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John Leatherman, Compiler

with assistance from

Alana McLain, Research Assistant

Rebecca Bishop, Extension Associate

Department of Agricultural Economics

Kansas State University

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Investigating Interstate Skill Exchanges Using Public Use Micro-Sample Data

Dave Swenson
Liesl Eathington
Iowa State University[*]

Abstract

History has shown that most Midwest and Plains states like Iowa out-migrate many higher skilled workers, especially among recent college and university graduates, and they in turn in-migrate lower skilled talent resulting in net skills exchange deficits. Other states, usually those growing more rapidly, have more positive skills exchanges. This phenomenon is mainly explained by states' prevailing industrial mixes – states can only use so much of given levels of skills and must export any excess they generate in their colleges and universities to other areas. These dynamics are also explained by state rates of growth. The mix of skills exchanged, however, is not usually measured very precisely. Research has conventionally used education levels of in and out-migrants as a surrogate measure of skill mobility, with negative exchanges of, say college educated persons, often characterized as a "brain drain." Alternatively, researchers have also focused on sets of key occupational flows as indicators of higher-quality job competitiveness.

This analysis uses national Public Use Micro-Sample (PUMS) data from the U.S. Census along with O*NET data from the Department of Labor to translate occupational designations among the PUMS sample into sets of desirable, higher-level skills categorizations. The assessment then calculates the net exchanges states realize from people moving from one state to another using the 2015 American Community Survey 5-year data. This analysis helps discern the types of demand signals states send to prospective workers. In addition it allows us to quantify the net flow of skills by level of skill among the many states and contributes both substantively and quantitatively to the "skills gap" discussion that currently preoccupies economic development planners and policymakers. This exercise is investigatory in that it is intended to initially establish and evaluate a set of higher-skill measures and the degree to which those measures vary across the states.

[*] Staff scientists in the Department of Economics, Iowa State University. Paper prepared for the MidContinent Regional Science Association Annual Meeting, Toledo, OH, June 2017.

1. Introduction

An important component of economic development analysis involves understanding the key characteristics of regional economies. Industrial growth over time, for example, can be deconstructed using basic shift-share methods to determine the degrees to which national, local mix, or competitiveness characteristics explain change over time. Occupations, too, can be deconstructed broadly using the same techniques to discern and explain changes in occupational demand. These are perfectly useful tools for planning purposes, and they help analysts evaluate recent change. Nonetheless, they only indirectly inform us about the skill based performance of economies.

Occupational data can be further analyzed along a range of dimensions. State-level occupational projections often include scores for educational requirements and levels of preparation needed for those types of jobs. As an example, Table 1 tells us expected job change in Iowa for different occupational groups plus the kinds of education, work experience, and job training required for those jobs. Analysts can compile gains and reductions controlling for those career preparation categories and understand quite a bit about expected workforce needs as well as characteristics of the existing workforce.

Table 1

2014-2024 STATE OF IOWA OCCUPATIONAL PROJECTIONS						
		Employment		Career Preparation		
SOC	Occupational Title	2014 Estimated	2024 Projected	Educ	Work Exp	Job Training
13-2011	Accountants & Auditors	13,020	15,110	BA	N	None
19-3031	Clinical, Counseling, & School Psychologists	1,315	1,500	Doc / Prof	N	Intern
19-4011	Agricultural & Food Science Technicians	1,085	1,190	Associates	N	Moderate

In recent years, regional economic growth evaluators have introduced additional methods and mechanisms for substantively and objectively grading occupations. Florida's (2002) work on the "creative class," as perhaps the most discussed (and derided) earlier example, was an attempt to differentiate among higher-level knowledge-based workers across a range of occupational groups. The typology grouped occupations as follows:

- The creative class, within which was the super-creative core of very highly trained occupations,

- Working class (construction, skilled trades, manufacturing)
- Service class (retail and broad service delivery)
- Agriculture

Others, notably Feser (2003), used much more rigorous categorizations to understand occupational value hierarchies. His work was quite useful for evaluation purposes because it rigorously developed, using objective scoring techniques, sets of occupational clusters that took into account skills and knowledge. This allowed for the creation of a matrix of values that scored knowledge (and skill) categories against sets of common occupational clusters. This work relied heavily on the, new at the time, Occupational Information Network (O*NET).

Moving closer to the present, we see many examples of states or organizations attempting to grade and prioritize different occupations. The Missouri Department of Economic Development (2016), for example, developed an ABC grading system to help guide people into more or less rigorous and profitable career choices. The Bureau of Labor Statistics, too, assists in classifying occupations by providing guidance about STEM (science, technology, engineering, and mathematics) jobs (Vilorio, 2014)

For our purposes, however, we are not interested in clusters of desirable occupations, whether classified as STEM jobs or not, or in more crude designations as to whether our economy is attractive or not to "creative" types. Instead, we are investigating more broadly the relative flow of higher-level skills across the states. In particular, we are interested in knowing whether and the degree to which some states are able to attract workers with higher levels of skills while others cannot. As was the case with the Feser work above, we rely significantly on the resources at O*NET and we pair information derived from that resource with data gleaned from the American Community Survey.

Our previous research (Eathington and Swenson, 2015) found that comparatively stronger occupational growth was expected nationwide in more highly skilled positions and among lower skilled positions – that the broad concern about a middle skills gap was likely an overstatement of future occupational needs. Unlike much recent work in this regard, we are not interested in "middle" skills supplies or flows (e.g., Deloite and The Manufacturing Institute, 2011, National Center for Education Statistics, 2014, or Iowa Department of Workforce Development, 2013). This research looks at states' abilities to attract higher-skilled talent.

2. The Data

Our research question involves determining the extent to which states are competitive in attracting workers with higher-level skills. The first step of that process involved getting a handle on the flow of migrants into and out of the 50 states and DC. The Public Use Micro-sample (PUMS) data set from the American Community Survey (ACS) for the years 2011 through 2015 was accessed. Of that entire data set, respondents were chosen if they indicated they had moved from another state in the past year. As the survey covered 2011 to 2015, moving in the "last year" could have been at any time between 2010 and 2014. Only a handful of other variables were downloaded for this initial, and very large, data set covering the entire U.S., to include ages, sex, educational attainment levels, weeks worked, their occupations, and their current and former states of residence. Person-weights were also used to infer to the entire U.S. population from the sample. The resulting sample, after applying the person-weights, represented 4.8 million persons who had worked in the past year and who moved from one state to another over the 2011-2015 sampling period.[1]

Our analysis looks at domestic moves only. International moves are not assessed. Our final sample was of people who had moved from another state and for whom there was an occupational classification.

