HOW SPECIALIZED IS "TOO" SPECIALIZED? OUTMIGRATION AND INDUSTRY DIVERSIFICATION IN NONMETROPOLITAN COUNTIES ACROSS AMERICA

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TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

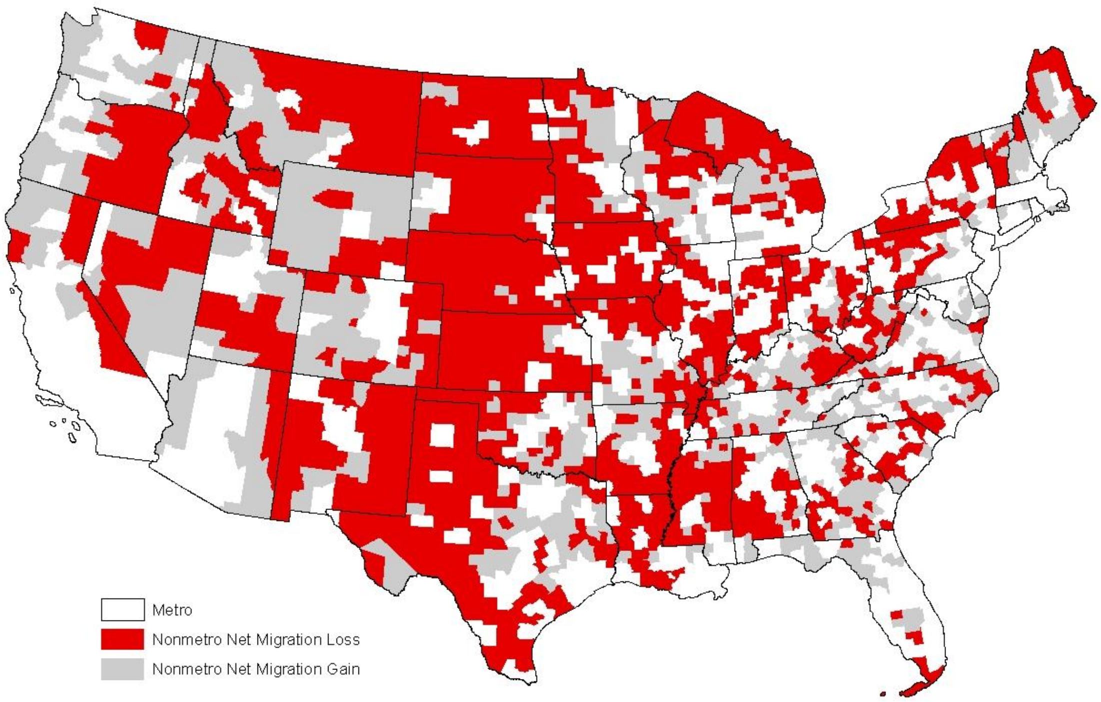
CHAPTER I. INTRODUCTION

I.1 PROBLEM STATEMENT

Outmigration is a problem that plagues nonmetropolitan counties across America. Between 2005 and 2006, 957 nonmetropolitan counties lost population; the total nonmetropolitan counties with population loss jumped to 1,123 during 2008-2009. This research focuses on the 2000-2009 time period, and as shown by **Figure 1** on the following page, far more nonmetropolitan counties experienced outmigration than counties experienced in-migration during the period of interest. In fact, 1,347 nonmetropolitan counties (65.74%) experienced outmigration over this period. Outmigration leads to obvious problems for nonmetropolitan communities, such as fewer human resources and a reduced tax base. As the population decreases, tax revenues also decrease resulting in a loss of funding for public services. Also, the demand base for private industry shrinks as outmigration increases. Given the multitude of negative consequences associated with outmigration, it is not surprising that many studies have tried to uncover its determinants. What is surprising, however, is a lack of focused attention on a variable that is often of interest to economic developers: the level of industrial diversification.

In past decades nonmetropolitan economic activity largely centered on rural activities, like farming or manufacturing, meaning that nonmetropolitan counties had a tendency to be heavily specialized in a particular industry. The USDA ERS defines counties as being specialized if more than a certain percentage of the county's earned income comes from a particular industry.

Figure 1: Nonmetropolitan Net Migration Gains and Losses



For example, a county is classified as a farming county if more than 15% of the earned income comes from farming. Likewise, if more than 25% or 45% of the earned income is from manufacturing or services, respectively, a county is classified as specialized in that particular industry. However, the USDA classifications for a specialized county are only one example of how county specialization can be defined; many other studies and different research areas define a specialized county differently using a wide variety of tools and methods, like the Herfindahl-Hirschman Index provided from Census County Business Patterns (Diamond and Simon). While county specialization can be defined differently from study to study, its place in the existing migration literature is very limited.

Economic literature commonly claims that heavy industry specialization, or lack of diversification, results in an overly sensitive economy in terms of employment and income (Nissan and Carter). Areas that are industrially specialized tend to have a surplus of available labor and offer lower wages; in contrast, areas that are industrially diversified tend to have a shortage of available labor and offer higher wages (Mahasuweerachai, Whitacre and Shideler). Therefore, the possibility exists that people will migrate from highly specialized areas to industrially diverse areas, especially during times of economic hardship. As a result, heavily specialized nonmetropolitan areas face an increased likelihood of experiencing significant levels of outmigration. This presents a major problem to rural economic developers and leaders of nonmetropolitan counties. If these leaders had a more specific idea of the industry specialization threshold where this migration impact is seen, perhaps they would be better able to influence and change the industry composition of their county and deter outmigration.

Previous studies have linked nonmetropolitan outmigration to various county-level factors such as the median income level, natural amenities, median age, gender, poverty, broadband access, educational attainment levels, and a host of other variables. This research will focus on the relationship between outmigration and industry specialization, while including the other relevant variables in several econometric specifications to control for their own effects on migration. Industry specialization levels will be defined using several different measures, including USDA ERS characterizations of "dependency" as well as alternative thresholds using North American Industrial Classification (NAICS) breakouts at the 2-digit level. This will allow the definition of "specialized" to vary between, say, 10% of employment in one industry and 30% employment in that industry. Discovering the industry specialization threshold that is most heavily linked to outmigration would allow local leaders to focus on a specific industry composition goal first when targeting the outmigration problem in order to save time and resources. This research will provide local economic leaders or developers with more knowledge and understanding of their outmigration problem, and will allow for more informed policy decisions when it comes to understanding the role of industry specialization.

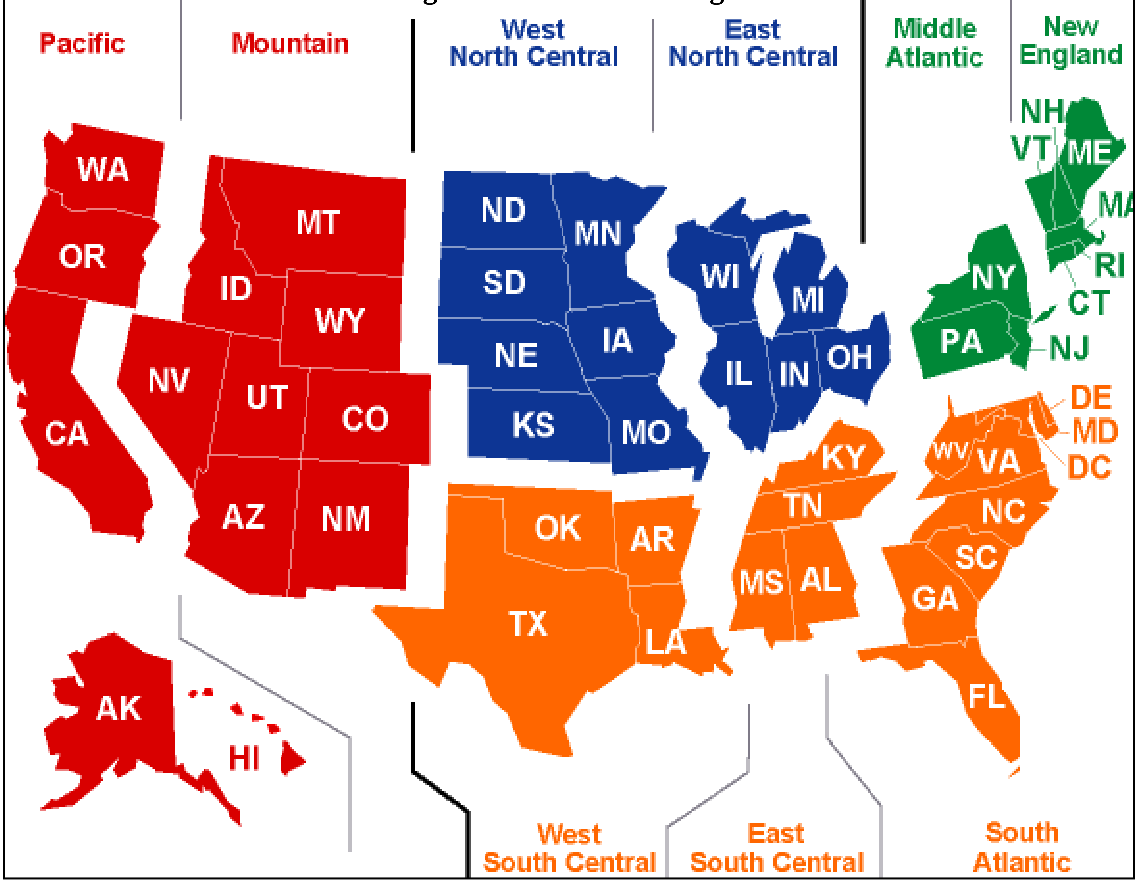
I.2 OBJECTIVES

The general objective of this research is to identify what industry specialization level is "too specialized" in terms of outmigration – that is, to determine the level where specialization starts to have a damaging effect. Specifically, this study will establish the linkage between county outmigration and specific industry concentration using two different econometric techniques. First, a multivariate regression will be performed using a variety of variables typically used in the migration literature with county level net migration from 2000 to 2009 as the dependent variable. The regression will include a dummy variable for whether or not the county is considered to be too specialized, and the industry specialization – outmigration relationship will be observed. This approach will allow for observation of the relative importance of the different variables included – for example, whether having a diversified economy is more important than having residents with higher levels of education. The second method used involved the average treatment effect and propensity score matching, increasingly common nonparametric tools used to evaluate "treatment effects." These techniques allow us to make statements about causality with respect to outmigration, rather than being limited to discussion of simple relationships as with multivariate regression. In this case, counties that are defined as too specialized (the treated group) will be matched with otherwise similar counties (the non-treated group) in terms of population, per capita income, median age, etc. The objective is to determine if the two groups vary in terms of their net migration rate, or the average treatment effect. Finally, results from the two techniques will be compared to one another. Uncovering various detrimental levels of specialization across different industries should allow local economic leaders to develop and apply specific policy solutions that focus on the outmigration problem.

Finally, this study will individually focus on the outmigration and industry specialization level relationship for each of the 9 different Census Bureau Divisions to determine if there are any regional differences in results for this study. Census regions include Pacific, Mountain, West-

North Central, East-North Central, Middle Atlantic, New England, West-South Central, East-South Central, and South Atlantic. **Figure 2** shows the specific Census region break-outs by state.

Figure 2: U.S. Census Regions



CHAPTER II. LITERATURE REVIEW

II.1 INTRODUCTION TO LITERATURE REVIEW

There are currently two distinct sets of literature focusing on the key topics in this research: literature on outmigration and literature on industrial specialization. A wide assortment of research has been conducted on both of the topics separately, but not typically as a combination. This research will mesh these two important areas of research. Literature on each of the research areas is further explored below.

II.2 OUTMIGRATION

A number of studies have focused on domestic migration and its consequences over the past 30 years. The Census began publishing county level data on migration following the 1990 Census, which sparked new research on the topic. The majority of the available literature focusing on outmigration uses the Census reports for data sources. Since 1991, the Internal Revenue Service has also published data on domestic migration based upon personal tax return filing addresses (Gunderson and Sorenson 2010). While the IRS data on migration is likely more accurate due to its direct tracking method, it is rarely used due to extreme limitations on the demographic variables associated with the migration patterns. Therefore, all but one of the sources reviewed for this research use the Census databases. Consistent with most other literature, this research will use the migration data provided by the Census Bureau.

Early studies on migration focused on theoretical foundations but stopped short of policy prescriptions. Greenwood (1975) suggests using simultaneous-equation methods for measuring the externalities associated with migration. No policies should be implemented that encourage or discourage migration, following the belief that natural market forces should allow for optimal population disbursement (Greenwood 1975). One possible externality resulting from policies supporting migration is increased social costs. If migrants flood into an area rapidly as a result of a public policy, there may be an increased need for schools, waste management, traffic management and other public services (Greenwood 1975). Greenwood (1975) suggests that local public sectors should be a primary focus or consideration in state or national level migration policies. Furthermore, “migration cannot be viewed in isolation; complementary investments in the human agent are probably as important as or more important than the migration process itself” (Sjaastad 1962). Policy implications are an important concluding step to any research dealing with migration, but very few early studies go so far as to make actual suggestions. This research will not only consider the theory underlying migration but will also conclude with some policy suggestions for tempering outmigration.

Many different variables must be considered when addressing the outmigration problem. Some studies focused on individual motivators as drivers of outmigration. An early study by Bilsborrow (1987) based in Ecuador obviously differs greatly in terms of data and result comparability with this study; however, the inclusion of variables addressing individual motivations presents a unique method of addressing the outmigration problem, and conclusions reached in this study are surprisingly consistent with findings in the United States. The study is based on the belief that variables in addition to the typical household or individual variables are at play with respect to outmigration. Specifics of the individual and their motivation likely pose equal importance as the household makeup when considering who is migrating in and out of an area (Bilsborrow 1987). Within a household, those in their 20s were found to be the most mobile; children younger than twenty were the least likely to migrate (Bilsborrow 1987). This is consistent with findings by Nord which conclude from a pure mobility standpoint, college-aged persons are typically the most mobile of any age group within the United States (1996). Bilsborrow also concluded that those with only a primary education and are seeking work are more likely to migrate compared to individuals with higher level educations (1987). Although the Bilsborrow study was conducted in Ecuador, the results are consistent with findings in the United States, and refer to a problem commonly known as the "brain drain." A study by Johnson et al found that United States metropolitan areas commonly gained large numbers of migrants in their 20s, while the same area typically lost all other age groups (2005). McGrannahan concluded that young adults (age 14-24) tend to move away from nonmetropolitan counties, likely to pursue higher education or the military (2010). When reviewing the results for all studies, it is clear that nonmetropolitan outmigration occurs consistently with college-aged persons; these same conclusions can even be reached in countries outside of the United States. This type of study is similar to the research conducted here: it will include individual motivator variables indirectly: median age and education levels will be included as independent variables in my research.

Using a different methodology but still focusing primarily on age related factors, Johnson et al. concluded that both spatial and temporal variability in age-specific migration patterns exist within the United States (2005). The research focused on the 1950 to 1990 time period. Counties with similar demographic and economic patterns tended to have similar migration patterns, either gaining or losing population, but the gain or loss was predictable given the typical county variable composition of factors such as age, income and retirement/recreation classification. Over the past 40 years minorities have had an increasing influence on migration patterns of all races (Johnson et al. 2005). Spatial analysis revealed counties that were either long-term population losers or gainers. Boundaries of these spatial areas tended to fluctuate, but core areas of perpetual gains or losses were easily identified for the period of interest (Johnson et al. 2005). Suburban areas were shown to commonly attract those aged around 30 with children in the household. Recreational counties were popular migration destinations among adults nearing retirement age. The 1970s and 1990s were found to be periods of atypical population distribution compared to other decades in the study (Johnson et al. 2005). This research supports the belief that migration is driven by temporal, spatial and age-specific variations and motivators; therefore, developers focused on migration should consider all three aspects when creating policies or development goals.

Another group of literature focuses on the differences in migration patterns for domestic migrants versus international immigrants. A study by Frey (1996) did not focus on county level data, but it did find that international migrants tended to migrate to California, New York, Texas, Illinois, New Jersey and Massachusetts. States with the highest internal migration were Florida, Georgia, North Carolina, Virginia, Washington and Arizona. A study by Perry (2006) concluded that the states with the highest in-migration rates during 2000-2004 were Nevada, Arizona, Florida, Idaho, Maine, New Hampshire, Delaware, Georgia, North Carolina, and South Carolina. States with the lowest migration rates for the same time period included New York, Massachusetts, North Dakota, Illinois, Kansas, Utah, Louisiana, New Jersey, Nebraska and Iowa (Perry 2006). A later study by Frey (2005) focused on metropolitan areas rather than states when considering international and domestic migrants. Los Angeles, San Francisco, and New York were the most common migration destinations for international migrants; whereas, Phoenix, Atlanta and Charlotte were common destinations for domestic migrants (Frey 2005). A third group of metropolitan areas commonly experienced heavy outmigration of the educated Caucasian youth, such as Detroit and Cleveland (Frey 2005). Many factors were at play with both domestic immigration and outmigration, but Frey concluded that the most heavily influencing factors were natural attractions and regional economic conditions such as the labor market (1996). Domestic migrants are more strongly linked to ebbs and flows of the labor market as they were typically more highly educated, whereas international immigrants are heavily influenced by where their family members live and have established job contacts since they were often low skilled (Frey 2005). Furthermore, Frey (2005) suggests that different metropolitan areas are "developing distinct race-ethnic profiles, [and] the continued dispersion of immigrant minorities is affecting the population profiles of all three types of areas." Studies of this nature are similar to my research in that I will assess ebbs and flows in the labor market via changes in the unemployment rate over time, and I will assess natural attractions by including the ERS Natural Amenity Scale as an independent variable in all regressions. In contrast to the discussed literature, my research will focus on county level data rather than state level.

Other studies focus specifically on the migration patterns of the poor population, and variables related to these patterns. High poverty areas aren't evenly spread over the country; instead, they are mainly found in the Deep South, in highly Hispanic populous areas in the Rio Grande Valley and the High Plains of the Central Southwest, in highly Native American populous areas in the Southwest, Northern Great Plains, and Alaska, and in highly Caucasian populous areas in the Appalachian Highlands and the Ozark – Ouachita Plateau. Nord (1996) attempts to build on previously published literature when testing hypotheses regarding the migration patterns of the poor. Nord (1996) hypothesized that the poor migrate due to differences in job opportunities. Nord (1996) observed that educated Blacks migrate towards areas with growing professional job bases, while Blacks in poverty migrate towards lower-paying service or blue-collar jobs and low cost of living. This type of migration pattern tends to exacerbate the rate differences between poverty and non-poverty counties. Another key finding of this study was that the poor were actually more mobile than the non-poor: 17 percent of the poor moved across county lines, whereas 16.8 percent of non-poor migrated during the same time period (Nord 1996). In a study related to the topic considered in this thesis, Frey (1996) concluded that the industry composition of a county was more strongly linked to migration patterns of the non-poor than the poor. Mining was the industry with the strongest negative relationship to net migration, followed closely by wholesale trade and labor occupations (Frey 1996). The sole industry with a significantly positive relationship to net migration was retail trade (Frey 1996). As expected, natural amenities had a strong positive relationship with net migration for the non-poor; the relationship was also positive for the poor, but not nearly as strong (Frey 1996). The study by Frey is most similar to mine when considering its hypotheses related to county industry composition (1996). The regressions used to test this hypothesis included many different industry level variables, as well as the natural amenity scale. All of these variables are essential in my research, which assesses net migration. Frey's study differs from my research in that it focuses primarily on two groups: the poor and the non-poor. Rather than assess the two groups individually with separate regressions, my research will include variables to account for the poor in all regressions, such as a persistent poverty dummy variable and per capita income. Instead of focusing on the poor versus the non-poor, I will assess outmigration nonmetropolitan areas and in particular, the role of industry composition.

Slightly different from the previously discussed research, another group of literature focuses on the relationship of outmigration and many variables with respect to high poverty and low poverty counties. Over the 1988-2008 time period, roughly 733 of 2,049 nonmetropolitan counties lost greater than ten percent of their population. Counties that exhibited particularly high outmigration rates typically fell into one of two categories: high poverty areas with a lack of economic opportunity and low poverty areas with poor natural amenities (McGrannahan 2010). Factors of most significance in the areas with poor economic opportunities included high unemployment, high poverty rates (average over 30%), and loss of manufacturing jobs (McGrannahan 2010). The poor natural amenities county category typically had good economic statistics such as low unemployment, low high school dropout rates, average household incomes; however, these counties were likely unable to attract new citizens or retirees due to unattractive landscapes, remoteness, and below average population density (McGrannahan 2010). Quality-of-life was likely a strong factor in deterring residents from migrating to these counties. When considering industry preferences (e.g. manufacturing industry leaders' location survey), areas with high poverty were unlikely locations for new plants due to poor school systems (McGrannahan 2010). On the other hand, areas with low poverty were unlikely locations due to unattractiveness of the area and conceived inability to attract industry professionals to the area (McGrannahan 2010). In McGrannahan's 2010 studies, low-poverty outmigration counties had a primary industry focus in agriculture; whereas, high-poverty outmigration counties had primary industry focuses in health, education and government. When considering entrepreneurship, low-poverty outmigration counties often excelled in this area while high-poverty outmigration counties fell drastically short of other county averages for creative class share of employment (McGrannahan 2010). Regression analysis revealed that only counties with extremely high poverty rates (greater than twenty-five percent) had a strong relationship to outmigration; in counties where the poverty rate was lower, no significant relationship was found between poverty and outmigration (McGrannahan 2010). McGrannahan's studies are similar to my research in that they include many different variables in the consideration of outmigration relationships. All of the variables mentioned in these studies will be included in all regressions for my research. My study will differ from these articles in that I will further explore the industrial composition of counties in relationship to outmigration, and I will also seek to answer questions of causation in relation to outmigration. These studies focused on variable relationships to outmigration, and not whether the existence of variables at certain thresholds actually causes outmigration.

