological Perspective on the Economy." In *The Handbook of Economic Sociology*, edited by N. Smelser and R. Swedberg. Princeton NJ: Princeton University Press.

Smith, E.D., B.J. Deaton and D. Kelch. 1978. “Location Determinants of Manufacturing Industry in Rural Areas.” *Southern Journal of Agricultural Economics* 23-37.

Swaminathan, H. and J.L. Findes. 2004. “Policy Interventions and Poverty in Rural America.” *American Journal of Agricultural Economics* 86: 1289-1296.

Tabachnick, B.G. and L.S. Fidell. 1996. *Using Multivariate Statistics*. New York NY: HarperCollins Publishers.

Tickamyer, A.R. 2000. "Space Matters! Spatial Inequality in Future Sociology." *Contemporary Sociology* 29: 805-813.

Tickamyer, A.R. and C.M. Duncan. 1990. "Poverty and Opportunity Structure in Rural America." *Annual Review of Sociology* 16: 67-86.

Tolbert, C.M., T.A. Lyson and M.D. Irwin. 1998. “Local Capitalism, Civic Engagement, and Socioeconomic Well-Being.” *Social Forces* 77: 401-428.

Tomaskovic-Devey, D. 1988. "Industrial Structure, Relative Labor Power and Poverty Rates." In *Poverty and Social Welfare in the United States*, edited by D. Tomaskovic-Devey. Boulder CO: Westview Press.

Tomaskovic-Devey, D. 1987. "Labor Markets, Industrial Structure and Poverty: A Theoretical Discussion and Empirical Example." *Rural Sociology* 52: 56-74.

U.S. BLS – Bureau of Labor Statistics. 2002. *Geographic Profile of Employment and Unemployment, 2000*. BLS Bulletin 2550. Washington DC: U.S. Department of Labor.

U.S. Census. 2002. *Census 2000 Summary File 3 Technical Documentation*. Census Bureau SF3/16(RV). Washington DC: U.S. Department of Commerce.

U.S. ERS-USDA – Economic Research Service. 2004. *Rural Poverty at a Glance*. Rural Development Research Report 100, July. Washington DC: U.S. Department of Agriculture.

U.S. OMB - Office of Management and Budget. 2002. *North American Industry Classification System*. OMB, Executive Office of the Vice President. Washington DC: National Technical Information Service.

U.S. OMB - Office of Management and Budget. 2000. *Standard Occupational Classification Manual*. OMB, Executive Office of the Vice President. Washington DC: National Technical Information Service.

Ullman, E.L., M.H. Dacey, and H. Brodsky. 1971. *The Economic Base of American Cities*. Seattle WA: University of Washington Press.

Van Es, J.C., D.L. Chicoine and M.A. Flotow. 1988. "Agricultural Technologies, Farm Structure, and Rural Communities in the Corn Belt: Policies and Implications for 2000." In *Agriculture and Community Change in the U.S.: The Congressional Research Reports*, edited by L.E. Swanson. Boulder CO: Westview Press.

Wasylenko, M. and T. McGuire. 1985. "Jobs and Taxes: The Effect of Business Climate on States Employment Growth Rates." *National Tax Journal* 38: 497-511.

Weber, M. 1922. [1978]. *Economy and Society*. Berkeley CA: University of California Press.

Weber, M. 1920. [1964]. *The Theory of Social and Economic Organization*. New York NY: The Free Press.

Weber, B. and L. Jensen. 2004. *Poverty and Place: A Critical Review of the Literature.* RPRC 04-03, RUPRI Rural Poverty Research Center. Columbia MO: Rural Policy Research Institute.

Wilson, W.J. 1987. *The Truly Disadvantaged: The Inner City, the Underclass and Public Policy*. Chicago IL: University of Chicago Press.

Wojan, T.R. 2000. "The Composition of Rural Employment Growth in the New Economy." *American Journal of Agricultural Economics* 82: 594-605.

Yanagida, J.F., B.B. Johnson, J. Young and M. Lundeen. 1991. "An Analysis of Economic and Non-Economic Factors Affecting Retail Sales Leakages." Review of Regional Studies 21: 53-64.

VITA

David J. Peters was born in Minneapolis, Minnesota on September 18, 1970. After attending public schools in Prior Lake, Minnesota, he received the following degrees: Bachelor of Science *cum laude* in Sociology from the University of Minnesota – Twin Cities in 1994; Master of Science in Rural Sociology from the University of Missouri – Columbia in 1998; and Doctor of Philosophy in Rural Sociology also from the University of Missouri – Columbia in 2006. After working for five years for the research division of the Missouri Department of Economic Development, he has accepted the position of Assistant Professor of Agricultural Economics at the University of Nebraska – Lincoln. He is married to the former Sandra Hurtado of Columbia, Missouri and has one son named Karsten Peters.