The next step involved tapping into the O*NET system to establish sets of higher-skill metrics to use to eventually score the occupations of the migrants in our study. The O*NET system has scores assigned to a very wide array of occupational attributes to include abilities, interests, knowledge, skills, work activities, work levels, and work values. Those attributes are scored separately in terms of their importance in the occupation and level of development one typically has. Example scores are displayed in

[1] While person weights were used to infer total population sizes, this analysis does not calculate confidence intervals for the results displayed in the tables or the maps that were subsequently generated. This assessment is investigatory in nature and intended to determine the initial utility of the chosen higher-skill measures.

Table 2

Table 2 Example of O*NET Skill Scores

Skills — Critical Thinking Save Table (XLS/CSV)

Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.

Sort by:

Importance ▲	Level	Code	Occupation
94	80	23-1023.00	Judges, Magistrate Judges, and Magistrates
88	71	15-2091.00	Mathematical Technicians

For our purposes, however, sets of skills were chosen that we felt were indicative of higher levels of occupational preparation

Table 3. For each occupation and for each skill grouping, individual "Importance" scores were obtained from O*NET resources and then summed to get

and performance. The chosen higher skill categories and their constituent skills are contained in

composite values for the three high skill categories. The O*NET data set had 974 occupations. Every occupation received a critical basic skills score, a problem solving skills score, and a high level technical skills score.

Table 3 Higher Skill Category Groupings

Critical Basic
Critical Thinking
Mathematics
Science
Writing

Problem Solving
Complex Problem Solving
Judgement and Decision Making
Systems Analysis
Systems Evaluation

High Level Technical
Operations Analysis
Programming
Quality Control Analysis

The skill categories and their constituent components were designated such because we felt

- critical basic skills represented core higher-level skills that one would expect in the management, supervisory, and technical occupations of industries,
- problem solving skills represented skills required to evaluate and solve problems as well as adapt to a changing economic environment, and
- high level technical skills were considered those most able to maintain technological competitiveness across a wide range of industries.

O*NET also scores occupations according to job zones, which are composite indicators ranging from one to five that are based on levels of education, experience, and training needed to perform a particular occupation. Those zones are

1. Little or no preparation required
2. Some preparation needed
3. Medium preparation needed
4. Considerable preparation needed
5. Extensive preparation required

Job zone scores were assigned to every occupation in the data set as a complement to our three higher skills categories

The O*NET data set was next reconciled with the Standard Occupation Codes (SOC) used in the PUMS data base. That data set had 474 occupational categories, which required averaging many of the more highly detailed O*NET scores into the SOC aggregations used for the PUMS sample.

Analysis of the original O*NET scores across the occupations indicated that there was a normal distribution for the critical basic and the problem solving subgroup of skills. The high level technical group however was skewed: a large fraction of occupations have low scores, or zeros, while a much more discrete set of occupations had moderate to very high scores. These same distribution patterns were evident after reducing the original scores to align with the PUMS occupational codes.

Given that there were normal distributions for the first two skills groups and there was a pronounced skew to the left of the higher level technical skills group, it was decided that an occupation had a "high" score in a category if the z-score for that occupation was greater than 0.5. A z-score of 0.5 means that score is in the upper 30 percent of values, and which was the case with the first two skill categories. Because of the skewing, the cut-off for the high level technical skills was a z-score of 1.0, which accounted for about 12 percent of all occupations. These cutoffs are certainly arbitrary, but felt to be reasonable given the higher-skill dimensions that we were interested in.

In addition, in the instances where collapsing occupational classifications to align with the SOC data set produced job preparation zone values that were not whole numbers, results were rounded to the nearest integer.

The results of the higher skill groupings chosen for analysis were plotted against the job zone data to see how well the scores clustered along the levels of preparation. A comparison with the critical basic skills category is displayed in Figure 1. In the highest job zone (5), occupational scores ranged from 231 to 407, in the middle zone (3), the scores ranged from 151 to 319, and in the bottom zone, the range was 88 to 198. Though there is a decided linear pattern in that higher preparation yields, on average, higher critical basic scores, there is also substantial dispersion of the critical basic scores that overlaps succeeding job zones. This same pattern was evident for the problem solving category and for the higher level skills classification.

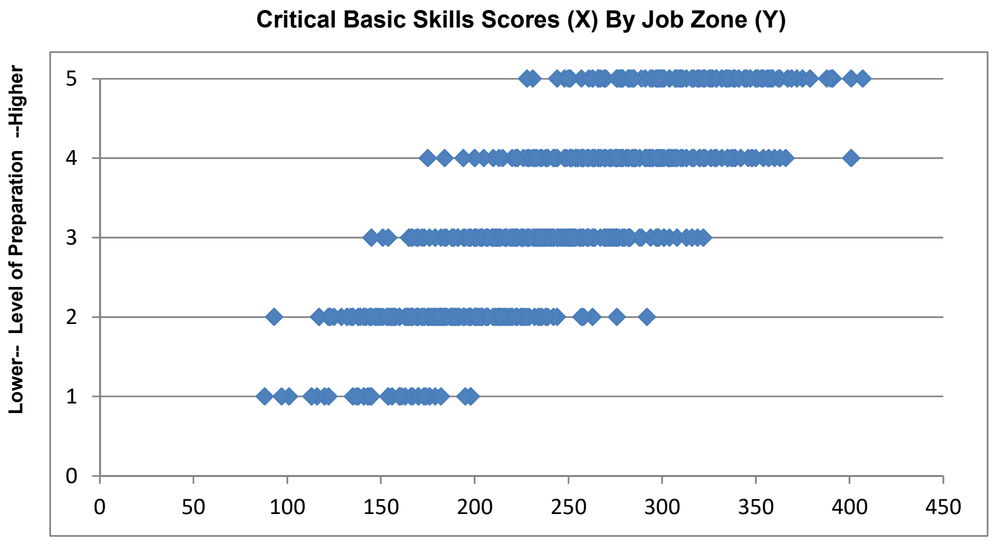

Figure 1

3. Initial Results

The first evaluation of the higher-skill subdivisions of occupations involved matching up the occupational scores with the actual distribution of U.S. workers by occupation.