A variety of outmigration literature is available that focuses on one state at a time. My research will focus on the United States as a whole, but variables have been included to allow for regional analysis. One study by Gunderson and Sorenson in 2010 is very similar to method one of my research; however, they focus on California counties rather than all counties within the United

States. Gunderson and Sorenson project that many migrants who leave the state of California do so because of distance, climate, and economic opportunity; these migrants choose to relocate to amenity-rich regions such as Colorado, Washington, Florida, Oregon, Texas, Arizona and Nevada. This study is similar to my research in that it takes into account different economic and demographic variables when considering outmigration. Overall, I will examine many more variables than this study included and use additional methods of data analysis.

Shifting to a focus on the industrial composition of a county, Johnson et al. (2005) found that nonmetropolitan counties that were heavily dependent on agriculture in the 1950s experienced heavy outmigration as the dependence on domestic agriculture began to decrease in the 1960s and 1970s. Similar to the findings of other studies, the researchers concluded that nonmetropolitan counties with exceptional natural amenities and a healthy outdoor recreation industry did not suffer from outmigration; in contrast, they often had steady levels of population increases (Johnson et al. 2005). Recreational nonmetropolitan counties were particularly appealing to age groups nearing retirement (Johnson et al. 2005).

Traditional economic theories infer that migration is driven by differences in the supply and demand for labor across regions. “People who live in labor-surplus areas, which usually have lower wages, tend to migrate to labor-scarce areas with higher wages; generally, labor-scarce areas have relatively high economic growth with more industries and greater manufacturing concentration than do labor surplus areas” (Mahasuweerachai, Whitacre and Shideler 2010). Many of the previous studies on the topic are relatively old and likely do not account for the addition of broadband and high-speed internet access. Population loss in rural areas is particularly troublesome, so uncovering the underlying relationships of different variables (such as broadband access) to outmigration would be beneficial to rural developers. The Mahasuweerachai et al. study aims to address the relationship between rural outmigration and broadband access. A key data analysis method used in this study is the average treatment effect (ATE). The average treatment affect looks further than a simple regression analysis, and seeks to establish causation. For this research, a “treated” group is considered to have broadband access, and an “untreated” group does not have broadband access. This methodology allows the researcher to measure the effect of broadband on migration by separately analyzing areas with and areas without broadband access.

A key result for the spatial econometric model for this research is that spatial interdependence of migration exists, but the availability of broadband access is not a factor in attracting new migrants (Mahasuweerachai, Whitacre, Shideler 2010). The study also concludes that when both Cable and DSL broadband access are available in a rural area, a positive and significant relationship to net migration is found (when compared to other similar counties without broadband). A limitation of this study is the data used. The broadband variable only includes counties with infrastructure prior to 2000.

This study is similar to my research in several ways. The study is primarily interested in the relationship of a single variable (broadband access) to migration. My research also focuses on the relationship of a variable (industrial composition) to migration. Both studies explore the topic further by using the average treatment effect and propensity score matching techniques, in an attempt to establish causation rather than only verify simple relationships. Becker (2002) cautions that using the ATE method poses the possibility of creating a biased treatment. To correct for this bias, propensity score matching can be employed, by assuring that the treated and control subjects are as similar as possible (Becker 2002). Propensity score matching can be defined as the conditional probability of receiving a treatment, given the pre-treatment characteristics (Becker 2002). Matching estimators of the ATE of the treated based on the propensity score include nearest neighbor, radius, kernel and stratification matching. While nearest neighbor simply looks for the difference between closest treated/non-treated observations, the other techniques weight observations between groups since this simple difference could be very large. For my research, the ATE based on propensity score matching will be used, and three matching techniques will be included in the analysis to address Becker's cautions and to verify consistency between the methods. Due to the large amount of results produced from using all three methods, only the results from the Kernel method will be shown in this research since that is the method most commonly referred to and used in similar research.

II.3 INDUSTRY SPECIALIZATION

Studies commonly define industry specialization differently; therefore, it is important to make note of several of the more popular specialization classifications used in related studies. An early study by Diamond and Simon used the Herfindahl-Hirschman Index to define industry specialization (1990). This study compared industry specialization levels to returns to labor. The Herfindahl-Hirschman Index provides a measure of industry concentration. This index is most commonly used in reference to anti-trust laws, but it is also occasionally used in studies focusing on industry specialization. Perhaps a more common measure of industrial specialization is the USDA's designated thresholds for earned income percentages. The USDA classifies a county as dependent on (or specialized in) farming if 15% or more of the earned income and 15% or more of the total employment is accounted for by farming. Likewise, if 25% or 45% of the earned income comes from manufacturing or services, respectively, then a county is said to be specialized in those specific industries. Dependency or specialization thresholds for mining or federal/state government are reached when earnings in the respective industries exceeds 15% of total county earnings. These USDA ERS definitions of dependence are widely recognized and have been used in many economic studies. Also, specialization levels can be calculated by the researcher for many different industries based on employment data provided by the Bureau of Economic Analysis.

Economic literature often suggests that diversity, rather than specialization, is preferred and serves as a buffer during times of economic hardship. A study by Nissan and Carter (2006) suggests that communities that are industrially diverse generally have more stable employment and income levels. Diversification leads to a more robust economy, which in turn supports positive economic development and performance in the form of the growth rate, per capita income and the unemployment rate (Attaran 1986). Nonmetropolitan counties are often heavily specialized in agriculture, forestry, mining or manufacturing, and the livelihood of their economy is dependent on the specific industry (Smith and Gibson). A study by Smith and Gibson found that nonmetropolitan counties specialized in mining, lumbering, automotive equipment and textiles had particularly volatile economies, while nonmetropolitan counties specialized in education and government were typically more stable (1988). Communities that are heavily specialized in areas such as mineral mining or exportation of petroleum are especially susceptible to economic shifts, and are therefore likely to suffer from periods of heavy outmigration (Nissan and Carter). Thus, the existing research suggests that nonmetropolitan counties with a diverse industrial makeup are likely more cyclically stable, and therefore have lower outmigration rates than counties that are highly specialized. While these studies focus heavily on industry specialization in nonmetropolitan counties, none look explicitly at the resulting impact on outmigration.

Furthermore, economic instability in one region likely has an effect on the economic stability of neighboring regions (Trendle 2003). Diversity was found to be most common in Texas, Oklahoma, Louisiana, Kentucky, and West Virginia; meanwhile, the most specialized states included Nevada, Montana, North Dakota, South Dakota, Michigan, Indiana, and Connecticut (Attaran 1986).

Findings from the study by Smith and Gibson revealed that indiscriminant diversification should not be promoted by policy makers; rather, more research should be done at the county level to determine which industries would be most beneficial for the county's specific diversification strategy, in accordance with the natural resources available and comparative advantages (1988). Also, regional planners should include both the detailed industrial mix and diversity in planning policies, rather than simply target diversification in general (Attaran 1986).

II.4 CONTRIBUTIONS TO CURRENT LITERATURE

While some of the studies noted above included industrial makeup in their migration analysis, no current literature was found that specifically focused on the relationship between industrial specialization and outmigration. There have been a great deal of studies focused on industrial specialization or diversification and the economic consequences of their existence, but none detailed their relationship to migration. There have also been a number of studies conducted focusing on outmigration and its relationship to various demographic variables, but none detailed the relationship between outmigration and industrial specialization. Regarding the studies focused on outmigration, very few included more than 3-4 variables. This study will include more than ten different economic and demographic variables, with the primary focus being on the impact of industrial specialization.

Further, only a limited number of studies have observed outmigration at the county level for the United States as a whole, and even fewer focused explicitly on nonmetropolitan counties. This study will include dummy variables for the nine United States Census regions, so if differences occur in different regions throughout the U.S., they will be observed. Typically studies have chosen to only focus on one region or a state; including all 9 Census regions will make this research applicable throughout the entire United States rather than just in an isolated region. Also, only a small number of relatively new studies have included an intuitive variable such as rate of broadband adoption, which will be included in this research. This research will attempt to fill in the gaps from the previous literature and include many different variables observed at the county level across the United States. Current literature has focused on industrial specialization or outmigration as individual problems; this research will bridge the gap between the two areas.

CHAPTER III. METHODOLOGY

III.1 CONCEPTUAL FRAMEWORK

Outmigration in nonmetropolitan counties will likely have an endless number of related variables, and would therefore be impossible to completely eliminate via public policy. However, it is likely that certain county level variables can be identified as significant contributors to outmigration. The literature review in Chapter II provided a host of variables that might impact migration. Pinpointing the variables that impact outmigration would allow local leaders to develop policies or programs catered to remedying the problem variable or variables in order to reduce outmigration and potentially spur economic development. To satisfy this need, this study will focus on the relationship between industrial specialization and outmigration. Findings from this study will give local leaders a specific area to focus on when targeting an outmigration problem: the industrial makeup of their county. The variables detailed in **Table 1**, were used to econometrically estimated the impact of being "too specialized" on migration across nonmetropolitan counties. Two techniques were used: multivariate regression (ordinary least squares, or OLS) and average treatment effects (ATE). Results were reviewed at the national level, and for each Census region. The next subsection discusses the data collected and the various definitions of "specialized," followed by the OLS and ATE modeling approaches. This section is concluded with several research hypotheses, or expected findings.

Table 1: Variables to be Included in the Regression Analysis				
Variables	Mean	Standard Deviation	Min	Max
Net Migration Rate (2000-2009)	-2.23	8.91	-37.31	85.74
College Plus Percent (2005-2009)	23.51	7.30	7.46	70.43
Female Headed Household Percent (2005-2009)	10.68	4.78	0.00	45.06
Hispanic Percent of Population (2005-2009)	7.19	13.24	0.00	98.63
Home Ownership Percent (2005-2009)	73.54	7.23	0.00	90.55
Low Employment (2004)	0.19	0.39	0.00	1.00
Ln(2000 Census Population)	9.63	1.04	4.20	12.11
Ln(Per Capita Income) (2009)	10.35	0.20	9.62	11.92
Median Age (2005-2009)	40.49	5.18	0.00	63.60
Natural Amenities Scale	-0.05	2.25	-6.40	11.15
Nonmetropolitan, Not Adjacent	0.48	0.50	0.00	1.00
Per Capita Income Percent Change (1990-2000)	53.84	16.04	-30.26	194.89
Percent of homes with broadband availability (05-09)	73.30	22.69	0.00	100.00
Percent with <High School Education (2005-2009)	18.73	7.90	0.00	53.49
Persistent Child Poverty (1970-2000)	0.29	0.46	0.00	1.00
Persistent Poverty (1970-2000)	0.17	0.37	0.00	1.00
Population Change Percent (1990-2000)	9.84	81.67	-99.91	3,053.64
Property Crime Rate (2004)	18.29	13.42	0.00	82.58
Unemployment Percent Change (1990-2000)	-14.26	63.53	-80.45	2,000.00
Unemployment Rate (2009)	9.00	3.53	2.40	24.20
Violent Crime Rate (2004)	2.02	2.04	0.00	22.22
Census Regions				
Pacific	0.05	0.21	0.00	1.00
Mountain	0.12	0.31	0.00	1.00
WN Central	0.25	0.43	0.00	1.00
WS Central	0.16	0.37	0.00	1.00
EN Central	0.13	0.34	0.00	1.00
ES Central	0.12	0.33	0.00	1.00
Middle Atlantic	0.03	0.17	0.00	1.00
South Atlantic	0.15	0.35	0.00	1.00
New England	0.02	0.13	0.00	1.00
N=2,049				

III.2 DATA COLLECTION

The USDA Economic Research Service provides a useful database with many different variables for each county in the United States, such as net migration (as a rate) for years 2000-2009, natural amenities (ranked on a scale), education and income levels. The ERS provided definition accompanying the dataset for the 2000-2009 county net migration rates is the change in population between April 1, 2000 and July 2, 2009 due to net migration (including both domestic migration and immigration) as a percentage of the initial population. It is important to note the difference between net migration (the difference in the number of people moving to and from a given area in a given time period) and the natural change rate (the number of births minus the number of deaths in a given area in a given time period). This research focuses exclusively on net migration. The ERS database also provides dummy variables for certain specialization categories: farming, manufacturing, mining, retirement and recreation dependent counties. These dummy variables are used as one method of calculating “too specialized” counties. These variables are detailed and definitions are provided in **Table 2**. A visual representation of the distribution of the counties across the United States that qualify for the various dependency statuses is provided below via maps (See **Figures 3-9**).

The second specialization method uses data from the Census Bureau’s County Business Patterns 2-Digit NAICS code industry data. It is important to note that the NAICS 2-digit employment data, provided by the Census Bureau County Business Patterns, does not include self-employed persons. Therefore, self-employment or sole proprietorships are not captured or accounted for at all with the NAICS specialization categories.

To create the specialization categories for the NAICS 2-digit employment data, the percentage of employment in each 2-digit category was calculated, and dummy variables were created if a county had at least 10%, 20%, or 30% of their employment in any single industry. It is important to note that specialization was also reviewed at the forty and fifty percent levels but no significant results were found, so any specialization levels above thirty percent are omitted from further discussion. **Table 3** summarizes the percentage of nonmetropolitan counties that met the criteria for being "too specialized" at each of these levels for each NAICS 2-digit industry. By using several different thresholds with varying specialization limits, we were able to determine at what exact specialization level an impact on outmigration is noticed. For instance, if a county has more than 30% of total employment in one sector, they may be considered "too specialized" with respect to outmigration; this is the specialization level at which migration is negatively impacted. The overall goal of creating many different "too specialized" dummy variables was to find which dummy variables, and therefore specialization levels, significantly impact net migration. Maps that provide a visual representation of the distribution of the counties across the United States that fit into the key[1] "too specialized" categories are represented in **Figures 10-14**.

Statistics on other variables that might impact migration were pulled from the United States Census Bureau, the BLS, the BEA, the FCC, and other online resources. **Table 1** provides summary statistics for all variables included in the analysis (note that only the 2,049 nonmetropolitan counties are included, since the analysis focused on them). Using data for the same calendar year was a priority to maintain uniformity and predictive ability within the model; however, deviations with some variables was unavoidable since some data sources used do not publish annual material until years after the data year has passed.

[1] Key industries included agriculture, manufacturing, construction, health care, manufacturing, and accommodation and food services. These industries were found to have significant relationships to net migration. Specific findings are detailed in later sections.

III.3 ERS DEPENDENCY DATA

As previously mentioned, **Table 2** outlines the dependency qualification requirements for the ERS dependency dummy variables included in the models. A total of seven categories are provided by the ERS, and dependency is attained once earnings or employment thresholds are met.

As shown in **Figure 3**, the majority of the farming dependent counties fall within the central area of the United States. A fair number of counties in the northwestern area of the

Table 2: ERS Dependency Dummy Variables Defined

Dependency[2]	% of NM Counties	Qualification
Farming	19.67%	Farm earnings ≥ 15% total earnings OR Farm employment ≥ 15% total employment
Manufacturing	28.55%	Manufacturing earnings ≥ 25% total earnings
Mining	5.51%	Mining earnings ≥ 15% total earnings
Federal/State Gov	10.79%	Federal/state earnings ≥ 15% total earnings
Services	5.56%	Services earnings ≥ 45% total earnings
Recreation	14.54%	Based on income, employment, recreational housing units, and hotel/motel receipts
Retirement	13.52%	Based on average age, and migration patterns of the elderly in the 1980s

country also fall into the farming dependent classification. Census regions most heavily populated with farming dependent counties include West-North Central, West-South Central, and Mountain. When considering the 9 Census regions, the West-North Central region has the largest percentage of farm dependent nonmetropolitan counties. Of the 506 nonmetropolitan counties falling within

[2] It is important to note that some of the categories are mutually exclusive: farming, manufacturing, mining, federal/state government, and services. Therefore, some counties may be dependent on more than one industry, but only one is recognized by the ERS according to their predetermined rank order. However, recreation and retirement dependent counties are not mutually exclusive. Therefore, counties may be classified as dependent on any industry, plus recreation and/or retirement if applicable.

the West-North Central Census region, 39.92% are classified as farm dependent, according to the ERS qualifications outlined in **Table 2**. When considering all nonmetropolitan counties in the United States, 19.67% are classified as farm dependent.

Figure 3: Farming Dependent

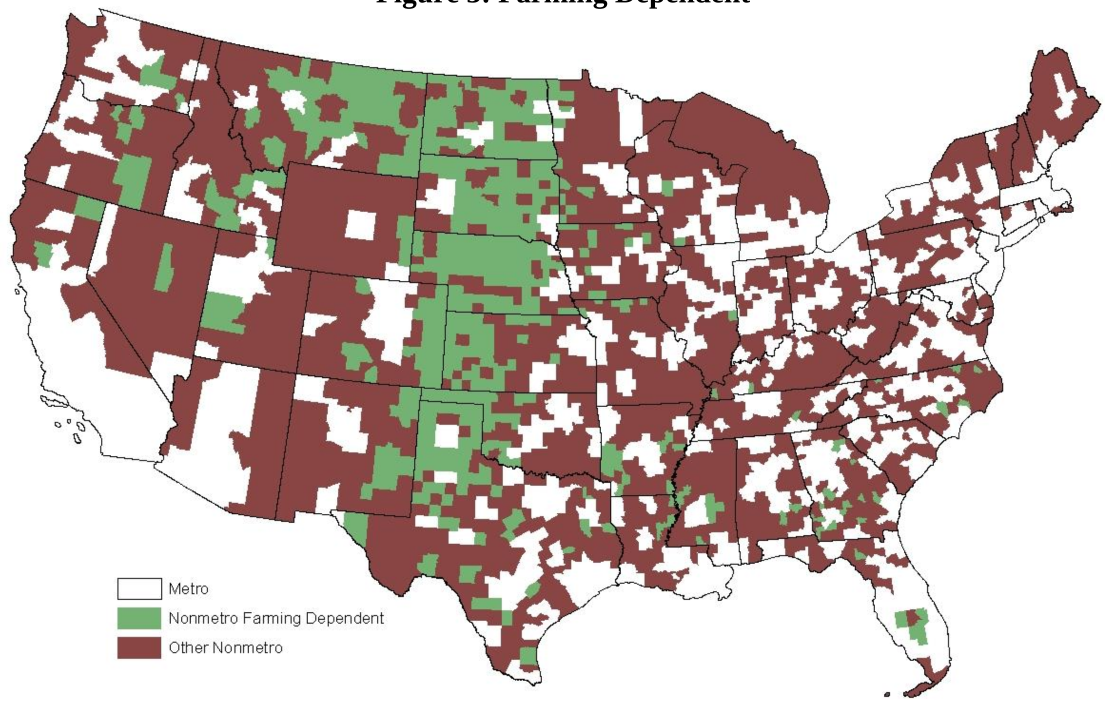
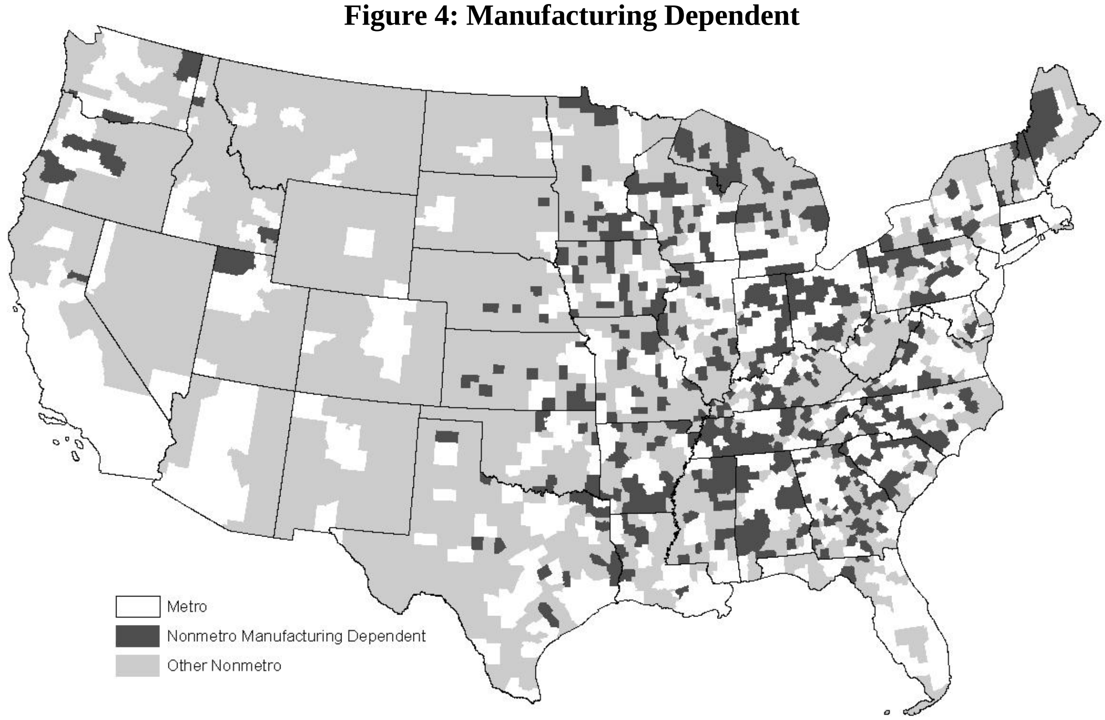


Figure 4 highlights counties that are considering manufacturing dependent by the ERS qualifications provided in **Table 2**. Manufacturing dependent counties are predominantly located in the eastern United States. Census regions most heavily populated with manufacturing dependent counties include East-North Central, East-South Central, Middle Atlantic and South Atlantic. All of these regions had greater than 40% of the nonmetropolitan counties classified as manufacturing dependent. The most heavily dependent region was the East-North Central region,

with 53.41% of the nonmetropolitan counties dependent on manufacturing. When considering all nonmetropolitan counties in the United States, 28.55% are classified as manufacturing dependent.

