The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

How Specialized is "too" Specialized? Outmigration and Industry Diversification in Nonmetropolitan Counties across America

Ashley Jackson
Dr. Brian Whitacre
Oklahoma State University
ashley.jackson10@okstate.edu
brian.whitacre@okstate.edu

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Birmingham, AL, February 4-7, 2012

Copyright 2012 by Ashley Jackson and Brian Whitacre. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Introduction

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. 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. For example, a county is classified as a farming county if more than 20% of the earned income comes from farming. Likewise, if more than 30% or 50% 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.

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 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 is known as propensity score matching, an increasingly common nonparametric tool used to evaluate "treatment effects." 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.

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.

Outmigration

Many different variables must be considered when addressing the outmigration problem. Some studies have focused on individual motivators as drivers of outmigration. 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 (1996) which conclude that from a pure mobility standpoint, college-aged persons are typically the most mobile of any age group within the United States. A study by Johnson et al (2005) 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. McGrannahan (2010) concluded that young adults (age 14-24) tend to move away from nonmetropolitan counties, likely to pursue higher education or the military. Recreational counties were popular migration destinations among adults nearing retirement age (Johnson et al 2005). The above results suggest that variables such as age, education, and natural amenities should be included in any migration study.

Other studies focus specifically on the migration patterns of the poor population, and variables related to these patterns. It is hypothesized that the poor migrate due to differences in opportunities. A 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). Frey (1996) was one of the few studies that explicitly looked at industrial composition in relation to migration, although his analysis focused more on the differences between poor and non-poor migrants. 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). Thus, variables reflecting the local labor market will likely impact migration.

McGrannahan (2010) looks at nonmetropolitan counties with high outmigration rates between 1988-2008, and eventually categorizing them 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). Factors of most significance in the areas with poor natural amenities areas included low unemployment, low high school dropout rates, average household incomes (McGrannahan 2010). Quality-of-life was likely a strong factor in deterring residents from migrating to these counties. This study did look at the industrial composition of the 2 groups: 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.

This demonstrates some potential relationship between industrial makeup and outmigration; however, these are simply descriptive statistics and do not account for other potentially influential factors. 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).

In addition to all of the variables noted in the studies above, at least one other variable has recently increased in importance to the migration decision: broadband access. Many of the previous studies on migration are relatively old and likely do not account for the addition of broadband and high-speed internet access. Mahasuweerachai et al (2010) study aimed to address the relationship between rural outmigration and broadband access. A key result for the study is the simple availability of broadband access is not a factor 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).

Industry Specialization

While the studies noted above focused mostly on the migration decision, others have looked explicitly at industry specialization. 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. A study by Smith and Gibson (1988) 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.

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, it can be concluded 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.

Findings from a study by Smith and Gibson (1988) 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. Also, regional planners should include both the detailed industrial mix and diversity in planning policies, rather than simply target diversification in general (Attaran 1986). This falls in line with the research being conducted in this paper, where the goal is to be able to identify what industries might have a negative or positive impact on migration.

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 existence of industrial specialization.

Very few studies have observed outmigration at the county level for the United States as a whole, and even fewer focused on all of the nonmetropolitan counties. This study will include dummy variables for the nine United States Census regions. Typically researchers 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, few 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.

Methods

Conceptual Framework

The literature review for this research provided a host of variables that might impact migration. We collect data on most of these variables, and econometrically estimate the impact of being "too specialized" on migration across nonmetropolitan counties. Two techniques are used: multivariate regression (OLS) and average treatment effects (ATE). The next section discusses the data collected and the various definitions of "specialized," followed by the OLS and ATE modeling approaches.

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. 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 (not that only the 2,049 nonmetropolitan counties are included, since the analysis focused on them). The ERS database also provides dummy variables for certain specialization categories: farming, manufacturing, and recreation dependent counties. These dummy variables are used as one method of calculating "too specialized" counties.

Table 1: Variables to be Included in the Regression Analysis		
Variables	**Mean**	**Standard**
Net Migration Rate (2000-2009)	-2.23	8.91
College Plus Percent (2005-2009)	23.51	7.30
Female Headed Household Percent (2005-2009)	10.68	4.78
Hispanic Percent of Population (2005-2009)	7.19	13.24
Home Ownership Percent (2005-2009)	73.54	7.23
Low Employment (2004)	0.19	0.39
SLn(2000 Census Population)	9.63	1.04
Ln(Per Capita Income) (2009)	10.35	0.20
Median Age (2005-2009)	40.49	5.18
Natural Amenities Scale	-0.05	2.25
Nonmetropolitan, Not Adjacent	0.48	0.50
Per Capita Income Percent Change (1990-2000)	53.84	16.04
Percent of homes with broadband availability (05-09)	73.30	22.69
Percent with <High School Education (2005-2009)	18.73	7.90
Persistent Child Poverty (1970-2000)	0.29	0.46
Persistent Poverty (1970-2000)	0.17	0.37
Population Change Percent (1990-2000)	9.84	81.67
Property Crime Rate (2004)	18.29	13.42
Unemployment Percent Change (1990-2000)	-14.26	63.53
Unemployment Rate (2009)	9.00	3.53
Violent Crime Rate (2004)	2.02	2.04

The second method uses data from the Census Bureau's County Business Patterns 2-Digit NAICS code industry 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. Table 2 summarizes the percentage of nonmetropolitan counties that met the criteria for being "too specialized" at each of these levels. 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" in terms of 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, are significant.

Table 2: Percentage of Counties Meeting "Too Specialized" NAICS 2-Digit Criteria			
Variables	**10%**	**20%**	**30%**
Agriculture	4.88%	0.10%	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%

OLS

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 variable potentially impacting migration, and 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, along with a list of the 20 NAICS categories to be used in defining industrial specialization.