Table 4

Characteristics of U.S. Occupations With High Skills Scores

	Percentage of All Occupations in 2016	Percentage of Forecasted Growth, 2014-2024
Critical Basic	23.8%	36.7%
Problem Solving	26.9%	36.6%
ligh Level Technical	8.0%	11.1%

tells us that between 8 percent and 27 percent of workers possess these higher skills, depending on the particular mix emphasized, according to current BLS occupational employment tables. However, when looking at the expected occupational growth using the 2014-2024 BLS forecast, the expectation is that 37 percent of new jobs will be in the highest scores subset of the critical basic group, followed also by 37 percent in the highest subset of the problem solving group, and 11 percent in the high level technical group. There is a pronounced expectation that the future workforce will be composed of significantly more workers with the skill groups used in this analysis.

Table 4

Characteristics of U.S. Occupations With High Skills Scores

	Percentage of All Occupations in 2016	Percentage of Forecasted Growth, 2014-2024
Critical Basic	23.8%	36.7%
Problem Solving	26.9%	36.6%
High Level Technical	8.0%	11.1%

Table 4 presents the preparation zone distribution of the current U.S. workforce, as well as expected growth. Nearly two-thirds of workers are in zones two and three, and just a quarter of the workforce is in the upper two zones. There are, however, clear expected preparation demand changes expected by 2024. Zone two jobs, those requiring "some" preparation, are expected to decline sharply as a fraction of new jobs. In contrast, jobs with "considerable" preparation, zone four, are expected to make up nearly a third of all job growth over the forecasted period even though they constitute fewer than 19 percent of current occupations.

Table 4

Characteristics of U.S. Occupations by Preparation Zone Level

Preparation Zone	Percentage of All Occupations in 2016	Percentage of Forecasted Growth, 2014-2024
5	6.1%	6.8%
4	18.9%	32.9%
3	23.9%	26.9%
2	39.3%	21.5%
1	11.7%	12.0%

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Table 4

Characteristics of U.S. Occupations With High Skills Scores and

	Percentage of All Occupations in 2016	Percentage of Forecasted Growth, 2014-2024
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Table 4 show that there are both skill-based and preparation-based areas of sharp change that are linked strongly to education, knowledge, and skills.

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Table 6 shows the expected distribution of gains in high skill jobs by subset and major occupational category. The large fraction of anticipated demand in this subset occurs in health-related, business and finance, management, education and training, and computer and mathematical occupations.

Table 6

Expected Change in High Skills Employment Occupations by Broad Occupational Group, 2014 - 2024, Sorted by Critical Basic

	Higher-Skill Subsets		
Occupational Category	Critical Basic	Problem Solving	High Level Technical
		In thousands	
Healthcare practitioners and technical	1,153	1,047	47
Business and financial operations	523	552	221
Management	445	445	146
Education, training, and library	423	367	10
Computer and mathematical	352	405	518
Community and social service	183	195	11
Healthcare support	139	-	-
Sales and related	128	58	5
Life, physical, and social science	98	91	44
Architecture and engineering	69	67	61
Legal	44	44	-
Arts, design, entertainment, sports, and media	17	48	14
Construction and extraction	8	94	-
Protective service	7	11	-
Transportation and material moving	3	10	0
Office and administrative support	3	119	(5)
Food preparation and serving related	-	-	-
Building and grounds cleaning and maintenance	-	-	-
Personal care and service	-	28	-
Installation, maintenance, and repair	-	18	-
Farming, fishing, and forestry	(0)	(4)	-
Production	(0)	(11)	19
Overall Occupational Total	3,595	3,583	1,090
As a Percentage of All Projected Job Growth	*36.7%*	*36.6%*	*11.1%*

Table 7

Expected Change in High Skills Employment Occupations by Broad Occupational Group, 2014 - 2024, Sorted by Critical Basic

	Higher-Skill Subsets		
Occupational Category	Critical Basic	Problem Solving	High Level Technical
		In thousands	
Healthcare practitioners and technical	1,153	1,047	47
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Architecture and engineering	69	67	61
Legal	44	44	-
Arts, design, entertainment, sports, and media	17	48	14
Construction and extraction	8	94	-
Protective service	7	11	-
Transportation and material moving	3	10	0
Office and administrative support	3	119	(5)
Food preparation and serving related	-	-	-
Building and grounds cleaning and maintenance	-	-	-
Personal care and service	-	28	-
Installation, maintenance, and repair	-	18	-
Farming, fishing, and forestry	(0)	(4)	-
Production	(0)	(11)	19
Overall Occupational Total	3,595	3,583	1,090
As a Percentage of All Projected Job Growth	*36.7%*	*36.6%*	*11.1%*

Table 7 lists expected occupational gains for preparation zones four and five only. Almost three-quarters of the growth for this higher preparation grouping is in the top five categories. Negligible or no growth is anticipated in 10 of the broad occupational categories.

Table 8

Expected Change in Preparation Zones 4 and 5 Occupations, 2014 - 2024

	Zones 4 & 5 (in thousands)
Business and financial operations	548
Education, training, and library	517
Management	484
Healthcare practitioners and technical	446
Computer and mathematical	417
Sales and related	291
Community and social service	258
Life, physical, and social science	92
Architecture and engineering	76
Arts, design, entertainment, sports, and media	67
Legal	43
Personal care and service	39
Transportation and material moving	1
Protective service	0
Healthcare support	-
Food preparation and serving related	-
Building and grounds cleaning and maintenance	-
Farming, fishing, and forestry	-
Construction and extraction	-
Installation, maintenance, and repair	-
Production	-
Office and administrative support	(2)
Overall Occupational Total	3,275
As a Percentage of All Projected Job Growth	*33.5%*

Error! Reference source not found. shows the exchange of workers from the 2011-2014 PUMS data. Green shaded areas represent net gains given eight control variables: net overall worker exchange, workers ages 44 and under, workers ages 45 and older, workers with educational attainment through high school, workers with a college degree or higher educational attainment, and workers in the critical basic, problem solving, and high level technical occupation subsets.