Figure 4: Manufacturing Dependent



As shown in **Figure 5**, very few nonmetropolitan counties in the United States are classified as mining dependent according to the ERS qualifications listed in **Table 2**. The Census regions most heavily populated with mining dependent nonmetropolitan counties included Mountain (13.24%), West-South Central (11.31%), South Atlantic (5.33%), East-North Central (4.17%) and East-South Central (4.07%). The New England Census region is the only region in the United States with absolutely no counties specialized in mining. When considering all nonmetropolitan counties in the United States, only 5.51% are classified as mining dependent.

Figure 5: Mining Dependent

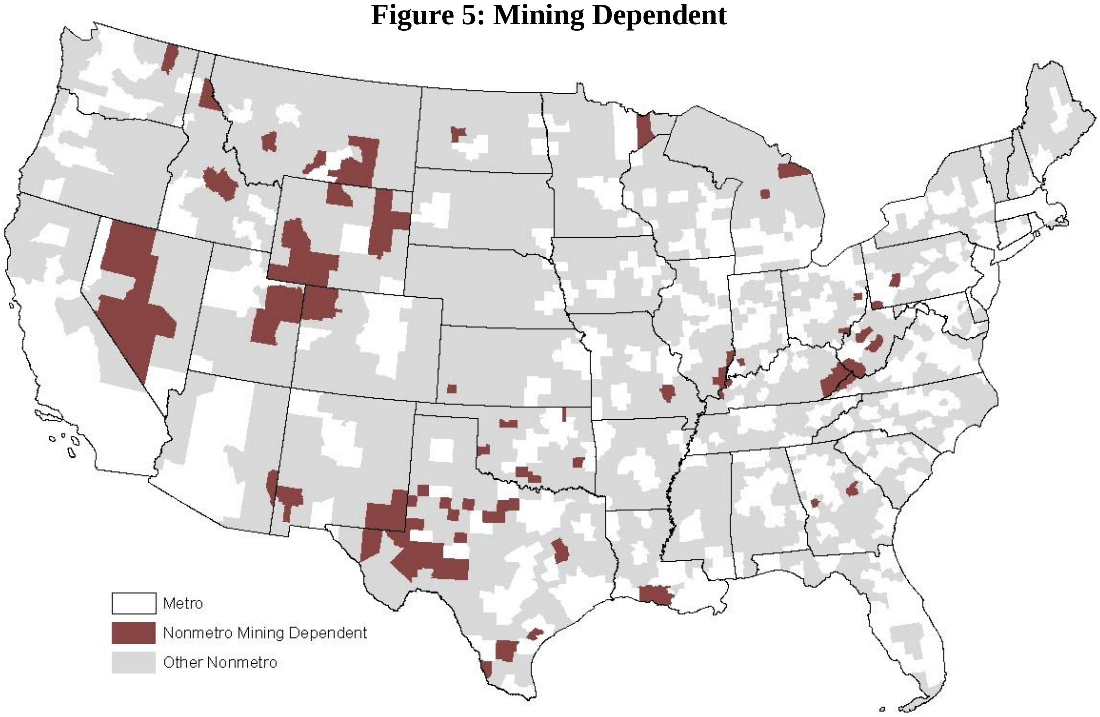
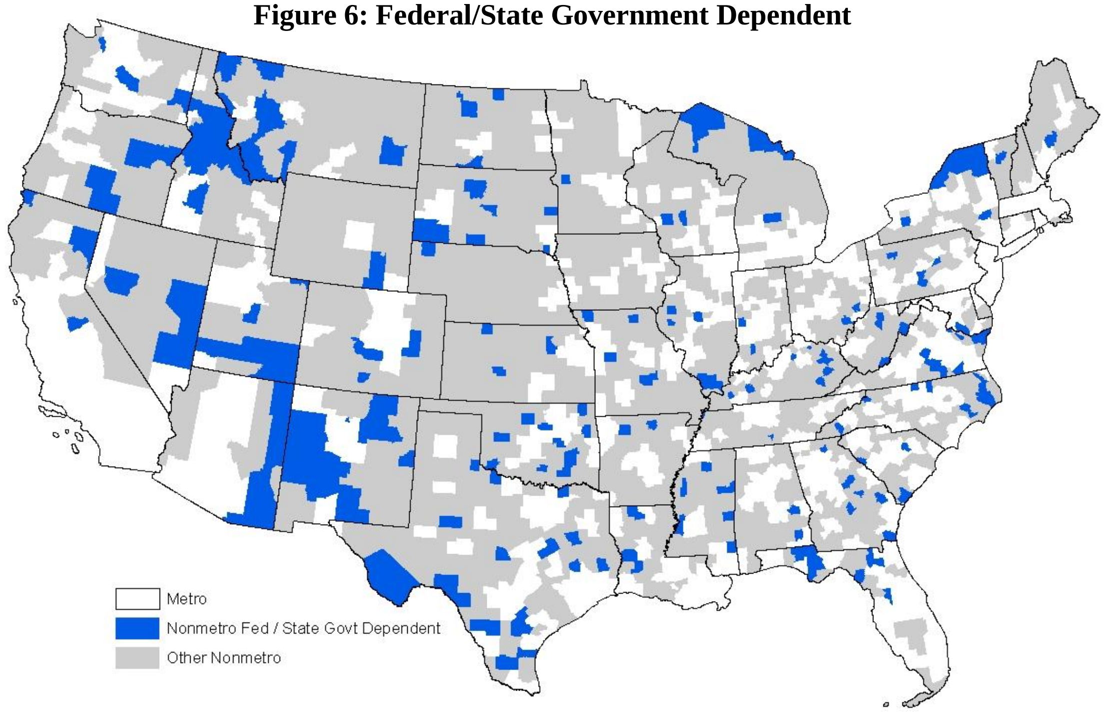


Figure 6 represents counties classified as federal/state government dependent, according to the ERS qualifications detailed in **Table 2**. Counties falling within this dependency category are fairly well-disbursed throughout the United States. The map shows that counties dependent on federal/state government tend to be clustered with other counties having the same dependency. Census regions with the highest percentages of counties classified as federal/state government dependent included Mountain (20.55%), Pacific (18.28%), Middle Atlantic (16.39%), South Atlantic (14.67%), and West-South Central (12.23%). The only Census region with a percentage of counties classified as federal/state government dependent lower than five percent was West-North Central, with only 4.35% of its counties qualifying for the dependency classification. When considering all nonmetropolitan counties in the United States, 10.79% are classified as federal/state government dependent.

Figure 6: Federal/State Government Dependent



As shown in **Figure 7**, very few counties are classified as service dependent, according to the ERS qualifications detailed in **Table 2**. Only 5.56% of all nonmetropolitan counties can be classified as service dependent. This is expected, since service-dominated economies are much more likely to be found in metropolitan areas. However, all Census regions had at least 4 nonmetropolitan counties classified as service dependent. The New England Census region is by far the most densely populated with nonmetropolitan service dependent counties, with 39.39 percent of all nonmetropolitan counties in the region being dependent on services. This is likely due to the fact that many of the nonmetropolitan counties are adjacent to metropolitan counties, which often specialize in services. Other Census regions with a high percentage of their nonmetropolitan counties dependent on services include: Mountain (12.33%), Pacific (9.68%), South Atlantic (7.67%), and Middle Atlantic (6.56%).

Figure 7: Services Dependent

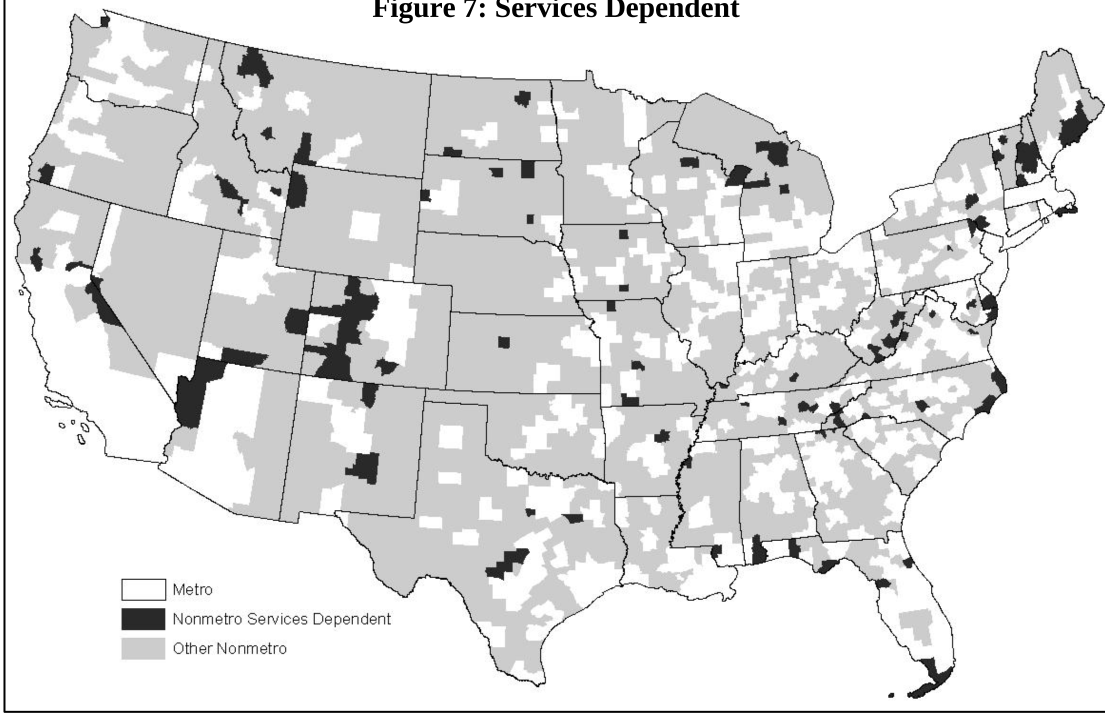
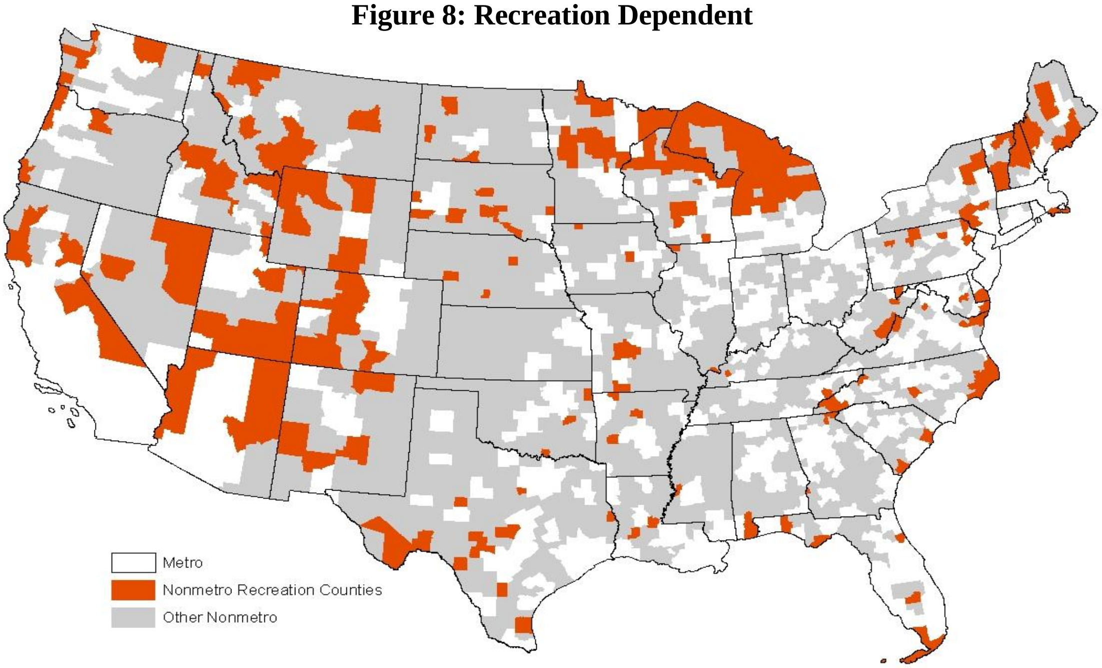


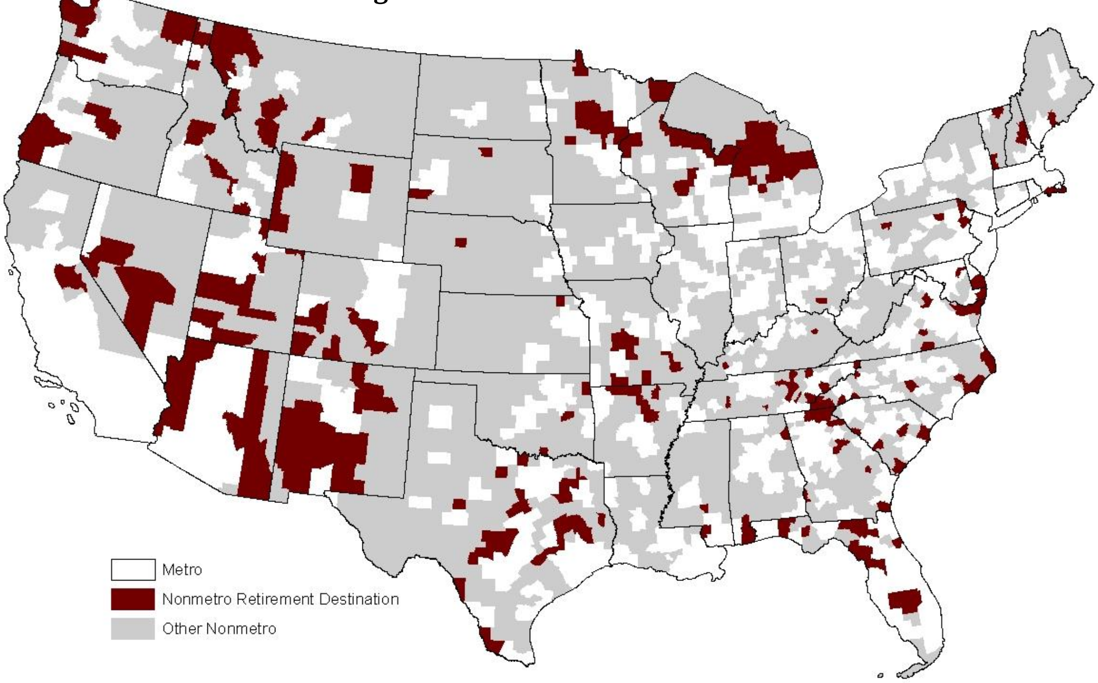
Figure 8 details the nonmetropolitan counties classified as recreation dependent, according to the ERS qualifications detailed in **Table 2**. A good portion of the nonmetropolitan counties in the United States falls under this classification (14.54% of all nonmetropolitan counties). From the map it is clear that the majority of these counties are in the western and north eastern sections of the United States. The following Census regions have the highest percentage of nonmetropolitan counties classified as recreation dependent: New England (57.78%), Pacific (37.63%), Middle Atlantic (35.48%), Mountain (34.25%), and East-North Central (22.35%). All other Census regions have relatively low percentages of nonmetropolitan counties classified as recreation dependent. The Census region with the lowest percentage of nonmetropolitan counties fitting into this classification was East-South Central, with only 1.63% of its nonmetropolitan counties dependent on recreation.

Figure 8: Recreation Dependent



The final dependency category provided by the ERS is retirement, and a map showing the distribution of counties meeting the qualifications for this dependency is shown in **Figure 9**. The qualification requirements for being classified as a retirement destination are detailed in **Table 2**. As **Figure 9** shows, retirement dependent counties are disbursed similarly to recreation dependent counties, with the majority falling in the western and north eastern United States. There are also a fairly large number of retirement dependent counties located in the south eastern United States as well. Census regions most heavily populated with nonmetropolitan retirement dependent counties include: Mountain (26.48%), South Atlantic (21.67%), Pacific (21.51%), and New England (21.21%). Of all nonmetropolitan counties in the United States, 13.52% are classified as retirement dependent counties.

Figure 9: Retirement Destination



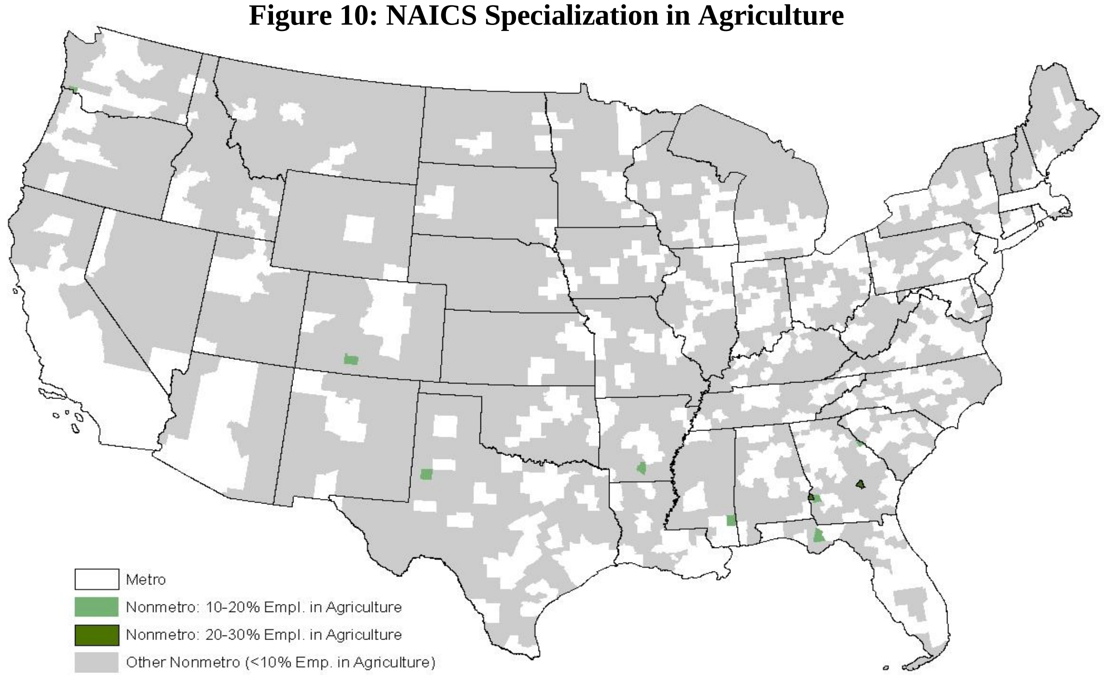
III.4 NAICS 2-DIGIT INDUSTRY SPECIALIZATION DATA

As previously mentioned, **Table 3** displays the percentage of nonmetropolitan counties falling in each of the NAICS 2-digit industry specialization categories. Again, these definitions are based on 10, 20 or 30 percent of all employment in a county being in a single 2-digit industry category. As **Figure 10**shows, a very small fraction of all nonmetropolitan counties can be classified as specialized in agriculture based on the NAICS 2-digit employment data, provided by the Census Bureau. Only ten counties fit into the 10% specialization level, two into the 20% level and zero counties are specialized at any higher levels. The majority of the counties are located in the southern half of the United States. Census regions with any counties specialized in agriculture at the 10% level include: Pacific, Mountain, West-South Central, East-South Central, South Atlantic and New England. The South Atlantic Census region had 5 counties specialized in