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 allowed 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:

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

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, 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 (e.g. population, income, ethnicity). 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.

Results

OLS

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

Table 3: Basic OLS Coefficients		
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

increase in the net migration rate (see Table 3). 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.

To determine whether or not various types of industrial dependency had any impact on net migration, dummy variables for ERS dependency classifications and NAICS 2-digit specialization at 10, 20 and 30% 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, while service dependent and retirement counties had positive impacts on migration (see Table 4). In particular, communities defined as retirement dependant were associated with a 6.03 percentage point increase in the net migration rate, while those that were farm dependent had a 1.64 percentage point decrease. Counties dependent on mining or the federal/state government were not found to have significant relationships with the net migration rate.

Table 4: ERS Dependency Classification Coefficients

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.

Moving to the "too specialized" categories created for the NAICS 2-digit industry data, some interesting results were found. Referring to Table 5, 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 always 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 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 5).

Table 5: NAICS 2-Digit Specialization Category Coefficients

	10%	**20%**	**30%**
Agriculture	NS	7.46*	O
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.

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.

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. 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. Other matching specifications were used for the propensity score, with similar results. 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.

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 6). 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 6: ATT/Propensity Score Matching (Neighbor) ERS Dependency Classification Coefficients		
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.		

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 7). 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.

Table 7: ATT/Propensity Score Matching (Neighbor)
NAICS 2-Digit Specialization Level Coefficients

	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.

OLS/ATE Results Comparison

With regards to the ERS dependency classifications, the results for the traditional model and results for the ATE method were mostly similar (see Table 8). 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 relationships followed the same pattern: the direction of change remained the same for both methods, but the coefficient increased with the ATE method.

Table 8: OLS/ATE Results Comparison- ERS Dependent				
	OLS		ATE	
Farm Dependent	-1.64	***	-6.17	***
Mining Dependent	-0.36	NS	-3.25	NS
Manufacturing Dependent	-1.39	***	-1.54	***
Fed/State Gov Dependent	-0.72	NS	0.00	**
Service Dependent	2.25	***	6.99	***
Recreation	1.15	*	2.92	***
Retirement	6.03	***	7.28	***
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.				

Focusing on the NAICS 2-digit industry specialization categories, results were again typically very similar between the OLS model and the ATE method (see Table 9). 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.

Table 9: OLS/ATE Results Comparison- NAICS 2-digit Specialization Categories						
	OLS			ATE		
	10%	**20%**	**30%**	**10%**	**20%**	**30%**
Agriculture	NS	7.46*	O	-0.71*	5.33**	NS
Mining	NS	NS	NS	NS	NS	NS
Construction	4.07***	12.16***	NS	3.38***	12.95**	NS
Manufacturing	NS	-0.82*	NS	NS	-1.56***	NS
Wholesale Trade	NS	NS	NS	NS	NS	NS
Retail Trade	NS	NS	NS	NS	NS	NS
Transportation & Warehousing	NS	NS	NS	NS	NS	NS
Health Care	NS	-0.59*	NS	-1.63*	-2.71**	NS
Accommodation & Food Services	1.25***	NS	-2.93*	0.63***	1.95***	-0.74*
***, **, * Represents significance at the .001, .01, and .10 levels, respectively.						
O = "Omitted because of collinearity"						

Conclusion

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 lower levels of specialization (10 and 20%), 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) 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.

References

Attaran, Mohsen 1986. “Industrial Diversity and Economic Performance in U.S. Areas.” *The Annals of Regional Science* 20(2): 44-54.

Bilsborrow, Richard, Thomas McDevitt, Sherrie Kossoudji, Richard Fuller 1987. “The Impact of Origin Community Characteristics on Rural-Urban Out-Migration in a Developing Country.” *Demography Journal* 24(2): 191-210.

Diamond, Charles, Curtis Simon 1990. “Industrial Specialization and the Returns to Labor.” *Journal of Labor Economics* 8(2): 175-201.

Frey, William 1996. “Immigration, Domestic Migration and Demographic Balkanization in America: New Evidence for the 1990s.” *Population and Development Review* 22(4):741-763.

Frey, William 2005. “Immigration and Domestic Migration in US Metro Areas: 2000 and 1990 Census Findings by Education and Race.” *Population Studies Center Research Report* 05-472.

Johnson, Kenneth, Paul Voss, Roger Hammer, Glenn Fuguitt, Scott McNiven 2005. “Temporal and Spatial Variation in Age-Specific Net Migration in the United States.” *Demography* 42(4): 791-812.

Mahasuweerachai, Phumsith, Brian Whitacre, Dave Shideler 2010. “Does Broadband Access Impact Migration in America? Examining Differences between Rural and Urban Areas.” *The Review of Regional Studies* 40(1): 5-26.

McGrannahan, David, John Cromartie, and Timothy Wojan 2010. “Rural Outmigration Counties: Some Are Poor, Many Are Prosperous.” ERR-107, U.S. Department of Agriculture, Econ. Res. Serv. Nov 2010.

McGrannahan, David, John Cromartie, and Timothy Wojan. “The Two Faces of Rural Population Loss Through Outmigration.” *Amber Waves* USDA ERS, Dec. 2010.

Nissan, Edward, George Carter 2006. “The Measurement of Employment Diversity for States and Regions.” *Journal of Economics and Finance* 30(2): 186-197.

Nord, Mark 1996. "Poor People on the Move: County-to-County Migration and the Spatial Concentration of Poverty." *Journal of Regional Science* 38(2): 329-351.

Smith, Stephen, Cosette Gibson 1988. "Industrial Diversification in Nonmetropolitan Counties and Its Effect on Economic Stability." *Western Journal of Agricultural Economics* 13(2): 193-201.