While 31 states posted overall net migration gains in that flows in were greater than flows out, just 19 had net inflows of college graduates, while 40 had net inflows of movers with just a high school diploma but no degree. Seven states (Alaska, Connecticut, Illinois, Michigan, New Jersey, New Mexico, and New York) posted net outmigration across the whole array of variables. Eleven states (Arizona, Colorado, Florida, Louisiana, Maine, Nevada, North Carolina, Oregon, Tennessee, Texas, and Washington) realized net inmigration across all of the variables. The remaining states had mixed results where the left-side of the table was positive and the right side of the table had more variable results. The only exception to this pattern was California. It had negatives on the left side, but all positives on the right side, the high skill variables of the table. California, however, is one the more rapidly expanding economies in the U.S. – in this instance, it is notably better at both retaining and attracting workers in the higher skill and education occupations.

Error! Reference source not found. stratifies net migration by O*NET occupational preparation zones. Five states (Alaska, Connecticut, Massachusetts, Michigan, and New York) posted net declines in all five zones. In contrast, there were ten states that posted occupational migration gains in all zones. Only 16 states, however, posted net gains in both zones four and five, the occupations requiring higher levels of overall preparation, skill, and knowledge.

Table 9

Worker Migration Net Exchanges Using the 2011 - 2015 PUMS Data of Movers

	All Workers	Age 44 or Younger	Age 45 or Older	High School / No Degree	College Graduate	Critical Basic	Problem Solving	High Level Technical
Alabama	+	+	+	+	-	-	-	-
Alaska	-	-	-	-	-	-	-	-
Arizona	+	+	+	+	+	+	+	+
Arkansas	+	+	+	+	-	+	+	+
California	-	-	-	-	+	+	+	+
Colorado	+	+	+	+	+	+	+	+
Connecticut	-	-	-	-	-	-	-	-
Delaware	+	+	+	+	-	-	+	+
District of Columbia	-	+	-	+	-	+	-	+
Florida	+	+	+	+	+	+	+	+
Georgia	-	-	+	+	-	-	-	+
Hawaii	-	+	-	+	+	+	+	-
Idaho	+	+	+	+	-	+	+	+
Illinois	-	-	-	-	-	-	-	-
Indiana	-	-	-	+	-	-	-	-
Iowa	+	+	-	+	-	-	-	-
Kansas	-	+	-	+	-	+	-	-
Kentucky	+	+	+	+	-	-	-	-
Louisiana	+	+	+	+	+	+	+	+
Maine	+	+	+	+	+	+	+	+
Maryland	-	-	-	-	+	+	+	-
Massachusetts	-	-	-	-	-	-	-	+
Michigan	-	-	-	-	-	-	-	-
Minnesota	-	-	-	-	+	+	-	+
Mississippi	-	-	+	+	-	-	-	-
Missouri	+	+	+	+	-	-	+	+
Montana	+	+	+	+	+	-	-	-
Nebraska	-	-	-	+	-	-	-	-
Nevada	+	+	+	+	+	+	+	+
New Hampshire	+	+	+	+	+	-	+	-
New Jersey	-	-	-	-	-	-	-	-
New Mexico	-	-	-	-	-	-	-	-
New York	-	-	-	-	-	-	-	-
North Carolina	+	+	+	+	+	+	+	+
North Dakota	+	+	+	+	-	+	+	-
Ohio	-	-	-	+	-	-	-	-
Oklahoma	+	+	+	+	-	-	-	-
Oregon	+	+	+	+	+	+	+	+
Pennsylvania	-	-	-	+	-	-	-	-
Rhode Island	-	-	-	+	-	-	-	-
South Carolina	+	+	+	+	-	+	+	+
South Dakota	+	+	-	+	-	-	-	-
Tennessee	+	+	+	+	+	+	+	+
Texas	+	+	+	+	+	+	+	+
Utah	+	+	+	+	-	-	-	-
Vermont	+	+	-	+	-	-	-	-
Virginia	+	+	-	+	+	+	+	-
Washington	+	+	+	+	+	+	+	+
West Virginia	+	+	-	+	-	-	-	-
Wisconsin	-	-	-	+	-	-	-	-
Wyoming	+	+	+	+	+	+	-	+

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Table 10

Worker Migration Net Exchanges Using the 2011 - 2015 PUMS Data of Movers by O*Net Zones

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
Alabama	+	+	+	-	+
Alaska	-	-	-	-	-
Arizona	+	+	+	+	+
Arkansas	-	-	+	+	+
California	-	-	-	+	+
Colorado	+	+	+	+	+
Connecticut	-	-	-	-	-
Delaware	+	+	+	-	+
District of Columbia	+	-	+	+	-
Florida	-	+	+	+	+
Georgia	+	-	+	-	-
Hawaii	+	-	+	+	-
Idaho	+	+	+	+	+
Illinois	-	-	-	-	-
Indiana	+	+	-	-	-
Iowa	-	+	+	-	-
Kansas	-	+	+	-	+
Kentucky	+	+	+	+	-
Louisiana	+	+	+	+	+
Maine	+	+	-	+	+
Maryland	-	-	-	-	+
Massachusetts	-	-	-	-	-
Michigan	-	-	-	-	-
Minnesota	-	-	-	+	+
Mississippi	+	-	-	-	-
Missouri	+	+	+	-	-
Montana	+	+	+	-	+
Nebraska	+	-	+	-	+
Nevada	+	+	+	+	+
New Hampshire	-	+	+	-	-
New Jersey	-	-	-	-	-
New Mexico	-	+	-	-	+
New York	-	-	-	-	-
North Carolina	+	+	+	+	+
North Dakota	+	+	+	+	-
Ohio	+	+	-	-	-
Oklahoma	+	+	+	-	-
Oregon	+	+	+	+	+
Pennsylvania	+	+	-	-	-
Rhode Island	+	-	+	-	-
South Carolina	+	+	+	-	+
South Dakota	-	+	+	-	-
Tennessee	+	+	+	+	+
Texas	+	+	+	+	+
Utah	+	+	+	+	-
Vermont	+	+	-	-	+
Virginia	-	+	+	+	+
Washington	+	+	+	+	+
West Virginia	+	+	-	+	-
Wisconsin	-	+	-	-	-
Wyoming	-	+	+	-	+

4. The Geography of Higher-Skilled Worker Flows

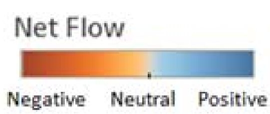
Error! Reference source not found. and **Error! Reference source not found.** display the net flows of the occupations of both lower-skilled and higher-skilled workers who moved from one state to another. This section maps the magnitude of change to allow for the visual determination of strong or weak higher- skilled worker movement.