Table 3: Percentage of Counties Meeting "Too Specialized" NAICS 2-Digit Criteria			
Variables	10%	20%	30%
Agriculture	0.49%	0.01%	0.00%
Mining	5.42%	1.90%	0.49%
Construction	7.08%	0.59%	0.10%
Manufacturing	45.58%	25.33%	10.20%
Wholesale Trade	5.66%	0.49%	0.10%
Retail Trade	87.41%	18.20%	1.61%
Transportation & Warehousing	3.46%	0.34%	0.05%
Health Care	70.52%	29.33%	5.32%
Accommodation & Food Services	37.29%	4.93%	0.98%

agriculture at the 10% level. The South Atlantic Census region was the only region to have any specialization in agriculture at the 20% level, with two counties fitting into the classification. **Table 3** displays total percentages of counties specialized in agriculture at each of the specialization levels, and as you can see less than one percent of all nonmetropolitan counties in

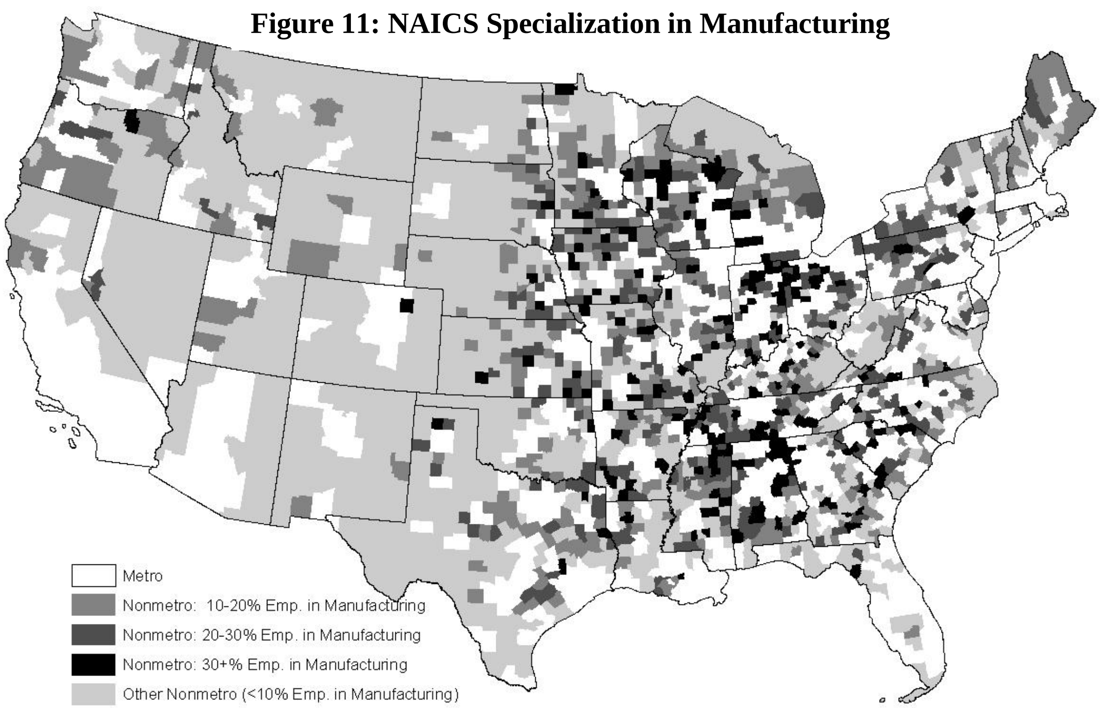
Figure 10: NAICS Specialization in Agriculture



the United States can be classified as specialized in agriculture at any given level. Note that this is significantly different from the ERS income-based definition of farming dependence shown in Figure 3.

Similar to the ERS manufacturing dependency map, **Figure 11** makes it clear that the majority of nonmetropolitan counties specialized in any level of manufacturing are located in the eastern half of the United States. Almost half of all nonmetropolitan counties are specialized in manufacturing at the 10% level, a quarter are specialized at the 20% level, and a tenth at the 30% level (see **Table 3**). Census regions with the highest percentages of nonmetropolitan counties specialized in manufacturing at the 10% level include: Middle Atlantic (78.69%), East-North Central (73.86%), and East-South Central (66.26%). The same Census regions have the highest percentage of nonmetropolitan counties specialized in manufacturing at the 20% level, but the corresponding percentage levels fall to 44.26%, 46.59% and 45.93%, respectively. Census

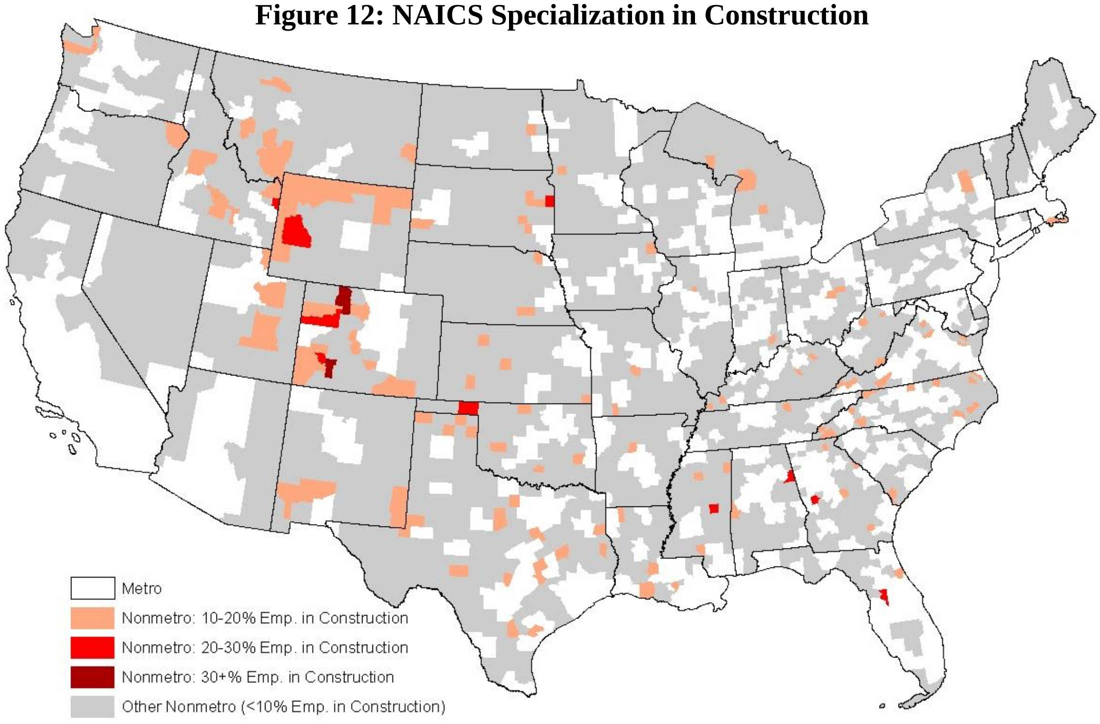
Figure 11: NAICS Specialization in Manufacturing



regions with the highest percentages of nonmetropolitan counties specialized in manufacturing at the 30% level include: East-South Central (22.76%), East-North Central (21.97%), and South Atlantic (10.67%). The data and maps clearly show that it is very common for nonmetropolitan counties to be specialized in manufacturing at various levels across the United States.

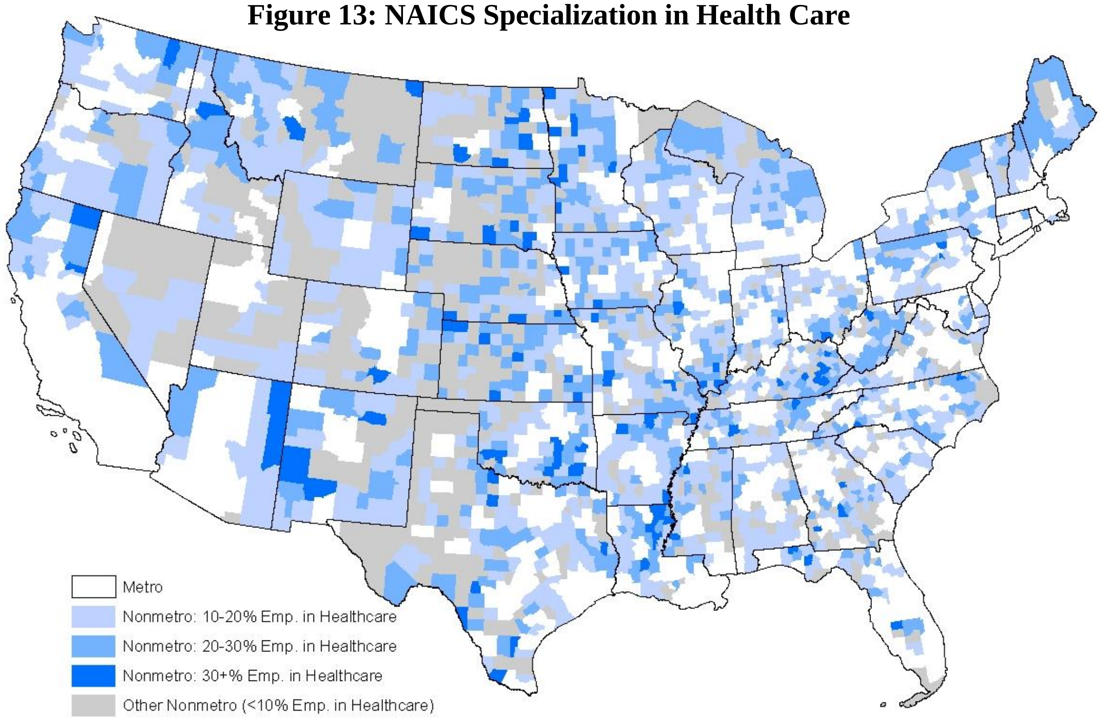
Figure 12 represents counties specialized in construction at the 10, 20 and 30 percent levels, according to the NAICS 2-digit employment data. Counties specializing in this industry are fairly well disbursed throughout the United States, but an exceptionally large portion of the counties are located in the west-central area of the country. When considering Census regions, Mountain (19.18%), South Atlantic (10.67%) and West-South Central (8.87%) have the highest percentages of counties specialized in construction at the 10% level. Out of all nonmetropolitan counties in the United States, 7.08% are specialized in construction at the ten percent level, 0.59% at the twenty percent level, and 0.10% at the thirty percent level.

Figure 12: NAICS Specialization in Construction



As **Figure 13** demonstrates, a large number of nonmetropolitan counties are specialized in healthcare at the 10 and 20 percent levels, according to the NAICS 2-digit employment data. Of all nonmetropolitan counties in the United States, 70.52% are specialized in healthcare at the ten percent level, 29.33% at the twenty percent level, and 5.32% at the thirty percent level. When considering healthcare specialization at the ten percent level by Census region, Middle Atlantic (90.16%), New England (87.88%), and East-North Central (84.09%) have the highest percentage of counties fitting into the category. All Census regions have over half of their nonmetropolitan counties specialized in healthcare at the ten percent level. Moving to the twenty percent specialization level, Middle Atlantic (40.98%), New England (36.36%) and West-North Central (33.40%) are the Census regions with the highest percentage of their counties meeting the

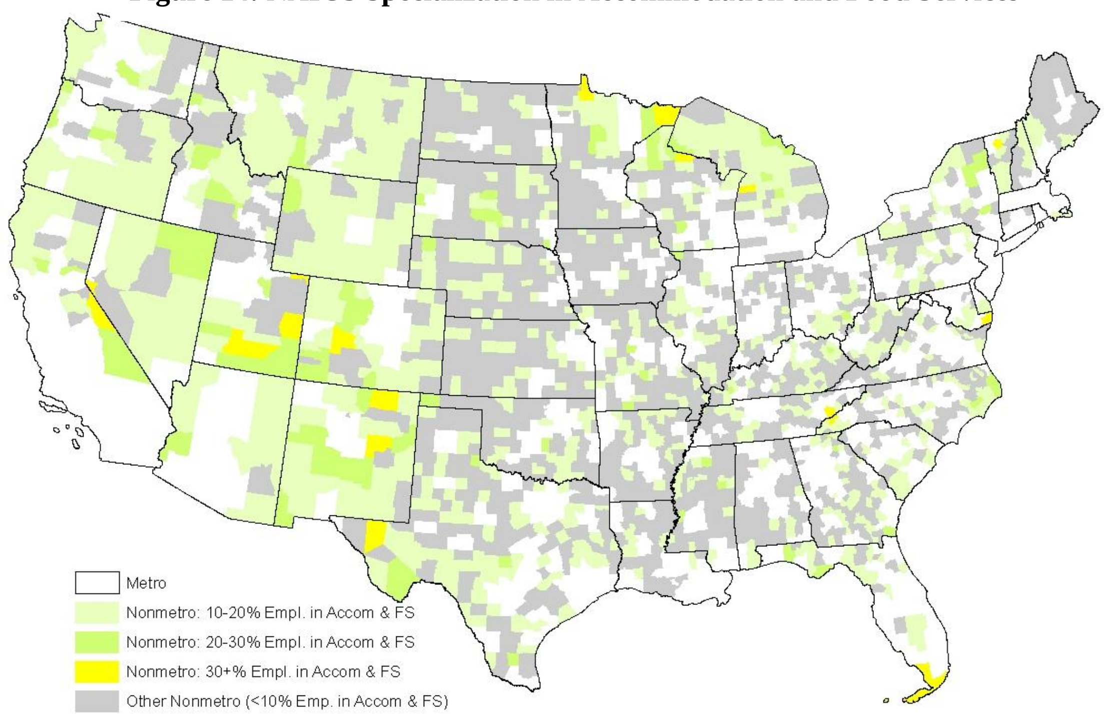
Figure 13: NAICS Specialization in Health Care



specialization criteria. All Census regions have less than 10% of their nonmetropolitan counties specialized in healthcare at the thirty percent level, but West-South Central (7.95%) and West-North Central (7.31%) had the highest percentages of counties specialized at this level.

To conclude the discussion of the key NAICS 2-digit industry specialization maps, **Figure 14** displays the various specialization levels for the accommodation and food service industry. The majority of nonmetropolitan counties specializing at any level in this industry are located in the western half of the United States. Out of all nonmetropolitan counties in the United States, 37.29% are specialized in accommodation and food services at the ten percent level, 4.93% at the twenty percent level, and 0.98% at the thirty percent level. Census regions with the highest percentages of counties specialized in accommodation and food services at the ten percent level are Mountain (67.12%), Pacific (60.22%), and New England (45.45%). Mountain and

Figure 14: NAICS Specialization in Accommodation and Food Services



Pacific also have the highest percentage of counties specialized in accommodation and food services at the twenty percent level, with 16.89% and 11.83%, respectively. Very few counties are specialized in accommodation and food services at the thirty percent level, but Census regions with the highest percentages of counties specialized at this level are Mountain (3.65%), New England (3.03%), and Pacific (2.15%).

III.5 ORDINARY LEAST SQUARES

Two modeling approaches were employed in this research. The first method used a traditional OLS model:

$$y_i = \beta_1 x_1 + \ldots + \beta_k x_k + \gamma_1 z_1$$

Where y_i is the net migration rate between 2000-2009 for county i, x_1 through x_k are variables potentially impacting migration, z_1 is the dummy variable denoting "too specialized" counties, β_1 through β_k are parameters associated with the control variables, and γ_1 is the parameter of interest. Thus, variable z_1 represents the different "too specialized" industry classifications, as they relate to either the NAICS 2-digit classifications or the ERS classifications. OLS was run multiple times, using the different measures of specialization (different dummy variable for the value z_1) to see if and when this "too specialized" variable had a significant impact on migration. The factors affecting migration are represented by x_k.

A detailed summary of those factors is presented in **Table 1**. The nine[3] NAICS industries used are detailed in **Table 3**, and the ERS dependency categories used and their requirements can be found in **Table 2**.

III.6 AVERAGE TREATMENT EFFECT

The second approach for this research involved the average treatment effect and propensity score matching technique. The main benefit the average treatment effect provides is that it allows us to make statements about the causality relative to outmigration, whereas OLS only allows us to speak about variable correlation. The average treatment effect technique involves splitting the data into two groups: treated and untreated observations. The treated group includes counties that are determined to be "too specialized." The untreated group includes all other counties. The purpose of the ATE is to measure the average *causal* differences in outcomes of the two groups, or the percentage difference in the migration rate between counties that are too specialized and counties that are not. This percent difference is known as the average treatment effect, or the average effect of counties being "too specialized" (treated). The average treatment effect can be represented as:

$$ATE = E(\Delta M_{j1} \mid T_j = 1) - E(\Delta M_{j0} \mid T_j = 1)$$

[3] A total of 20 NAICS 2-digit industry codes are provided by the Census Bureau; however, only 9 of these industries were found to have any significant results. Therefore, the remaining 12 industries are omitted from further discussion. Those industries included: utilities; information; finance and insurance; real estate rental and leasing; professional, scientific, and technical services; management of companies and enterprises; administration and support and waste management and remediation services; educational services; arts, entertainment and recreation; other services (except public administration), and public administration.

where ΔM_{j1} and ΔM_{j0} represent the migration rate of counties that are too specialized and counties that are not, respectively, and T_j equals 1 for treated counties (counties considered "too specialized") and 0 for non-treated counties (counties not considered overly specialized).

However, the latter part of the equation is unobservable in reality, because by definition counties that are not specialized (ΔM_{j0}) cannot have been treated ($T_j = 1$). So, propensity score matching was used to correct for this problem. The goal of the propensity score matching technique is to match communities that are determined to be too specialized (treated) with otherwise similar non-specialized (not treated) communities. The similarity of these groups will be based on the variables used in approach one and in **Table 1** (e.g. population, income, ethnicity, etc.). Unfortunately, more than a simple estimate of the propensity score (calculated using a logit model) is needed to adequately estimate the average treatment effect since the probability is zero of units in the treated and non-treated group having the exact same propensity score (Becker). To satisfy this problem and match observations, additional matching techniques were used, including Nearest Neighbor Matching and Kernel Matching. The Nearest Neighbor Matching technique individually matches treated and non-treated units by searching for a non-treated unit that has the closest propensity score to an individual treated unit. A disadvantage to this method is that there is no guarantee that the matches are in fact "close" because the distance between the two closest treated and non-treated propensity scores can be vast. To solve this problem, Kernel Matching can be employed. Kernel Matching pairs treated units with a weighted average of all non-treated units. The weights of these averages are inversely proportional to the distance between the propensity scores of treated and non-treated units (Mahasuweerachai, Whitacre and Shideler).

III.7 RESEARCH HYPOTHESES

Several hypotheses regarding the relationship between industry specialization and outmigration can be answered regression analysis. In particular, this thesis will explicitly test the following hypotheses:

> [H1] Nonmetropolitan counties that are highly specialized in the manufacturing and agriculture industries will exhibit higher outmigration rates than counties not highly specialized in these areas.

Manufacturing job availability tends to fluctuate with economic conditions. Also, many manufacturing jobs previously housed in the United States have been transferred overseas. As previously mentioned, the agriculture industry has experienced drastic shifts over the past century. As the average basic farm structure has changed, small rural farms have decreased in numbers. It is likely these nonmetropolitan citizens are outmigrating to metropolitan areas that present more opportunities. Also as the literature suggests, counties highly specialized in manufacturing are more economically sensitive, and as a result they will likely exhibit higher outmigration rates since citizens will choose to relocate more often as economic conditions fluctuate.

While [H1] focuses specifically on manufacturing and agricultural specialization, [H2] allows the definition of specialization to vary by looking at varying thresholds of specialization across many NAICS categories. Testing [H2] will showcase the differences in migration rates across varying definitions of what might be considered “too specialized.”

[H2] After controlling for other variables[4], nonmetropolitan counties that are too specialized in terms of their industrial composition will have higher rates of outmigration.

By restricting the regression analysis to each of the nine Census regions, or including dummy variables in the regression analysis, the impacts of belonging to a specific region can be observed. Also, while some regions of the country are losing dramatic amounts of population, others are experiencing in-migration. Observing the differences across Census regions in both migration and industry specialization will provide some initial evidence about the importance of regionalization in this relationship. As [H3] suggests, the nine different Census regions potentially have dramatic differences in migration rates and industry specialization levels.

[H3] The outmigration – industrial specialization relationship will vary across the nine Census regions.

The previous hypotheses can all be answered using simple multivariate regression analysis. These hypotheses only addressed proposed relationships between migration and different variables; the hypotheses don't actually address causation of migration. Therefore, the average treatment effect and propensity score matching will be used to answer the more difficult questions related to actual causation of migration.

[4] Other variables to include Census region, 2000 population, Hispanic percent of population, median age, percent of population with less than high school education, female headed household percent, percent of homes owned, median household income, unemployment rate, nonmetropolitan dummy variable, persistent poverty, natural amenity scale, violent crime rate, property crime rate, and percent of households with broadband access.