There are two basic measures used:

1. Net inflow = group inflow/(group inflow + group outflow)

   Centers on .50

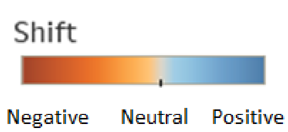
   Where in all of the net flow maps this simplified legend holds:



2. Net shift of occupations = group inflow/(group inflow + group outflow) less total inflow/(total inflow + total outflow)

   Centers on zero

   Where in all of the net shift maps this simplified legend holds:



The net inflow measure helps us understand the fraction of gain or loss given all migrating workers accessed in the PUMS sample. The shift calculation lets us understand relative competitiveness of the higher skill sectors given all in and out movement of workers in each state. That means a state might be suffering a net loss in total occupational exchanges, yet loses skilled workers at a lower rate. Conversely, a shift would be in negative territory if a net flow was positive but nonetheless slower than the rate of gain for all workers in that state.

The following maps demonstrate the relative flow of the selected highly skilled occupations. All of the measured variables are displayed regarding high-level skills categories, preparation, or education flows. Concluding observations follow this section.

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Figure 2 shows both the net flow in and out of all occupations in the PUMS 2011 to 2015 sample irrespective of the contrived higher-skill categories or preparation zone. As would be expected, the highest rate of positive net exchange is North Dakota, owing primarily to the shale oil boom in that state. Several other states with high positive net exchanges typically were high amenity states (Oregon, Montana, Utah, and Colorado) and a few states experiencing overall strong recoveries (Delaware and South Carolina, for example). New York, Connecticut, New Jersey, Illinois, and California had the higher rates of occupational net outmigration.

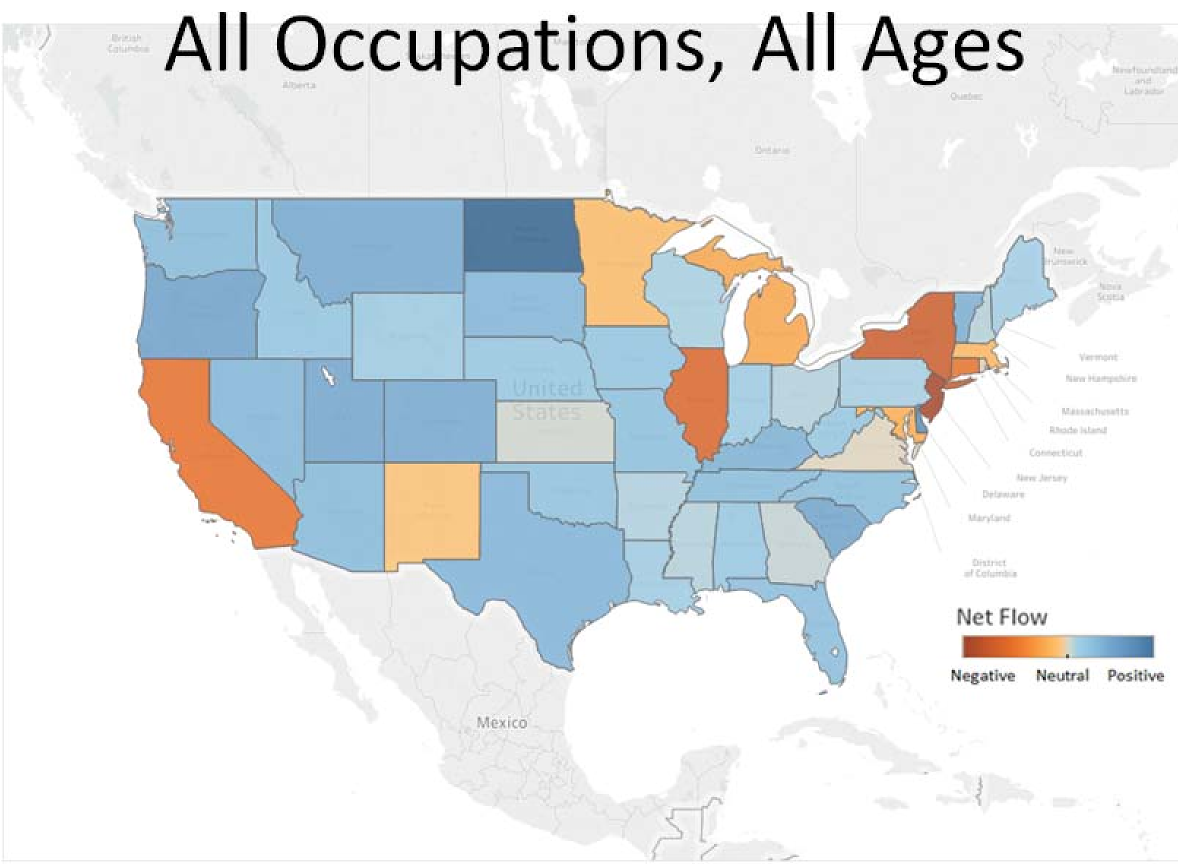

Figure 2

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The pattern of occupational migration is decidedly different when controlling for higher skilled workers. Figure 3 shows the net flow of workers for the critical basic skills group. This group included the skills of critical thinking, math, science, and writing. Now, many of the states that posted positive net exchanges of all occupations instead post negative exchanges. Comparatively stronger positive results are evident for Maine, Florida, Texas, Colorado, Nevada, Oregon, and Washington. Stronger negative exchange states include New York, New Jersey, Rhode Island, Illinois, and South Dakota. Twelve states posting positive overall worker flows in Figure 2 had net negative high skill flows in this measure.

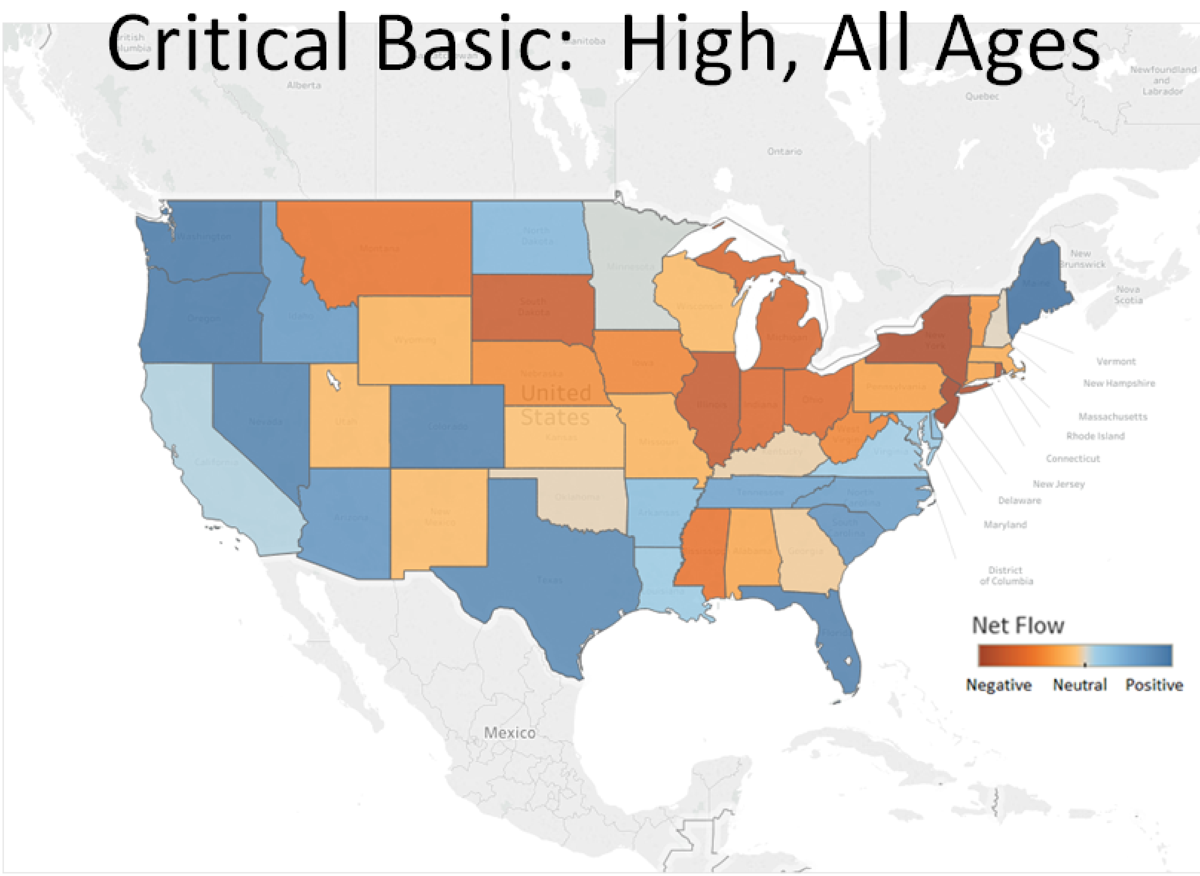

Figure 3

We next controlled for the age of the high-skilled occupation migrant. We define "young" migrants as those under 45. Those results are in Figure 4. Though there are minor changes in the magnitudes of shading, the only state that flipped was Delaware, which went from positive high skill occupational inflow to negative.