[H4] Being overly specialized in the agriculture and manufacturing industries *causes* nonmetropolitan county outmigration.

As previously mentioned, the manufacturing and agriculture industries tend to be economically volatile, and therefore cause difficulty in maintaining economic stability. As a result, becoming highly specialized in these areas could cause county outmigration since citizens will migrate towards areas with more economically stable industry composition, or industrially diverse counties.

[H5] Being industrially specialized *causes* a nonmetropolitan county to experience outmigration.

[H5] moves beyond just agriculture and manufacturing and looks at other ERS and Census Bureau County Business Patterns defined specializations. Following the same reasoning as the previous hypothesis, counties that are economically diverse are better apt to handle economic fluctuations, and therefore are more likely to retain their citizens and even attract more. A county that is highly specialized is also highly dependent on the prosperity of a small number of industries. If those industries happen to falter, the entire county is likely to experience hardship as well. As a result, citizens may relocate to a county with a more diverse industry mix where more jobs are available.

CHAPTER IV. FINDINGS

IV.1a ORDINARY LEAST SQUARES – BASIC MODEL NATIONAL RESULTS

Table 4 displays the results of the basic OLS regression. Most results from the simple OLS regression are as expected. For example, an increase in the college educated population by one percentage point in a nonmetropolitan county will result in a 0.11 increase in the net migration rate. Also, a one unit increase on the ERS's natural amenities scale will lead to an increase of 1.07 percentage points in the net migration rate. On the other hand, a one percentage point increase in the violent crime rate decreases the net migration rate by -0.30. Similarly, nonmetropolitan counties suffering from persistent poverty or persistent child poverty notice a decrease in the net migration rate of -1.70 and -1.63 percentage points, respectively. Variables in the OLS model that were shown to have a positive relationship with the net migration rate included: West-South Central census region, East-South Central census region, South Atlantic census region, the natural logarithm of the 2000 Census population, the percent change in population from 1990-2000, percent of citizens with at least a college education, home ownership percentage, percent change in per capita income from 1990-2000, the natural amenity scale, property crime rate, and broadband availability. Variables shown to have a negative relationship with the net migration rate included: Hispanic percent of population, percent of population with less than a high school education, female-headed household percentage, percent change in unemployment from 1990-2000, the natural logarithm of 2009 per capita income, counties that are nonmetropolitan and non-adjacent to a metropolitan county, persistent poverty, persistent child poverty, and the violent crime rate. Again most of the relationships have been determined in the previous outmigration literature. The R^2 is relatively high at 0.4898, suggesting a good overall fit for the basic model.

Table 4: Basic OLS National Coefficient Results		
Dependent Variable: Net Migration Rate	**Coefficient**	**Significance**
Pacific Census Region	-0.35	NS
Mountain Census Region	1.22	NS
West North Central Census Region	-0.18	NS
West South Central Census Region	3.32	**
East North Central Census Region	-1.54	NS
East South Central Census Region	4.05	**
Mid-Atlantic Census Region	-2.03	NS
South Atlantic Census Region	8.07	***
Natural Logarithm of 2000 Census Population	2.77	***
Population Change 1990-2000 Percent	0.00	*
Hispanic 2005-2009 Percent	-0.06	***
Median Age 2005-2009	-0.02	NS
<High School Education 2005-2009	-0.14	***
College Plus 2005-2009	0.11	**
Female Headed-Household Percent 2005-2009	-0.38	***
Own Home 2005-2009 Percent	0.17	***
Unemployment Change 1990-2000 Percent	-0.01	**
Unemployment Rate 2009	-0.06	NS
Per Capita Income Percent Change 1990-2000	0.06	***
Natural Logarithm Per Capita Income 2009	-12.44	***
Nonmetropolitan Not-Adjacent	-0.97	**
Low Employment 2004	-0.01	NS
Persistent Poverty 1970-2000	-1.70	**
Persistent Child Poverty 1970-0000	-1.63	***
Natural Amenity Scale	1.07	***
Violent Crime Rate 2004	-0.30	**
Property Crime Rate 2004	0.04	*
Broadband Availability 2005-2009	0.02	*
Intercept	87.36	***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively. N=2005; R^2=.4898		

IV.1b ORDINARY LEAST SQUARES – ERS DEPENDENCY NATIONAL RESULTS

To determine whether or not various types of industrial dependency had any impact on net migration, dummy variables for ERS dependency classifications were added to this bare specification. Results for the ERS dependencies were mostly consistent with the existing literature, a county dependent on farming and manufacturing demonstrates a negative relationship with the net migration rate. These findings are consistent with the expectations of [H1][5]. **Figure 15** represents the ERS dependency counties predicted to shrink by the OLS procedure. As the results suggest, the only industries associated with shrinkage for the ERS dependency categories are agriculture and manufacturing; therefore verifying the expectation under [H1]. Communities defined as farm dependent were associated with a 1.64 percentage point decrease in the net migration rate, while manufacturing dependent counties were associated with a 1.39 percentage point decrease in the net migration rate (see **Table 5**).

Table 5: ERS National Coefficient Results		
Farm Dependent	-1.64	***
Mining Dependent	-0.36	NS
Manufacturing Dependent	-1.39	***
Fed/State Gov Dependent	-0.72	NS
Service Dependent	2.25	***
Recreation	1.15	*
Retirement	6.03	***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.		

Service, recreation and retirement counties were found to have positive impacts on migration. In particular, communities defined as retirement dependant were associated with a

[5] [H1] Nonmetropolitan counties that are highly specialized in the manufacturing and agriculture industries will exhibit higher outmigration rates than counties not highly specialized in these areas.

6.03 percentage point increase in the net migration rate, while those that were service dependent were associated with a 2.25 percentage point increase in the net migration rate (see **Table 5**).

Figure 15: ERS Dependency Counties Predicted to Shrink

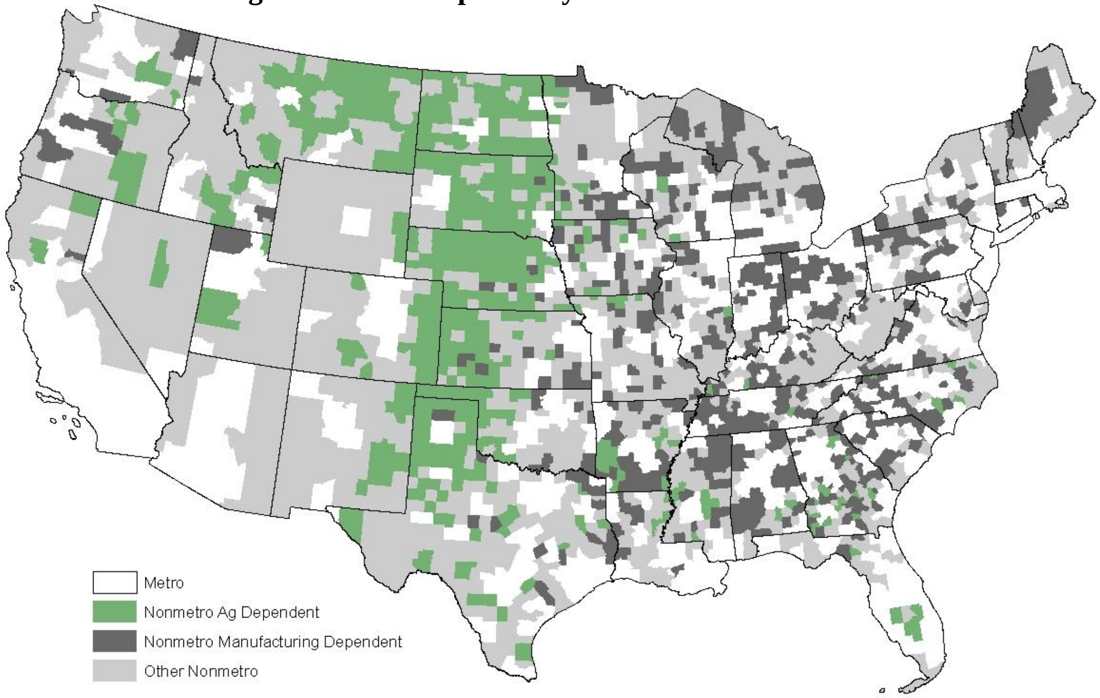


Figure 16 provides a map of nonmetropolitan counties that are expected to grow, categorized by their ERS dependency classification. When considering the ERS dependency results in regards to [H2][6], we find that our expectations weren't entirely met. If the hypothesis was correct, counties meeting the criteria for a dependency classification would exhibit outmigration, and the rate of outmigration would be higher than other non-specialized counties. When considering farm and manufacturing dependent counties, this is true; however, when services, recreation and retirement counties are considered, the hypothesis is incorrect. Therefore,

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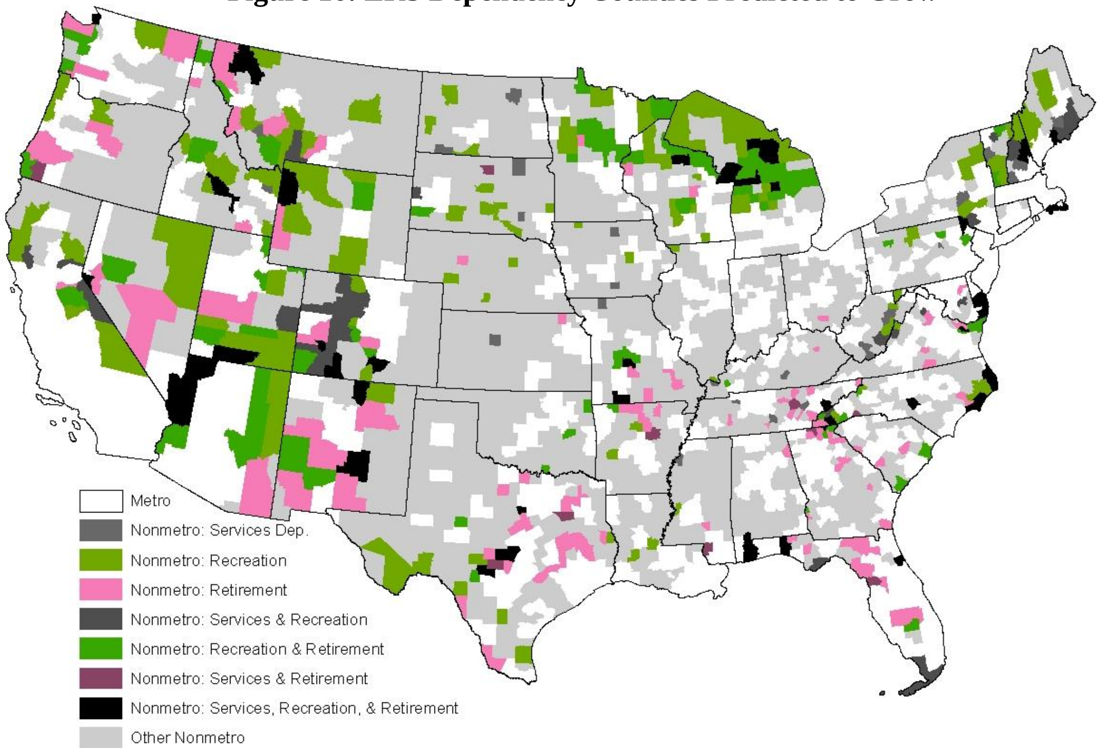
[6] [H2] After controlling for other variables (listed in **Table1**), nonmetropolitan counties that are too specialized in terms of their industrial composition will have higher rates of outmigration.

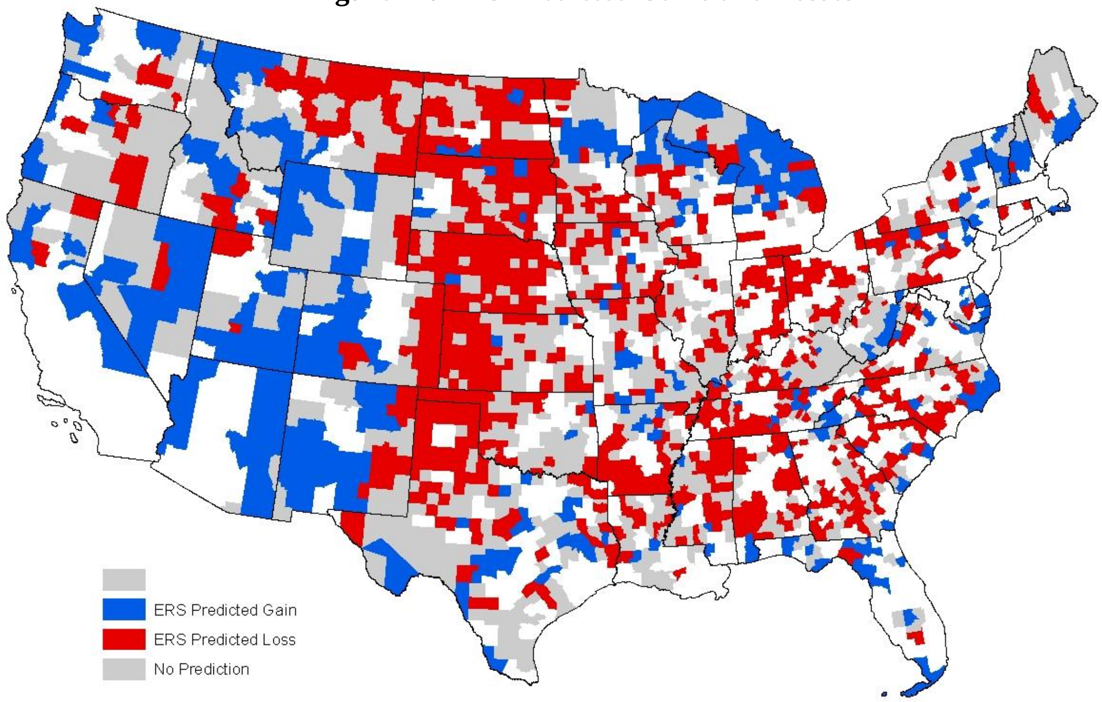
the ERS results do not explicitly show that industrial specialization is associated with higher rates of outmigration – in fact some types of specialization seem to encourage in-migration. But, retirement/services specialization includes more than just one specific industry.

Figure 16: ERS Dependency Counties Predicted to Grow



To summarize the findings of adding the ERS dependency classifications to the OLS model, **Figure 17** is provided. As you can see, most nonmetropolitan counties in the United States are associated with either a gain or loss in population, depending on their ERS dependencies. Most loss counties are located in the central United States, while counties expected to gain population are located in eastern and western areas.

Figure 17: ERS Predicted Gains and Losses



IV.1c ORDINARY LEAST SQUARES – NAICS SPECIALIZATION NATIONAL RESULTS

To determine whether or not various types of industrial dependency had any impact on net migration, dummy variables for NAICS 2-digit specialization at 10, 20 and 30% were added to the bare specification. When considering the “too specialized” categories created for the NAICS 2-digit industry data, some interesting results were found. Referring to **Table 6**, it was found that some industries had a significant relationship with net migration when one specialization level was concerned, but the relationship or its magnitude typically changed or became insignificant when the specialization level changed. Also, even though specialization levels were created and tested for up to 50% specialization in one industry, no significant relationships with the net migration rate were observed past the 30% threshold, so subsequent levels are omitted from this discussion. The construction industry was found to have the most

Table 6: OLS NAICS National Coefficient Results			
	10%	20%	30%
Agriculture	NS	7.46*	NS
Mining	NS	NS	NS
Construction	4.07***	12.16***	NS
Manufacturing	NS	-0.82*	NS
Wholesale Trade	NS	NS	NS
Retail Trade	NS	NS	NS
Transportation & Warehousing	NS	NS	NS
Health Care	NS	-0.59**	NS
Accommodation & Food Services	1.25***	NS	-2.93*
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.			

positive relationship with the net migration rate overall. If a county has 10% of their employment in the construction industry, the net migration rate will increase by 4.07 percentage points (see **Table 6**). If the construction specialization level increases to 20%, the net migration rate will increase by 12.16 percentage points. However, once the specialization level reaches 30% in the construction industry, there is no longer an observed statistical impact on the net migration rate – perhaps because very few counties experienced this level of specialization. Another specialization category that had a positive relationship with the net migration rate was agriculture, when 20% of the county employment was accounted for by this industry. This result is surprising, since the ERS farming dependency demonstrated negative impacts on migration. One industry that produced interesting results is the accommodation and food services industry. At the 10% level, a positive coefficient of 1.25 was observed. When the industry accounted for 20% of the county employment, no significant relationship was found. However, when total county employment in the industry jumped to 30%, a negative relationship to the net migration rate was found, revealing that this specialization level resulted in a 2.93 percentage point decrease in the net migration rate. Also of significance were the manufacturing and health care industries, each at the 20%

specialization levels, with a negative relationship to the net migration rate. These results demonstrate that different industries have different cutoff points associated with migration rates.

Table 7 provides an example of one of the models used to generate the results. The various demographic and economic variables are constants in each model, and the specialization industry and level vary in each model. The specialization level variable (in this example, construction at the 20% specialization level) is a dummy variable, simply signifying whether or not the county met the specialization threshold. The coefficient for this specialization level dummy variable is 12.16 (with a p-value of .0000), meaning that a nonmetropolitan county specialized at the 20% level in construction is associated with a 12.16 percentage point increase in the net migration rate. Therefore, in this example the specialization threshold positively impacts the net migration rate, and therefore promotes in-migration. The example shown in **Table 7** represents only one model for one specialization level. Separate models were created for each specialization level in every NAICS 2-digit industry, with results for the 2-digit NAICS sectors summarized in **Table 6**.

Figures 18 and 19 provide a visual representation of the counties predicted to grow and shrink, according to the NAICS 2-digit industry data. As the results suggest, most counties predicted to grow are located in the western United States and counties predicted to shrink are located in the eastern area of the nation. Consistent with the findings summarized in **Table 6**, industry specialization levels associated with in-migration include agriculture (20%), construction (10 and 20%), and accommodation and food services (10%). Specialization levels associated with outmigration include manufacturing (20%), healthcare (20%), and accommodation and food services (30%).