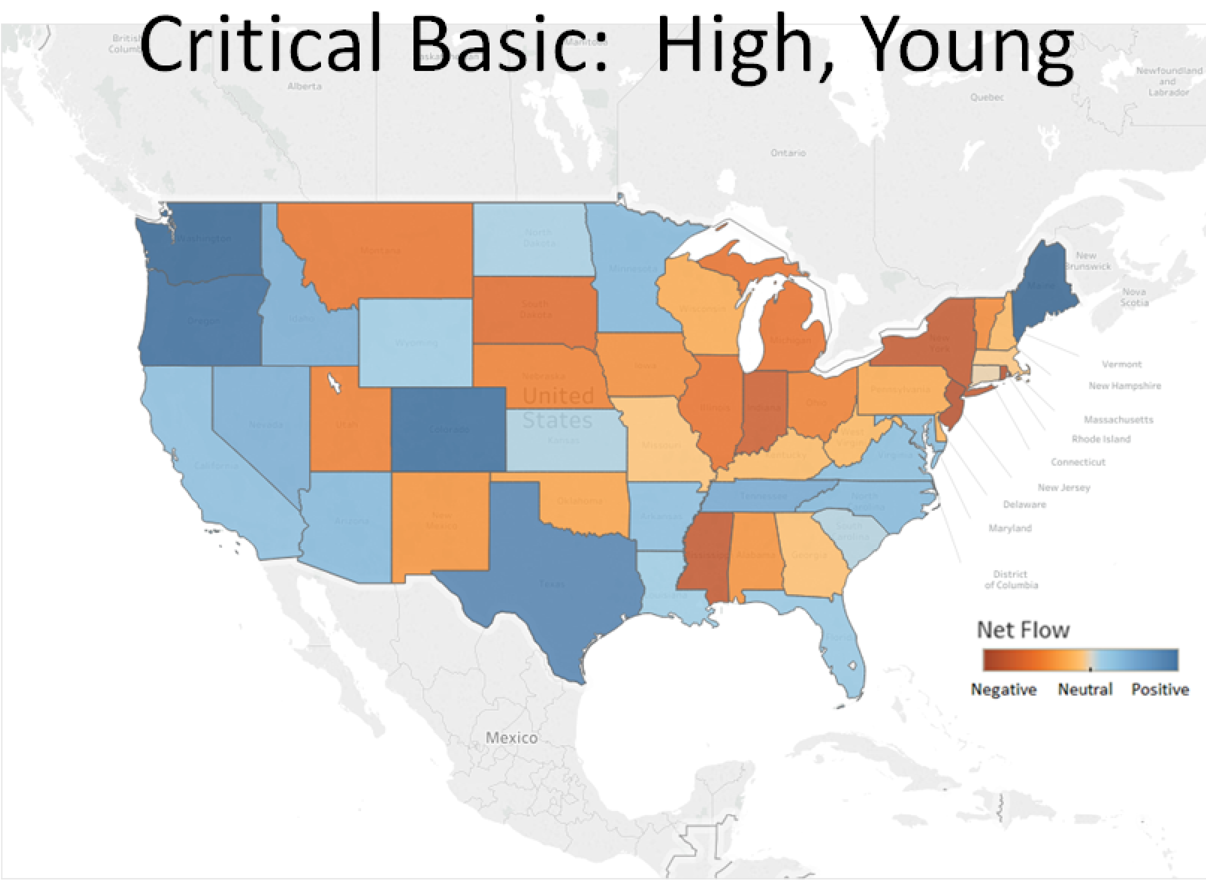

Figure 4

Figure 5 portrays the occupational shifting that occurred only among the young and higher skilled occupations. We focus here on just the young skilled worker shifts as this is a category of occupational demand that is acute, or perceived to be acute, for many states. The shifts measure the relative change in this occupational group as compared to overall occupational change in each state. While there are differences in relative magnitude compared with the previous graph, there are also several flips from positive to negative or vice versa. South Carolina, Louisiana, Florida, Nevada, Arizona, and North Dakota attracted these workers more slowly than their overall occupational growth would have suggested, while New York, Massachusetts, Connecticut, New Jersey, Illinois, and Kansas attracted or retained a greater than expected number of younger, higher skilled workers.

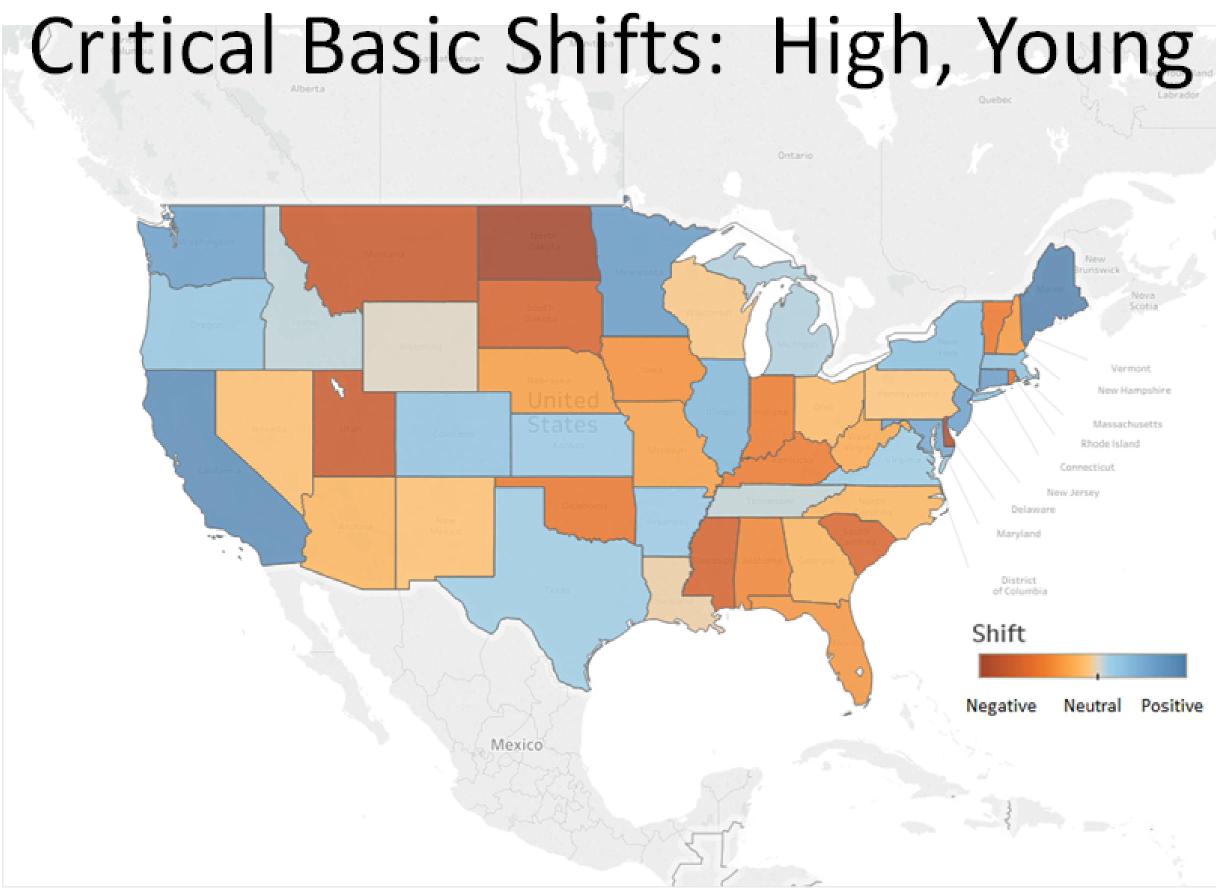

Figure 5

The problem solving skill group included complex problem solving, judgement and decision making, systems analysis, and systems evaluation. This occupational net migration pattern is in Figure 6. Overall, the net flows aligned with the all ages graph for critical basic skills. Only New Hampshire flipped to positive, and only Minnesota moved to net negative on this measure.