Table 7: Example of Model with NAICS Specialization Variable (Construction 20%)				
Net Migration Rate 00-09	Coefficient	Std Error	T-Stat	P-Value
Pacific CR	-0.29	1.45	-0.20	0.84
Mountain CR	1.00	1.27	0.79	0.43
WN Central CR	-0.28	1.21	-0.23	0.82
WS Central CR	3.17	1.26	2.52	0.01
EN Central CR	-1.76	1.24	-1.42	0.16
ES Central CR	3.73	1.28	2.92	0.00
Mid Atlantic CR	-2.22	1.39	-1.60	0.11
S Atlantic CR	7.78	1.24	6.26	0.00
ln 2000 Population	2.81	0.22	12.75	0.00
Population Chg 90-00 Pct	0.00	0.00	1.84	0.07
Hispanic 05-09 Pct	-0.06	0.02	-4.11	0.00
Median Age 05-09	-0.01	0.04	-0.18	0.86
<HS Education 05-09	-0.13	0.04	-3.16	0.00
College Plus 05-09	0.11	0.04	3.16	0.00
Female HHH Pct 05-09	-0.37	0.05	-7.46	0.00
Own Home 05-09 Pct	0.17	0.03	5.83	0.00
Unemp Chg 90-00 Pct	-0.01	0.00	-2.29	0.02
Unemp Rate 09	-0.05	0.07	-0.74	0.46
PCI Pct Chg 90-00	0.06	0.01	6.31	0.00
ln PCI 09	-12.88	1.15	-11.23	0.00
NM Not Adj	-1.00	0.32	-3.17	0.00
Low Employment 04	-0.04	0.47	-0.08	0.94
Pers Poverty 70-00	-1.78	0.59	-3.00	0.00
Pers Child Poverty 70-00	-1.66	0.48	-3.46	0.00
Natural Amenity Scale	1.02	0.10	10.25	0.00
Violent Crime Rate 04	-0.29	0.10	-2.93	0.00
Property Crime Rate 04	0.04	0.02	2.32	0.02
BB Availability 05-09	0.02	0.01	2.41	0.02
Construction (20%) Dummy Variable	**12.16**	**1.85**	**6.56**	**0.00**
Intercept	90.68	11.90	7.62	0.00
N = 2,005; R-Squared = 0.5007				

Figure 18: NAICS Counties Predicted to Grow

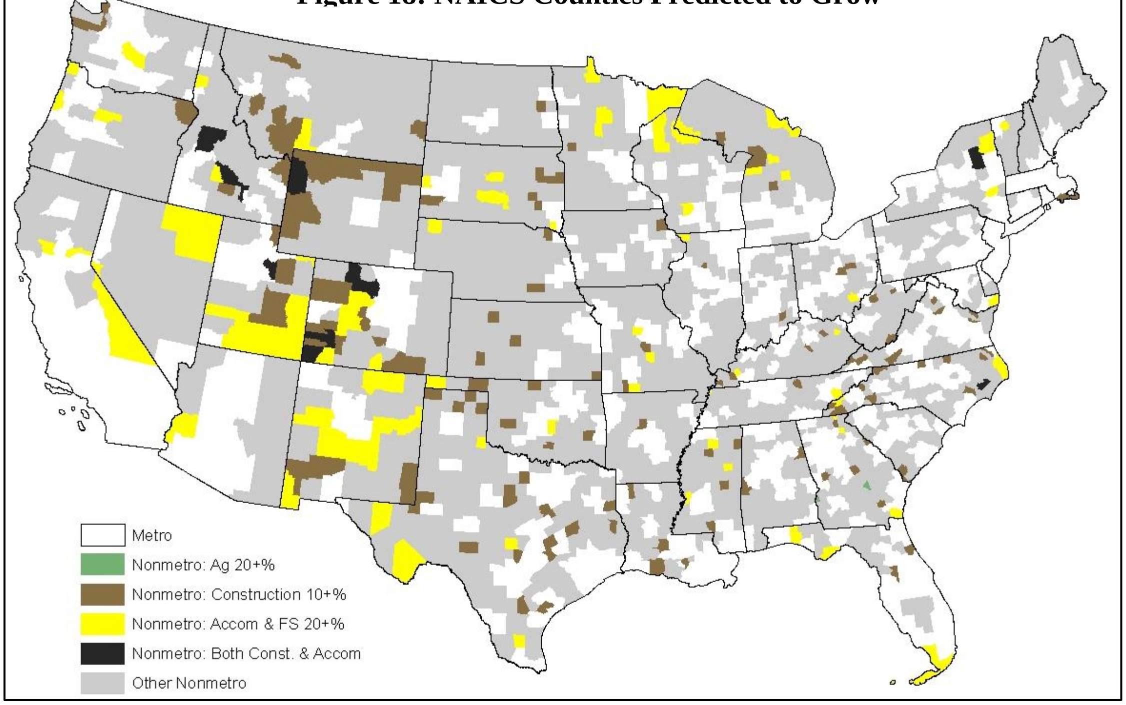
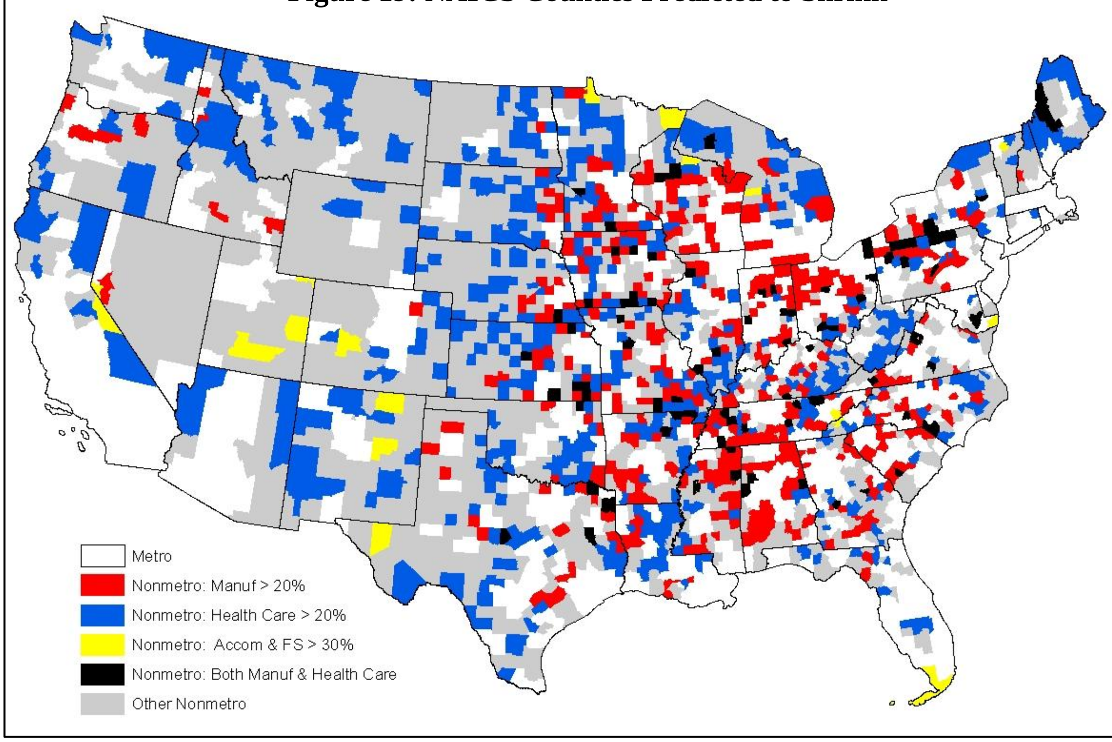


Figure 19: NAICS Counties Predicted to Shrink



The NAICS 2-digit employment data provide results that vary when considering [H1][7] and [H2][8]. Counties specialized in agriculture at the 20% level were associated with growth in population, while counties specialized in manufacturing at the 20% level were associated with shrinkage in population. Therefore, with regards to the NAICS specialization levels, [H1] expectations were correct when considering manufacturing, but incorrect when considering agriculture. A similar situation is found when considering [H2]. When a county is diversified by being specialized in both manufacturing and health care, outmigration is predicted. However, if a county is diversified by being specialized in construction and accommodation and food services, in-migration is predicted. Therefore, the expectations presented by [H2] cannot conclusively be proven or rejected with the NAICS specialization data. Some specialization levels were associated with higher levels of outmigration (as predicted), but there are also specialization levels that are associated with higher levels of in-migration (not predicted). Therefore, the NAICS results suggest that [H2] might appropriately be reconsidered by focusing on distinct NAICS industries.

Figure 20 summarizes the NAICS findings, by displaying expected gains and losses on one map. Each shaded county is specialized in at least one area, and is predicted to experience either outmigration or in-migration depending on the specific area(s) of specialization. This map is very similar to **Figure 17**, which displayed the expected gains and losses based on ERS dependency. The primary difference between the two maps is that the NAICS specialization categories predict more population movement for more nonmetropolitan counties in total. The ERS dependency categories project more outmigration in general, specifically throughout the migration for counties in the eastern United States, particularly for Wyoming, Nevada, and Montana.

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[7] [H1] Nonmetropolitan counties that are highly specialized in the manufacturing and agriculture industries will exhibit higher outmigration rates than counties not highly specialized in these areas.
[8] [H2] After controlling for other variables (detailed in **Table 1**), nonmetropolitan counties that are too specialized in terms of their industrial composition will have higher rates of outmigration.

Figure 20: NAICS Predicted Gains and Losses

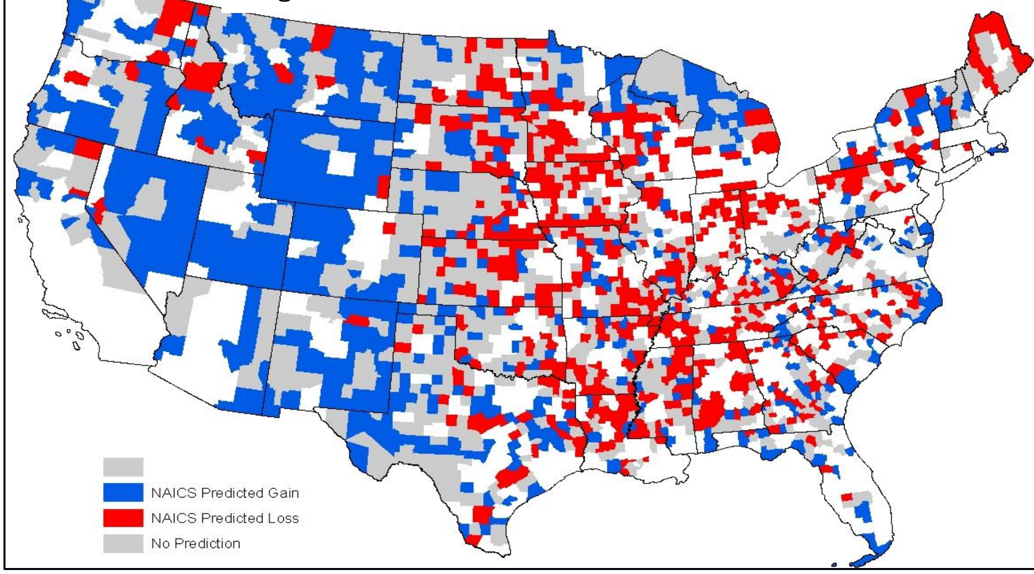
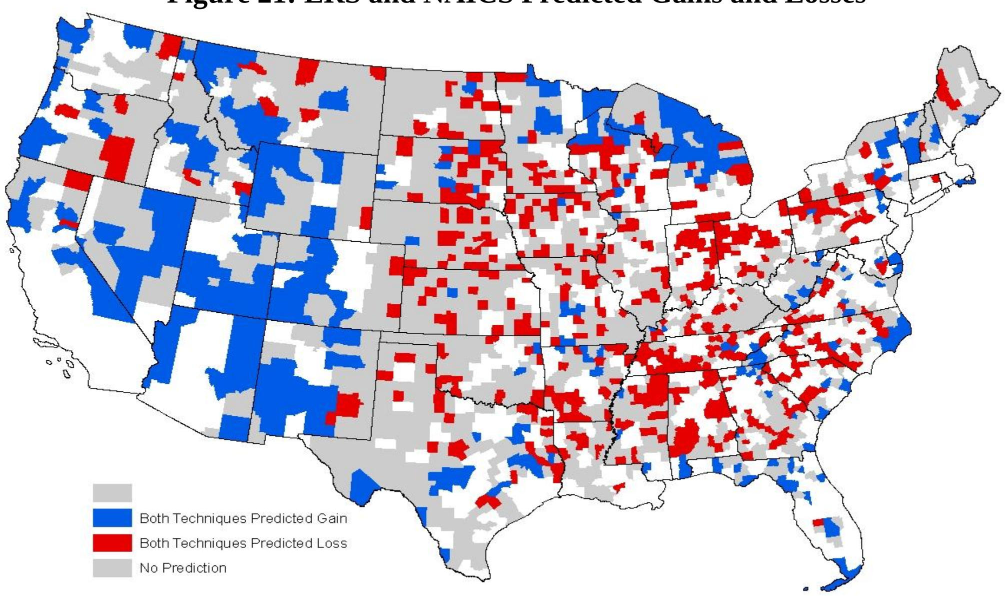


Figure 21 displays which ERS and NAICS gain/loss predictions overlap for nonmetropolitan counties across the United States. The key finding from combining both data sources is that gains are predicted in western areas, and losses are predicted in central and eastern areas.

Figure 21: ERS and NAICS Predicted Gains and Losses



IV.1d ORDINARY LEAST SQUARES – BASIC MODEL REGIONAL RESULTS

Table 8 summarizes the findings for each basic model for all nine census regions. The table displays the variables that were determined to be significant in each model for each region,

Table 8: Basic OLS Model Regional Coefficient Results

	Pac	Mntain	WNCen	WSCen	ENCen	ESCen	MidAtl	SAtl	NEng
Census Pop ‘00	3.19 **	3.33 ***	2.92 ***	3.94 ***	1.53 ***	1.47 *			
PopChange % (‘90-‘00)			0.24 ***		0.23 ***	0.32 ***			0.30 **
Hispanic % of Population			-0.24 ***				1.42 **	0.36 **	
Median Age					0.27 ***	0.29 *	-0.84 *		
% with <High School Edu						-0.16 *		-0.61 ***	
College Plus %				0.24 *	0.15 *			0.45 **	-0.44 *
Female Headed HH %		0.48 *	-0.15 *	-0.21 *		-0.54 ***			-0.86 *
Home Ownership %	0.53 **		0.08 *	0.27 ***	-0.13 *		0.69 *	0.32 *	
Unemp Rate (‘09)		1.14 ***			-0.29 **	-0.40 **		-0.51 *	
Unemp % Chg (‘90-‘00)									-0.14 *
Low Employment							13.55 *		
PCI % Change (‘90-‘00)			0.02 *	0.09 ***	0.06 ***	0.14 ***			-0.20 *
PCI (‘09)		10.17 **	-5.82 ***	-11.33 ***	-10.45 ***	-19.23 ***		-27.16 ***	
Nonmetro, Not Adjacent				-1.21 *		-1.18 *			-2.49 *
Persistent Poverty			-2.67 *		-9.44 ***				
Persistent Child Poverty	-12.45 *			-2.63 **					
Natural Amenities Scale			0.60 ***	1.06 ***	0.52 **	0.63 *			
Property Crime Rate		0.18 *							
Violent Crime Rate					-0.69 *				
Broadband Availability		-0.06 *	0.03 ***			0.04 **		0.08 *	
Observations	93	219	506	327	264	246	61	300	33
R^2	0.63	0.43	0.64	0.60	0.53	0.72	0.67	0.43	0.88

***, **, * Represents significance at the .001, .01, and .10 levels, respectively.

along with their corresponding coefficient. Again, most results are consistent with previous literature: positive impacts of natural amenities and increases in per-capita income, negative impacts of persistent poverty, unemployment and non-adjacent to a metropolitan area.

IV.1e ORDINARY LEAST SQUARES – ERS DEPENDENCY REGIONAL RESULTS

When the ERS dependency categories are added to the bare specification for each Census region, fairly consistent results were found when compared to national results (see **Table 9**). Two Census regions had significant negative coefficients for the farm dependency variable, West-North Central (-1.19) and East-South Central (-3.02). Recall that the national coefficient for this variable was -1.64. Two Census regions had significant coefficients for mining dependency with

Table 9: OLS ERS Dependency Regional Coefficient Results

	Pac	Mntain	WNCen	WSCen	ENCen	ESCen	MidAtl	SAtl	National
Farm			-1.19 *			-3.02 *			-1.64 ***
Mining					2.00 *		-11.69 **		
Manuf			-2.86 **	-2.39 **				-2.54 *	-1.39 ***
FS Gov		-5.24 **				-2.82 *			
Service								4.38 *	2.25 ***
Rec		2.90 *		4.81 ***				-5.23 *	1.15 *
Retire	5.90 *	4.55 **		7.37 ***		2.49 *	13.70 ***	5.55 ***	6.03 ***

***, **, * Represents significance at the .001, .01, and .10 levels, respectively. No significant findings were found for the New England Census region, so it is omitted from the table.

respect to the net migration rate, East-North Central (2.00) and Middle Atlantic (-11.69). Results for manufacturing dependency across the Census regions were also consistent with the national findings. Regions with significant, negative coefficients included: West-North Central (-2.86), West-South Central (-2.39), and South Atlantic (-2.54). While no significance was found at the national level for federal/state government dependency, the variable was found to have a significant negative coefficient in two Census regions: Mountain (-5.24) and East-South Central (-2.82). Service dependency was found to be positive and significant at the national level (coefficient equal to 2.25), and was also found to be positive and significant for the South Atlantic Census region (4.38). Results for recreation dependency varied somewhat when comparing Census region results to the national results. The coefficient for this variable at the national level was 1.15. Three Census regions had significant coefficients for this variable, two positive and one negative with a fair range between the coefficient values. Census regions found to have significant coefficients with respect to recreation dependence included: Mountain (2.90), West-South Central (4.81), and South Atlantic (-5.23). Results for the final ERS dependency classification, retirement, were exceptionally consistent across Census regions with respect to the national findings. The national coefficient for this variable was 6.03. Six Census regions had significant positive coefficients associated with the retirement dependency dummy variable. Census regions and their corresponding coefficients include: Pacific (5.90), Mountain (4.55), West-South Central (7.37), East-South Central (2.49), Middle Atlantic (13.70), and South Atlantic (5.55).

When considering [H3][9] with respect to the ERS findings by Census regions, the general expectations were not consistently met. This hypothesis assumed that different regions would have significantly different coefficients for each specialization category, and the direction of change would vary among regions as well. However, with the ERS dependency classifications the results were fairly consistent from one Census region to another. Almost all significant findings within each Census region were within three percentage points of the national coefficient value.

[9] [H3] The outmigration-industrial specialization relationship will vary across the nine Census regions.

Of the 19 significant coefficient findings across the nine Census regions, only five coefficient values were substantially different from the national parameter value or other Census region parameter values. This does suggest, however, that location does matter for dependency- East-North Central counties dependent on mining actually experienced in-migration (counter to the national trend), and South Atlantic counties dependent on recreation saw outmigration, again the opposite of what was experienced nationally.

IV.1f ORDINARY LEAST SQUARES – NAICS SPECIALIZATION REGIONAL RESULTS

Findings across Census regions are somewhat more varied when considering the NAICS specialization categories, when compared to national parameter values. **Table 10** shows the specialization categories that were found to have any significant coefficient value across the Census regions or nationally. Categories that had no significant coefficients for any region or nationally included: manufacturing (10%), retail trade (10 and 30%), agriculture (30%), mining (10 and 30%), construction (30%), wholesale trade (30%) and transportation and warehousing (30%).

Specialization categories that were closely consistent with one another and national levels included: manufacturing (20%), health care (20%), construction (10 and 20%), and accommodation and food services (10%). All other specialization categories varied substantially from region to region, and compared to national results. The West-South Central region had a significant negative coefficient (-1.97) for health care 20%. The coefficient for this specialization category at the national level was -0.82. No other census regions produced a significant result for this specialization level for manufacturing, but a coefficient of -6.46 was found for the Middle Atlantic Census region at the 30% specialization level.

Table 10: OLS NAICS Regional Coefficient Results

Industry	%	Pac	Mtn	WNC	WSC	ENC	ESC	MAt	SAt	NEng	US
Manuf	20				-1.97 *						-0.82 *
Manuf	30							-6.46 *			
Retail Trade	20									4.55 *	
HC	10	5.59 *				1.18 *					
HC	20								-2.25 *		-0.59 **
HC	30			2.68 ***			2.95 *				
Ag	10	12.17 *									
Ag	20										7.46 *
Mining	20							-50.41 ***			
Const	10	7.61 *	6.39 ***				3.36 *		5.08 **		4.07 ***
Const	20		20.55 ***						16.55 **		12.16 ***
Whlsl Trade	10	11.09 *									
Whlsl Trade	20		20.70 *								
Transp	10			2.02 *				6.97 *			
Transp	20			8.65 **							
AFS	10			1.24 *				3.58 *			1.25 ***
AFS	20						4.82 **				
AFS	30				-20.17 ***				-12.28 *		-2.93 *

***, **, * Represents significance at the .001, .01, and .10 levels, respectively

New England Census region's only significant specialization coefficient was for retail trade 20%, and the coefficient was positive (4.55). No other regions had significant relationships with any level of specialization in retail trade.

Consistent with the national findings, health care (20%) was associated with a negative parameter for the South Atlantic Census region (-2.25). The national coefficient for this specialization category was -0.59. Specialization in other levels of health care was associated with positive coefficients for other Census regions. For example, at the 10% health care specialization level the Pacific (5.59) and East-North Central (1.18) Census regions had significant positive coefficients. At the 30% specialization level, the West-North Central (2.68) and East-South Central (2.95) Census regions had positive parameter values. No significance was found for either of these specialization categories at the national level. This demonstrates that individual Census regions may be positively or negatively impacted by specialization even when no national significance was found.

Agriculture (10%) was only associated with one positive coefficient (12.17) for the Pacific Census region. No other Census regions had any significant relationship with specialization in agriculture at any level.

When considering mining, the Middle Atlantic Census region was associated with a significant and strongly negative value (-50.41) at the 20 percent specialization level. That coefficient value was by far the largest associated with any level of specialization for the NAICS industry specialization analysis, suggesting that a heavy dependence on mining in this region was extremely detrimental to their net migration.

Construction produced the most consistent results among Census regions, and compared to the national coefficients. At the ten percent specialization level, the Pacific (7.61), Mountain (6.39), East-South Central (3.36), and South Atlantic (5.08) Census regions all had significant positive coefficients, which is consistent with that national coefficient value of 4.07. Moving to the twenty percent specialization level in construction, two Census regions were associated with significant positive parameter values: Mountain (20.55) and South Atlantic (16.55). No significant results were observed when moving to the thirty percent specialization level. These significant and large parameter values lead us to the conclusion that specialization in construction at the ten and twenty percent levels would be advisable with regards to improving the net migration rate for the county. These robust results raise some question regarding causality, since counties with high in-migration would likely require more construction-oriented activities such as new housing and businesses.

Wholesale trade was found to be significant for two Census regions, each at different specialization levels. In the Pacific Census region, a parameter value of 11.09 was observed for the ten percent specialization level. For the Mountain Census region, a parameter value of 20.70 was observed for the twenty percent specialization level. This industry wasn't found to have any additional significant coefficients at any other specialization level for any other Census region or nationally.

Transportation and warehousing was associated with positive parameter values for some census regions at the ten and twenty percent levels. At the ten percent level, the West-North Central (2.02) and the Middle Atlantic (6.97) Census regions had significant positive coefficient values. At the twenty percent specialization level, the West-North Central Census region had a coefficient value of 8.65. No significant findings were reported at the national level.

Results were somewhat consistent across Census regions and compared to the national results for the accommodation and food services industry. At the ten percent level, coefficient values of 1.24 (West-North Central), 3.58 (Middle Atlantic) and 1.25 (nation) were observed. At the twenty percent specialization level the East-South Central Census region was associated with a parameter value of 4.82. At the thirty percent level, the parameter values switched to negative. Nationally, a parameter of -2.93 was observed while parameters of -20.17 and -12.28 were observed for the West-South Central and South Atlantic Census regions, respectively.

These OLS results provide some measure of support for [H3][10]. While, there were consistencies or patterns observed within the specialization levels across Census regions and

[10] [H3] The outmigration-industrial specialization relationship will vary across the nine Census regions.

nationally such as with the construction industry (10 and 20%) and the accommodation and food services industry (10 and 30%), the parameter values varied widely across regions. More generally, the outmigration-industrial specialization relationship did vary across some census regions; for example some regions produced highly significant parameter values for certain specialization levels, while other regions did not have signification relationships with the specialization level. **Table 10** demonstrates that the relationship between outmigration and industrial specialization varied greatly across Census regions.

IV.2 AVERAGE TREATMENT EFFECT

To address the issue of whether certain specialization levels can be said to actually *cause* a change in the net migration rate, the average treatment effect method (ATE) and propensity score matching were employed. “Treated” counties were said to have a specialization level at a certain percent (eg. agriculture, 20% of county employment falls in the industry), whereas “untreated” counties were not considered specialized at this level but were otherwise similar. A logit model was run on the likelihood of being “too specialized” at the percentage under consideration. For individual national-level logit model results, see **Appendices A-J**. The variables used to match the counties included the natural logarithm of the 2000 Census population, percentage change in unemployment from 1990-2000, percentage change in per capita income from 1990-2000, home ownership percentage from 2005-2009, and broadband availability from 2005-2009. The ATE then matched similar propensity scores from the treated and untreated groups to determine the impact of actually being “too specialized.” In most cases, results were found to be very similar to those uncovered using the simple OLS regression; however, some results differed and will be discussed at the conclusion of this section.

Three types of matching specifications were used for the propensity score, with similar results. The Nearest Neighbor Matching technique individually matches treated and non-treated united by searching for a non-treated unit that has the closest propensity score to an individual treated unit. A disadvantage to this method is that there is no guarantee that the matches are in fact “close” because the distance between the two closest treated and non-treated propensity scores can be vast. To solve this problem, Kernel Matching can be employed. Kernel Matching pairs treated units with a weighted average of all non-treated units. The weights of these averages are inversely proportional to the distance between the propensity scores of treated and non-treated units (Mahasuweerachai, Whitacre and Shideler). Another solution to the problem presented with Nearest Neighbor Matching is to use Radius Matching. Radius Matching uses the same basic technique as Nearest Neighbor matching, however treated units are only matched with non-treated units with propensity scores falling in a predetermined radius of the propensity score of the treated unit (Becker). By setting a small radius limit, it is likely that some treated units won’t be matched at all; however, a small radius limit guarantees that the occurring matches will be of higher quality than a radius with wide limits or no limits at all (as with Nearest Neighbor Matching). To maintain consistency with related literature, the Kernel Matching results are the only results shown and discussed in this research; however, results from the other two matching techniques were very similar to the Kernel results.

IV.2a AVERAGE TREATMENT EFFECT – ERS DEPENDENCY NATIONAL RESULTS

The ATE method was used to determine if being classified as a dependent county, according to the ERS, actually caused a change in the net migration rate. Focusing first on counties classified as farm dependent, a significant negative relationship was found, meaning that given a county is farm dependent, a decrease of 6.17 percentage points in the net migration rate will be observed, compared to otherwise similar non-farm dependent counties (see **Table 11**). This decrease is actually caused by the county's dependency on farming. A negative relationship was also found for manufacturing (-1.54). On the other hand, a significant positive relationship was found between the net migration rate and service dependency. Being dependent on the service industry actually causes the nonmetropolitan counties to observe an increase in the net migration rate by 6.99 percentage points. Positive relationships were also found for recreation (2.92) and retirement (7.28).

Table 11: ATE ERS National Coefficient Results		
Farm Dependent	-6.17	***
Mining Dependent	-3.25	NS
Manufacturing Dependent	-1.54	***
Fed/State Gov Dependent	0.00	**
Service Dependent	6.99	***
Recreation	2.92	***
Retirement	7.28	***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.		

While these results will be compared to their ordinary least squares counterparts later, in general the signs and significance levels are very similar to those in **Table 5**.

IV.2b AVERAGE TREATMENT EFFECT – NAICS SPECIALIZATION NATIONAL RESULTS

The ATE was also used to answer causation questions regarding the NAICS 2-digit industry specialization categories. Focusing on the construction industry, at the 10% specialization level a coefficient of 3.38 was observed meaning that given that a county is specialized in construction at the 10% employment level, the net migration rate will increase by 3.38 percentage points compared to otherwise similar non-specialized counties (see **Table 12**). A similar conclusion can be reached about construction at the 20% specialization level, with a coefficient of 12.95 observed. Shifting to the accommodation and food services industry, counties specialized at the 10% employment level notice a 0.63 percentage point increase in the net migration rate, compared to otherwise similar non-specialized counties. For the same industry, coefficients of 1.95 and -0.74 are observed at the 20% and 30% employment specialization levels. This again demonstrates that different levels of specialization can have dramatically different impacts on migration. Also of interest is a negative impact on the net migration rate for counties specialized at the 20% employment level in the manufacturing and healthcare industries, with coefficients of -1.56 and -2.71, respectfully. Specialization in healthcare at the 10% employment level was found to cause a decrease in the net migration rate by 1.63 percent, compared to otherwise similar non-specialized counties. Finally, when considering the agriculture industry, different results were found at different specialization levels for the ATE method. At the 10% level, a coefficient of -0.71 was observed, and at the 20% level a coefficient of 5.33 was observed, meaning that when 10% of a county's employment is in the agriculture industry, there is a negative impact on the net migration rate, but when the percentage employed in agriculture jumps to 20%, a positive impact on the net migration rate is observed compared to otherwise similar non-specialized counties. Again, these results will be compared in detail to the previous ordinary least squares findings shortly, but generally the results from the two methods are consistent.

When considering [H5][11], the expectations were met in some instances, and the opposite of the expected result was observed in other instances. For example, when considering agriculture

[11] [H5] Being industrially specialized *causes* a nonmetropolitan county to experience outmigration.

Table 12: ATE NAICS National Coefficient Results			
	10%	**20%**	**30%**
Agriculture	-0.71*	5.33**	NS
Mining	NS	NS	NS
Construction	3.38***	12.95**	NS
Manufacturing	NS	-1.56***	NS
Wholesale Trade	NS	NS	NS
Retail Trade	NS	NS	NS
Transportation & Warehousing	NS	NS	NS
Health Care	-1.63*	-2.71**	NS
Accommodation & Food Services	0.63***	1.95***	-0.74*
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.			

(10%), manufacturing (20%), healthcare (10 and 20%), and accommodation and food services (30%) the hypothesis is correct, and it can be concluded that industrial specialization *causes* these nonmetropolitan counties to experience outmigration. However, when considering agriculture (20%), construction (10 and 20%), and accommodation and food services (10 and 20%), specialization can be said to *cause* in-migration (the opposite of the expected result). Although some of these findings differ from the expectations, the results provide meaningful information. This shows that specialization in industries at certain levels can be associated with either outmigration or in-migration. Therefore, rather than simply learning which industry specialization levels should be avoided, the results also uncover which industry specialization levels a county should pursue with respect to increasing their net migration rate. So, these findings allow for not only the creation of policies that seek to lower outmigration, but also for the creation of policies that seek to increase in-migration.

IV.2c AVERAGE TREATMENT EFFECT – ERS DEPENDENCY REGIONAL RESULTS

When comparing the national results from the ATE method to the regional results, we find several consistencies among the industries (see **Table 13**). Farming dependent counties were found to have significant negative coefficients in both the Mountain (-5.38) and West-North Central (-9.30) Census regions. Recall that the national coefficient for this dependency category was -6.17. Results for these two Census regions can be considered to be consistent with the national findings. No other Census regions were associated with significant parameters for this dependency category.

Results for manufacturing among the Census regions were somewhat consistent with the national findings. The East-North Central (-3.66) and West-North Central (-5.64) Census regions are areas where being dependent on manufacturing can be said to cause outmigration. This is consistent with the national findings (coefficient of -1.54) although the magnitude of the regional coefficients is substantially greater than that of the national coefficient.

Results for the farming and manufacturing dependencies are consistent with the expectations of [H4][12]. Nationally, this hypothesis can be assumed to be accurate, and that specialization in farming or manufacturing actually *causes* outmigration in nonmetropolitan counties dependent on these industries. The same is true for the West-North Central Census region for both industries. Farm dependency can be said to cause outmigration in the Mountain Census region, and manufacturing dependency can be said to cause outmigration in the East-North Central Census region.

Mining dependency produced significant parameters in three Census regions: Middle Atlantic (-2.61), Pacific (2.89) and South Atlantic (-6.03). Mining dependency was not found to

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[12] [H4] Being overly specialized in the agriculture and manufacturing industries *causes* nonmetropolitan county outmigration.

Table 13: ATE ERS Regional Coefficient Results										
	Pac	Mtn	WNC	WSC	ENC	ESC	MAt	SAt	NEng	US
Farm		-5.38 *	-9.30 **							-6.17 ***
Mining	2.89 *						-2.61 *	-6.03 ***		
Manuf			-5.64 *		-3.66 *					-1.54 ***
FS Gov		-3.33 *						8.42 *		0.00 ***
Service	5.16 *	5.29 ***		14.03 **					8.84 ***	6.99 ***
Rec		3.41 *		4.87 *	-0.27 **	12.57 *				2.92 ***
Retire		5.66 *	2.21 ***	6.35 ***		7.09 **		8.06 **		7.28 ***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.										

be significant when considering the net migration rate at the national level, demonstrating that a lack of significance nationally does not imply the same result for all regions.

Federal/State government dependency produced somewhat varying results. The variable had a parameter value of -3.33 in the Mountain Census region, and 8.42 in the South Atlantic Census region, while having no impact elsewhere. Specialization in this industry may therefore produce varying results across the United States.

Results for service dependency were consistent among Census regions, and compared favorably to the national results. Nationally, the coefficient value for this variable was 6.99. Regionally, the coefficients remained fairly close to the national parameter value: Mountain (5.29), New England (8.84), Pacific (5.16) and West-South Central (14.03). Therefore, it can be concluded that in many Census regions, specialization in services can actually cause the net migration rate to increase by the corresponding percentage point value associated with the coefficients.

Findings for recreation dependency were also fairly consistent with the national parameter value of 2.92. Four Census regions had significant coefficients associated with recreation dependency: West-South Central (4.87), Mountain (3.41), East-North Central (-0.27), and East-South Central (12.57).

Retirement dependency produced the most consistent results among the Census regions and compared to the national results. The national coefficient value for this parameter was 7.28, and the parameter values for the Census regions were: East-South Central (7.09), Mountain (5.66), South Atlantic (8.60), West-North Central (2.21), and West-South Central (6.35). It can be concluded that specializing in retirement can cause in-migration. Over half of the Census regions are expected to gain in county population if that county specializes in retirement. When only considering the ERS ATE results, specialization in retirement or services would be the best way for a county to improve their net migration rate.

With regards to [H5][13], mixed conclusions are reached with the ERS dependency results. In some industries, industrial specialization does cause outmigration, but in other industries specialization causes in-migration. Therefore, we cannot explicitly state that industrial specialization actually *causes* outmigration in all instances. It is more beneficial to look at specialization on an industry by industry basis, rather than for the economy as a whole when making statements as to whether outmigration is caused by specialization.

[13] [H5] Being industrially specialized *causes* a nonmetropolitan county to experience outmigration.

IV.2d AVERAGE TREATMENT EFFECT – NAICS SPECIALIZATION REGIONAL RESULTS

When reviewing the ATE results for the Census regions, varying results are found across the regions and compared to the national results (see **Table 14**). Industries and specialization levels omitted from this discussion due to insignificance at both regional and national levels include: construction (30%), agriculture (30%), healthcare (30%), retail trade (10 and 30%), wholesale trade (20 and 30%) and transportation and warehousing (10 and 30%). Two Census regions had no significant findings for any industry or any specialization level: Middle Atlantic and New England. The following industries and specialization levels had significant findings at the national level, but none at the regional level: agriculture (10 and 30%) and accommodation and food services (20 and 30%) and are therefore omitted from **Table 14**.

Nationally, construction exhibited a positive coefficient for the ten percent level (3.38) and the twenty percent level (12.95). Regionally, these results varied. For the Mountain Census region, a coefficient of 6.40 was observed at the ten percent specialization level, while a coefficient of 23.00 was observed at the twenty percent level. This jump in magnitude is consistent with the national findings, but the Mountain region coefficients are much larger than the national coefficients. The only other Census region exhibiting significant results for construction (at the twenty percent level) was South Atlantic, with a coefficient of -1.68.

Results for the various specialization levels in manufacturing were inconsistent regionally and nationally. The East-North Central Census region had a coefficient of -3.06 for the ten percent specialization level, and -3.71 for the twenty percent specialization level. For the same levels, the East-South Central Census region coefficients were 0.99 and 1.50, respectively. The South Atlantic Census region had significant coefficients for each specialization level: the

Table 14: ATE NAICS Regional Coefficient Results

Industry	Level	Pac	Mntain	WNCen	WSCen	ENCen	ESCen	Satl	National
Const	10		6.40 *						3.38 ***
Const	20		23.00 *					-1.68 **	12.95 **
Manuf	10							2.16 *	
Manuf	20					-3.06 *	0.99 *	1.32 *	-1.56 ***
Manuf	30					-3.71 *	1.50 *	0.54 *	
HC	10							2.70 *	-1.63 *
HC	20		-3.09 *		-3.66 *				-2.71 **
AFS	10	15.76 **		-4.32 *	-0.70 **	-2.04 *	2.51 *		0.63 ***
Retail Trade	20							7.79 **	
Mining	10						-2.86 *	-3.49 **	
Mining	20				-8.89 ***			-6.33 **	
Mining	30		18.61 *						
Wholesale Trade	10	-7.55 *			-9.77 *		-5.84 *		
Transp	20			-3.74 *		1.53 *			

***, **, * Represents significance at the .001, .01, and .10 levels, respectively. There were no significant findings for the Middle Atlantic or New England Census regions, so they are omitted from the table. Insignificant specialization levels are also omitted.

ten percent coefficient equaled 2.16, the twenty percent coefficient equaled 1.32, and the thirty percent coefficient was 0.54. Nationally, the only specialization level with any significance was twenty percent (-1.56). These differences demonstrate that for some regions at least, a dependency on manufacturing can be a positive factor impacting net migration.

One of the most consistent industry specializations for the ATE NAICS method was healthcare at the twenty percent level. Nationally, the coefficient equaled -2.71, and regionally the coefficients were -3.09 (Mountain) and -3.66 (West-South Central). Specialization in healthcare at the ten percent level produced a positive coefficient of 2.70 for the South Atlantic

Census region, and -1.63 nationally. No other Census regions produced any significant coefficients for any level of specialization in healthcare.

Specialization in accommodation and food services at the ten percent level produced significant results in nearly every Census region, but they varied greatly: Pacific (15.76), West-North Central (-4.32), West-South Central (-0.70), East-North Central (-2.04), and East-North Central (2.51).

Specialization in mining at the ten and twenty percent levels resulted in negative coefficients in some regions, and specialization at the thirty percent level resulted in positive coefficients. At the ten percent specialization level, significant coefficients were found for the East-South Central (-2.86) and South Atlantic (-3.49) Census regions. At the twenty percent level, significant coefficients were found for the West-South Central (-8.89) and South Atlantic (-6.33) Census regions. When specialization jumped to the thirty percent level, a coefficient of 18.61 was observed in the Mountain Census region. This result is particularly interesting since mining generally has had a negative impact on migration.

Wholesale trade exhibited consistency in coefficient values among the Mountain (-7.55), West-South Central (-9.77) and South Atlantic (-5.84) Census regions. Other industries that had significant results were the South Atlantic (7.79) Census region for retail trade at the twenty percent level, West-North Central (-3.74) Census region for transportation at the twenty percent level and East-North Central (1.53) Census region also for transportation at the twenty percent specialization level.

When considering [H4][14], basic expectations were met with regards to the manufacturing industry, and they were partially met with regards to agriculture. Nationally, being specialized in agriculture at the ten percent level or manufacturing at the twenty percent level can be said to

[14] [H4] Being overly specialized in the agriculture and manufacturing industries *causes* nonmetropolitan county outmigration.

actually cause outmigration. However, being specialized in agriculture at the twenty percent level may actually cause in-migration. Regionally, the results varied so much across Census regions that we cannot explicitly conclude that being overly specialized in agriculture and manufacturing *causes* nonmetropolitan outmigration at the regional level. No significant findings were found for any level of agriculture specialization for any region. When considering regional specialization in manufacturing, varying results were found. Specialization in manufacturing at all three levels can be said to cause in-migration for specific Census regions, counter to national-level results. In-migration is also caused by specialization in manufacturing at the twenty and thirty percent levels for the East-South Central Census region. Outmigration is caused by specialization in manufacturing at the twenty and thirty percent levels for the East-North Central Census region. These results demonstrate that statements can be made about the individual specialization relationships with outmigration region by region, but a blanket statement about all regions in general should not be made as to whether or not specialization in agriculture or manufacturing causes outmigration.

IV.3a OLS/ATE NATIONAL AND REGIONAL RESULTS COMPARISON – ERS DEPENDENCY

With regards to the ERS dependency classifications, the national results for the traditional model and national results for the ATE method were very similar (see **Table 15**). The direction of the relationship did not change for any of the variables, but the magnitude of the coefficients was typically larger for the ATE method. For example, in the traditional OLS model farm dependency was associated with a 1.64 percentage point decrease in the net migration rate; whereas, for the ATE method, farm dependency actually caused a decrease of 6.17 in the net migration rate. All other significant national level relationships followed the same pattern: the direction of change remained the same for both methods but the coefficient increased with the ATE method. Dependency on farming and manufacturing exhibited negative relationships with the net migration rate, while dependency on services, recreation and retirement exhibited a positive relationship with the net migration rate.

Regionally, the dependency categories produced results consistent with the national findings for the most part. All predicted relationships for farming and manufacturing were negative, and the magnitude of the coefficients was larger with the ATE method. Similar to the national results, most predicted relationships for services, recreation and retirement dependency were positive. The coefficient prediction for the ATE method was almost always larger than the OLS prediction. There were negative relationships predicted within the recreation dependency category in the East-North Central and South Atlantic Census regions. Varying results were found from Census region to region with regards to mining and federal/state government dependency, but no significant results were found nationally for those industries.

Table 15: OLS/ATE National and Regional Coefficient Results Comparison for ERS Dependency											
		Pacific	Mountain	WN Central	WS Central	EN Central	ES Central	Mid Atlantic	South Atlantic	New England	National
Farm	OLS		-1.19 *				-3.02 *				-1.64 ***
	ATE		-5.38 *	-9.30 **							-6.17 ***
Mining	OLS					2.00 *		-11.69 **			
	ATE	2.89 *						-2.61 *	-6.03 ***		
Manuf	OLS			-2.86 **	-2.39 **				-2.54 *		-1.39 ***
	ATE			-5.64 *		-3.66 *					-1.54 ***
FS Gov	OLS		-5.24 **				-2.82 *				
	ATE		-3.33 *						8.42 *		
Services	OLS								4.38 *		2.25 ***
	ATE	5.16 *	5.29 ***		14.03 **					8.84 ***	6.99 ***
Rec	OLS		2.90 *		4.81 ***				-5.23 *		1.15 *
	ATE		3.41 *		4.87 *	-0.27 **	12.57 *				2.92 ***
Retire	OLS	5.90 *	4.55 **		7.37 ***		2.49 *	13.70 ***	5.55 ***		6.03 ***
	ATE		5.66 *	2.21 ***	6.35 ***		7.09 **		8.06 **		7.28 ***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.											

IV.3b OLS/ATE NATIONAL AND REGIONAL RESULTS COMPARISON – NAICS SPECIALIZATION

Focusing on the NAICS 2-digit industry specialization categories at the national level, results were again typically very similar between the OLS model and the ATE method (see **Table 16**). In three instances the ATE produced a significant relationship value when OLS did not: agriculture (10%), health care (10%), and accommodation and food services (20%). In all other cases, the direction of the relationship was the same for the OLS and ATE methods, and the estimated magnitude of the impact was also quite similar. In nearly all cases, the estimated impact of the two methods is within 1-2 percentage points of each other. This similarity gives some robustness to our results and suggests that there is, in fact, an important relationship between some types of industrial concentration and migration rate, in nonmetropolitan counties.

Regionally, the findings of the two methods differ in nearly all specialization levels for each industry. The only NAICS specialization categories exhibiting similar results from the OLS and ATE methods include are construction, 10 and 20%, for the Mountain Census region. Results from each method are consistent within themselves, but were discussed in previous subsections.

In most instances, a significant coefficient was found in one method, and the coefficient was found to be insignificant in the other method. Therefore, we cannot say that the two methods produce varying results when specific specialization levels are concerned, but the results are such that complete conclusions cannot be made about the robustness of our findings regionally for the NAICS industrial specialization variables. There were four instances when the direction of the coefficients was predicted to be different for the OLS and ATE methods. For construction (20%), the OLS method in the South Atlantic Census region produced a coefficient value of 16.55, while the ATE method produced a value of-1.68. Therefore, it is possible that specialization in construction at the twenty percent level simply exhibits a positive relationship with the net migration rate, but being specialized in this industry at that level does not actually cause in-migration. Other regions and industry specializations with similar findings include: accommodation and food services at the ten percent level for the West-North Central Census region (OLS 1.24, ATE -4.32), wholesale trade at the ten percent level for the Pacific Census region (OLS 11.09, ATE -7.55), and transportation at the twenty percent level for the West-North Central Census region (OLS 8.65, ATE -3.74).

The OLS/ATE comparison is particularly useful at the national level. Results for the methods were consistent with one another and the direction and magnitudes were very similar. Therefore, we can conclude that nationally the NAICS specialization coefficients are meaningful and results are robust. Regionally, more thorough or perhaps additional analysis is needed before similar conclusion can be reached.

Table 16 (Part 1): OLS/ATE National and Regional Coefficient Results Comparison for NAICS Specializations

Industry	Level		Pacific	Mountain	WN Central	WS Central	EN Central	ES Central	Middle Atlantic	South Atlantic	National
Agriculture	10	OLS	12.17*								
		ATE									-0.71*
	20	OLS									7.46*
		ATE									5.33**
Accommodation and Food Services	10	OLS			1.24*				3.58*		1.25***
		ATE	15.76**		-4.32*	-0.70**	-2.04*	2.51*			0.63***
	20	OLS						4.82**			
		ATE									1.95***
	30	OLS				-20.17**				-12.28*	-2.93*
		ATE									-0.74*
Construction	10	OLS	7.61*	6.39***				3.36*		5.08**	4.07***
		ATE		6.40*							3.38***
	20	OLS		20.55***						16.55**	12.16***
		ATE		23.00*						-1.68**	12.95**
Healthcare	10	OLS	5.59*				1.18*				
		ATE								2.70*	-1.63*
	20	OLS								-2.25*	-0.59**
		ATE		-3.09*		-3.66*					-2.71**
	30	OLS			2.68***			2.95*			
		ATE									

***, **, * Represents significance at the .001, .01, and .10 levels, respectively. No significant coefficients were found for the New England Census region for the industries represented in this table, so the region is omitted from the table.

Table 16 (Part 2): OLS/ATE National and Regional Coefficient Results Comparison for NAICS Specializations

Industry	Level		Pacific	Mountain	WN Central	WS Central	EN Central	ES Central	Middle Atlantic	South Atlantic	New England	National
Manufacturing	10	OLS										
		ATE								2.16*		
	20	OLS				-1.97*						-0.82*
		ATE					-3.06*	0.99*		1.32*		-1.56***
	30	OLS							-6.46*			
		ATE					-3.71*	1.50*		0.54*		
Mining	10	OLS										
		ATE						-2.86*		-3.49**		
	20	OLS							-50.41***			
		ATE				-8.89***				-6.33**		
	30	OLS										
		ATE		18.61*								
Retail Trade	20	OLS									4.55*	
		ATE								7.79**		
Transportation	10	OLS			2.02*				6.97*			
		ATE										
	20	OLS			8.65**							
		ATE			-3.74*		1.53*					
Wholesale Trade	10	OLS	11.09*									
		ATE	-7.55*			-9.77*		-5.84*				
	20	OLS		20.70*								
		ATE										

***, **, * Represents significance at the .001, .01, and .10 levels, respectively.

CHAPTER V: CONCLUSION

V.1 NATIONAL CONCLUSIONS

This study's findings suggest that significant thresholds exist in the relationship between migration and industrial specialization across nonmetropolitan counties. In particular, when counties have less than 20% of their employment in any particular industry, regression analysis does not uncover any negative impacts on migration rates. Crossing the 20% employment threshold in the manufacturing or health care industries, however, results in a decline in the net migration rate of around 1 percentage point. Specialization in other 2-digit NAICS industries demonstrated positive impacts on migration rates at various thresholds, including the surprising result that having more than 20% employment in agriculture leads to an increase in the net migration rate by 7 percentage points. When the earnings-based ERS dependency classifications are used, non-metro counties based heavily on farms or manufacturing were associated with declines in net migration, while those based on services, recreation, or retirement demonstrated increases. These results suggest that the traditional "smokestack-chasing" approach of recruiting manufacturing firms will only have a negative impact on migration rates.

Turning to the construction industry, specialization at the 10 and 20 percent levels was found to have a positive impact on the net migration rate, with an especially strong impact (12 percentage points) predicted at the 20% specialization level. When this industry reached the 30% specialization level, no significant relationship was found with the net migration rate. These results suggest that policy makers should consider attracting construction firms to their community until the 20% specialization in construction threshold is reached.

Another industry that produced especially interesting results was the accommodation and food service industry. A positive impact on migration could be observed at the lowest level of specialization (10%), but when specialization reached 30% the impact on migration turned negative. This result shows the importance of targeting a specific specialization level, with care taken not to exceed the beneficial level of specialization.

Generally, the Average Treatment Effect results agree with those for the multivariate regressions, giving a measure of robustness to the outcomes. Additionally, the methodology underlying the ATE results offers support for the claim that being too specialized actually *causes* the resulting change in migration.

In summary, specialization thresholds determined to be "too specialized" (and thus promote out-migration) at the national level included agriculture (10%), manufacturing (20%), healthcare (10 and 20%), and accommodation and food services (30%). Specialization levels determined to produce positive impacts on migration included agriculture (20%), construction (10 and 20%), and accommodation and food services (10 and 20%). Policy makers should consider these findings and take into account the existing and potential specialization levels in their communities when creating policies targeted at impacting the net migration rate.

V.2 REGIONAL CONCLUSIONS

Regionally, findings varied as expected with the NAICS 2-digit industry specialization categories. Within specific industry specialization levels (e.g. accommodation and food services 10%) coefficient values for each census region were drastically different. Some regions (West-North Central, West-South Central and East-North Central) produced negative coefficient values for the specialization category, while other regions (Pacific and East-South Central) produced positive coefficient values. All of the coefficients varied greatly in terms of their magnitude, ranging from -4.32 to 15.76. While this is the most drastic example of fluctuation within a specialization level, most other specialization levels followed the same pattern with respect to the Census regions. Some specialization level categories produced very large and significant values in certain Census regions. For example, the Middle Atlantic Census region had a coefficient value of -50.41 for mining at the twenty percent specialization level. On the opposite end of the spectrum, the Mountain Census region produced a coefficient of 18.61 for mining at the thirty percent specialization level. This drastic difference between regions makes apparent the importance of a thorough examination of the possible impacts of specializing in a particular industry. Policy makers should not only consider the national level results when creating policies targeted at changing their net migration rate, but they should also consider the potential impacts on their individual Census region.

Findings for the ERS dependency categories were fairly consistent among Census regions. Farming and manufacturing were consistently found to have a negative relationship with net migration, while service, retirement and recreation dependent counties were consistently found to have positive relationships with net migration. The regional ERS dependency category findings were also consistent with national category findings. Therefore, when creating a policy targeted at changing the net migration rate for a county, leaders should consider the ERS dependency thresholds. As mentioned earlier, these thresholds are based on employment or income statistics for the county. Results from this research suggest that crossing those thresholds can have either a positive or negative impact on the net migration rate, depending on the particular industry the county is becoming dependent on.

V.3 FINAL CONCLUSION

Economic development processionals utilize a large array of tools to encourage job growth and quality-of-life improvement in their regions. This research suggests that they should also consider current industrial employment thresholds when targeting long-term goals such as population growth. It is important to note that the results and conclusions drawn from this research are with respect to outmigration. Specialization levels are only deemed to be detrimental or beneficial with regards to the net migration rate.

In particular, this research provides policy makers with a variety of significant findings with regards to outmigration and industrial specialization. Dependency categories most commonly found to have a negative relationship with outmigration were farming and manufacturing. Service, recreation and retirement dependency were found to have a positive relationship with the net migration rate. It can also be concluded that each of these dependencies can *cause* either outmigration or in-migration, depending on the direction of the relationship previously stated. These conclusions are supported at both the national and regional levels.

Key “too specialized” categories with a positive relationship with the net migration rate included agriculture (20%), accommodation and food services (10% and 20%), and construction (10 and 20%). It can also be concluded that specialization in these industries can *cause* a county to experience an increase in their net migration rate. The “too specialized” categories with a negative relationship with the net migration rate included agriculture (10%), accommodation and food services (30%), healthcare (10 and 20%), and manufacturing (10 and 20%). It can also be concluded that specialization in these industries can *cause* a county to experience a decrease in their net migration rate.

Leaders should not only consider the “too specialized” categories when creating policies targeted at impacting the net migration rate, but also consider the dependency categories as well.

A thorough analysis of the results given for the nation in general and for individual regions should allow local leaders to efficiently create policies aimed at impacting their net migration rate by changing their industrial specialization and dependency levels to the optimal levels.

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APPPENDICES

A. LOGISTIC REGRESSION FOR CONSTRUCTION 10%

Logistic Regression						N = 2,026
Pseudo R2 =	0.03		LR chi2(5) =	34.95		
Log likelihood =	-499.44		Prob>chi2 =	0.00		
Construction 10%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-0.27	0.11	-2.53	0.01	-0.48	-0.06
Broadband Availability	0.00	0.00	0.59	0.56	-0.01	0.01
Percent Unemp Chg 90-00	0.00	0.00	-0.56	0.58	-0.01	0.00
Percent Per-Capita Income Chg 90-00	0.02	0.00	3.19	0.00	0.01	0.03
Home Ownership	0.05	0.02	3.31	0.00	0.02	0.08
_cons	-4.82	1.59	-3.04	0.00	-7.93	-1.71

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	3.38	-2.67	6.23	0.76	8.20
	ATT	3.38	-2.70	6.26	1.10	5.68

B. LOGISTIC REGRESSION FOR CONSTRUCTION 20%

Logistic Regression						N = 2,026
Pseudo R2 =	0.05			LR chi2(5) =	8.01	
Log likelihood =	-69.51			Prob>chi2 =	0.16	
Construction 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-0.58	0.32	-1.83	0.07	-1.20	0.04
Broadband Availability	-0.01	0.01	-0.73	0.47	-0.04	0.02
Percent Unemp Chg 90-00	-0.02	0.01	-1.73	0.08	-0.04	0.00
Percent Per-Capita Income Chg 90-00	0.00	0.01	0.30	0.77	-0.02	0.03
Home Ownership	-0.02	0.03	-0.56	0.58	-0.08	0.05
_cons	1.73	3.39	0.51	0.61	-4.91	8.36

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	12.95	-2.32	15.27	2.55	5.98
	ATT	12.95	-2.28	15.23	5.88	2.92

C. LOGISTIC REGRESSION FOR AGRICULTURE 10%

Logistic Regression						N = 2,026
Pseudo R2 =	0.08			LR chi2(5) =	10.28	
Log likelihood =	-57.95			Prob>chi2 =	0.07	
Agriculture 10%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-0.66	0.35	-1.88	0.06	-1.35	0.03
Broadband Availability	-0.01	0.01	-0.97	0.33	-0.04	0.01
Percent Unemp Chg 90-00	-0.01	0.01	-1.28	0.20	-0.03	0.01
Percent Per-Capita Income Chg 90-00	-0.02	0.02	-1.11	0.27	-0.06	0.02
Home Ownership	0.05	0.05	1.00	0.32	-0.05	0.15
_cons	-1.25	4.87	-0.26	0.80	-10.79	8.30

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	-0.71	-2.23	1.52	2.82	0.54
	ATT	-0.71	-2.24	1.53	2.77	0.55

D. LOGISTIC REGRESSION FOR AGRICULTURE 20%

Logistic Regression						N = 2,026
Pseudo R2 =	0.14		LR chi2(5) =	4.46		
Log likelihood =	-13.61		Prob>chi2 =	0.49		
Agriculture 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-1.01	0.73	-1.37	0.17	-2.45	0.43
Broadband Availability	-0.02	0.03	-0.70	0.48	-0.08	0.04
Percent Unemp Chg 90-00	-0.01	0.02	-0.68	0.50	-0.05	0.02
Percent Per-Capita Income Chg 90-00	-0.02	0.03	-0.64	0.52	-0.09	0.05
Home Ownership	0.04	0.09	0.43	0.67	-0.14	0.22
_cons	1.52	8.42	0.18	0.86	-14.99	18.03

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	5.33	-2.23	7.56	6.29	1.20
	ATT	5.33	-2.23	7.56	4.87	1.55

E. LOGISTIC REGRESSION FOR MANUFACTURING 20%

Logistic Regression						N = 2,026
Pseudo R2 =	0.09			LR chi2(5) =	202.76	
Log likelihood =	-1043.92			Prob>chi2 =	0.00	
Manufacturing 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	0.75	0.08	9.92	0.00	0.60	0.90
Broadband Availability	0.00	0.00	0.53	0.60	0.00	0.01
Percent Unemp Chg 90-00	0.00	0.00	-1.70	0.09	-0.01	0.00
Percent Per-Capita Income Chg 90-00	0.00	0.00	0.02	0.99	-0.01	0.01
Home Ownership	0.05	0.01	4.95	0.00	0.03	0.07
_cons	-12.11	1.11	-10.90	0.00	-14.28	-9.93

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	-1.56	-2.45	0.89	0.45	1.97
	ATT	-1.56	0.71	-2.27	0.42	-5.42

F. LOGISTIC REGRESSION FOR HEALTHCARE 10%

Logistic Regression						N = 2,026
Pseudo R2 =	0.21			LR chi2(5) =	524.03	
Log likelihood =	-961.91			Prob>chi2 =	0.00	
Healthcare 10%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	1.24	0.08	16.43	0.00	1.10	1.39
Broadband Availability	0.00	0.00	0.92	0.36	0.00	0.01
Percent Unemp Chg 90-00	0.00	0.00	-0.09	0.93	0.00	0.00
Percent Per-Capita Income Chg 90-00	0.01	0.00	1.58	0.11	0.00	0.01
Home Ownership	0.00	0.01	-0.04	0.97	-0.02	0.02
_cons	-11.32	1.00	-11.32	0.00	-13.28	-9.36

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	-1.21	-4.68	3.47	0.43	8.10
	ATT	-1.21	-0.05	-1.16	0.71	-1.65

G. LOGISTIC REGRESSION FOR HEALTHCARE 20%

Logistic Regression						N = 2,026
Pseudo R2 =	0.01		LR chi2(5) =	14.89		
Log likelihood =	-1220.00		Prob>chi2 =	0.01		
Healthcare 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	0.20	0.06	3.37	0.00	0.08	0.31
Broadband Availability	0.00	0.00	-1.29	0.20	-0.01	0.00
Percent Unemp Chg 90-00	0.00	0.00	-0.29	0.77	0.00	0.00
Percent Per-Capita Income Chg 90-00	0.00	0.00	0.02	0.99	-0.01	0.01
Home Ownership	-0.01	0.01	-0.82	0.41	-0.02	0.01
_cons	-2.09	0.80	-2.63	0.01	-3.65	-0.53

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	-2.71	-2.02	-0.68	0.43	-1.58
	ATT	-2.71	-1.35	-1.36	0.39	-3.47

H. LOGISTIC REGRESSION FOR ACCOMMODATION AND FOOD SERVICES 10%

Logistic Regression						N = 2,026
Pseudo R2 =	0.06			LR chi2(5) =	156.75	
Log likelihood =	-1259.50			Prob>chi2 =	0.00	
Accommodation and Food Services 10%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	0.23	0.06	3.89	0.00	0.11	0.35
Broadband Availability	0.01	0.00	4.39	0.00	0.01	0.02
Percent Unemp Chg 90-00	0.00	0.00	-2.49	0.01	-0.01	0.00
Percent Per-Capita Income Chg 90-00	0.00	0.00	0.78	0.43	0.00	0.01
Home Ownership	-0.05	0.01	-6.86	0.00	-0.06	-0.04
_cons	-0.09	0.78	-0.12	0.91	-1.63	1.45

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	0.56	-3.88	4.44	0.40	11.18
	ATT	0.63	-3.30	3.85	0.45	8.59

I. LOGISTIC REGRESSION FOR ACCOMMODATION AND FOOD SERVICES 20%

Logistic Regression						N = 2,026
Pseudo R2 =	0.06			LR chi2(5) =	40.15	
Log likelihood =	-381.23			Prob>chi2 =	0.00	
Accommodation and Food Services 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-0.27	0.12	-2.16	0.03	-0.51	-0.02
Broadband Availability	0.01	0.01	2.38	0.02	0.00	0.03
Percent Unemp Chg 90-00	-0.01	0.00	-2.47	0.01	-0.02	0.00
Percent Per-Capita Income Chg 90-00	0.02	0.01	2.80	0.01	0.01	0.03
Home Ownership	-0.06	0.01	-4.46	0.00	-0.08	-0.03
_cons	1.58	1.46	1.08	0.28	-1.28	4.44

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	1.82	-2.44	4.25	0.90	4.71
	ATT	1.95	-2.80	4.61	1.05	4.39

J. LOGISTIC REGRESSION FOR ACCOMMODATION AND FOOD SERVICES 30%

Logistic Regression						N = 2,026
Pseudo R2 =	0.01			LR chi2(5) =	3.05	
Log likelihood =	-110.74			Prob>chi2 =	0.69	
Accommodation and Food Services 20%	Coef.	SE	z	P>|z|	[95% CI]	
ln(2000 Census Pop)	-0.39	0.26	-1.49	0.14	-0.90	0.12
Broadband Availability	0.00	0.01	0.43	0.67	-0.02	0.03
Percent Unemp Chg 90-00	-0.01	0.01	-1.13	0.26	-0.02	0.01
Percent Per-Capita Income Chg 90-00	0.00	0.01	0.39	0.69	-0.02	0.03
Home Ownership	-0.01	0.03	-0.41	0.68	-0.07	0.05
_cons	-0.78	3.21	-0.24	0.81	-7.06	5.51

Kernel Matching						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Net Migration Rate 00-09	Unmatched	-0.74	-2.24	1.50	2.00	2.75
	ATT	-0.74	-2.21	1.47	2.41	2.61

VITA

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Candidate for the Degree of

Master of Science

Thesis: HOW SPECIALIZED IS "TOO" SPECIALIZED? OUTMIGRATION AND INDUSTRY DIVERSIFICATION IN NONMETROPOLITAN COUNTIES ACROSS AMERICA

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Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: HOW SPECIALIZED IS “TOO” SPECIALIZED? OUTMIGRATION AND INDUSTRIAL DIVERSIFICATION IN NONMETROPOLITAN COUNTIES ACROSS AMERICA

Pages in Study: 95 Candidate for the Degree of Master of Science

Major Field: Agricultural Economics

Scope and Method of Study:
Outmigration and industrial composition have separately been the focal points of a significant amount of research related to nonmetropolitan counties; however, few (if any) studies have explicitly looked at the relationship between the two topics. The primary objective of this research is to identify what industry specialization level is “too” specialized with regards to outmigration – that is, to determine the level where specialization begins to have a damaging effect on population change. County-level data from a variety of sources is used to explore the impact of both earnings-based and employment-based definitions of specialization on net migration in nonmetropolitan counties from 2000 – 2009. Two distinct techniques (ordinary least squares and average treatment effects) are then used to assess both the impact and causality of being “too specialized.”

Findings and Conclusions:
Economic development professionals utilize a large array of tools to encourage job growth and quality-of-life improvement in their regions. This research suggests that they should also consider current industrial employment thresholds when targeting long-term goals such as population growth. Dependency categories most commonly found to have a negative relationship with outmigration were farming and manufacturing. Service, recreation and retirement dependency were found to have a positive relationship with the net migration rate. It can also be concluded that each of these dependencies can *cause* either outmigration or in-migration, depending on the direction of the relationship previously stated. These conclusions are supported at both the national and regional levels. Key “too specialized” categories with a positive relationship with the net migration rate, and also said to *cause* in-migration included agriculture (20%), accommodation and food services (10% and 20%), and construction (10 and 20%). The “too specialized” categories with a negative relationship with the net migration rate, and also said to *cause* outmigration included agriculture (10%), accommodation and food services (30%), healthcare (10 and 20%), and manufacturing (10 and 20%). A thorough analysis of the results given for the nation in general and for individual regions should allow local leaders to efficiently create policies aimed at impacting their net migration rate by changing their industrial specialization and dependency levels to the optimal levels.

ADVISER’S APPROVAL: Dr. Brian Whitacre