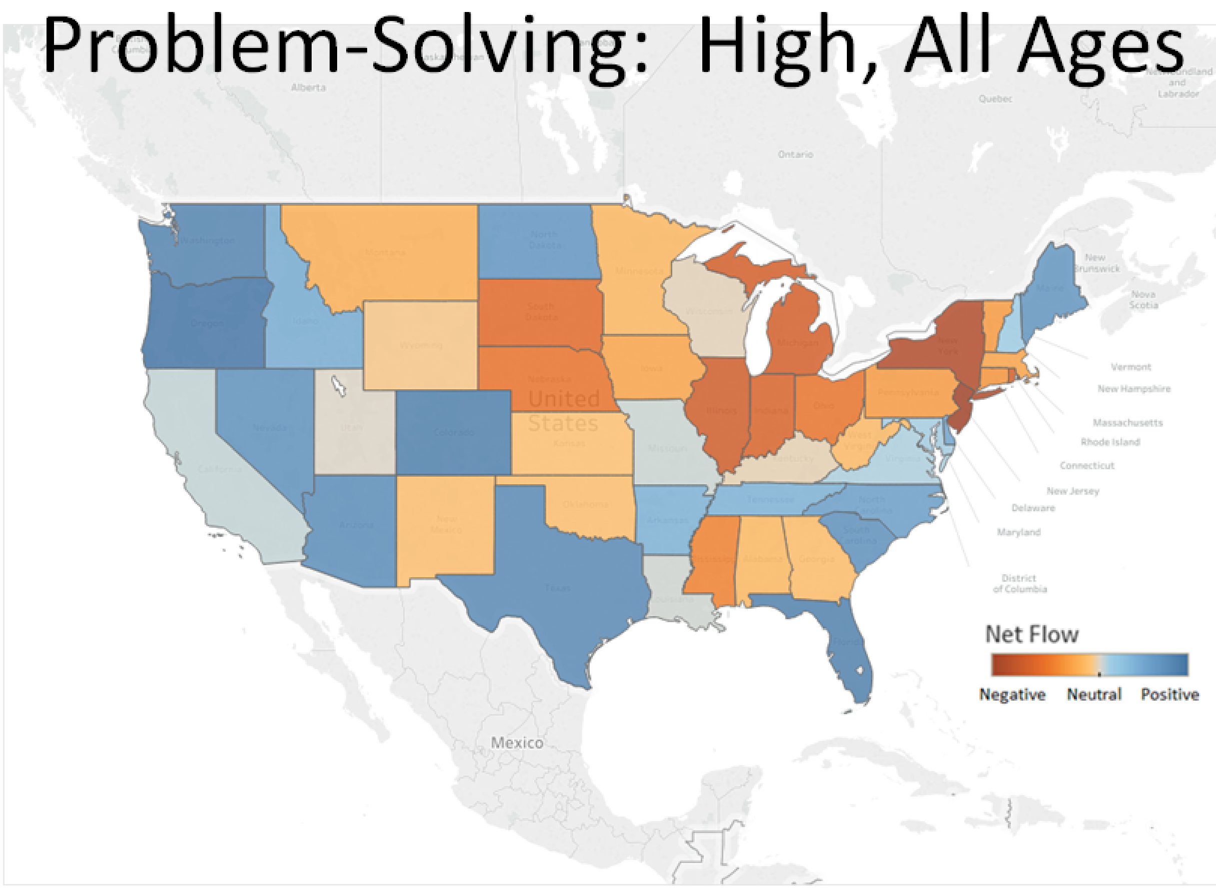

Figure 6

The younger migrant subset of the problem solving skill group yielded a slightly different pattern than for the overall group. Vermont and West Virginia turned net positive and Minnesota, Kansas, and Wyoming turned net negative. The number of states with relatively high positive flows decreased, but the number of states with relatively high negative flows stayed about the same.

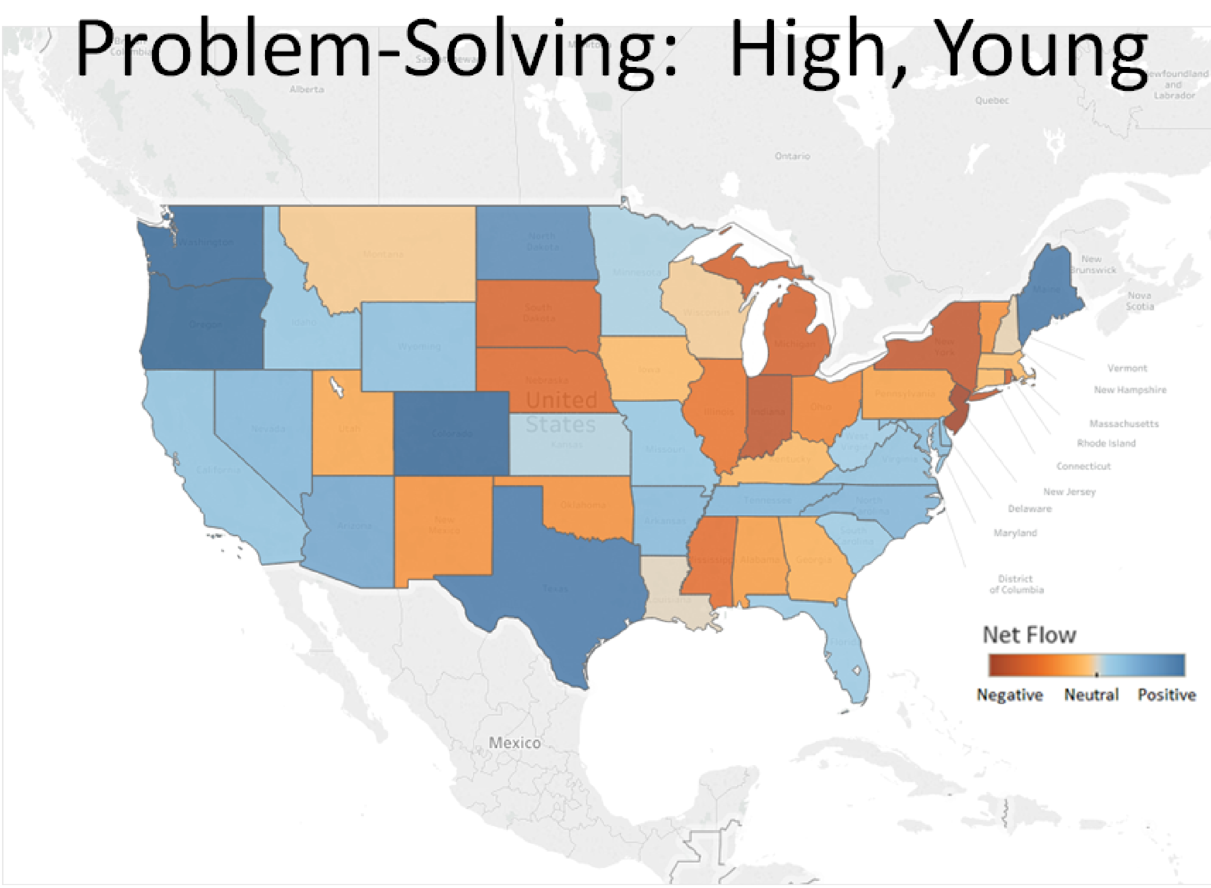

Figure 7

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Figure 8 shows the migration shifts of the young workers. As was the case in the previous skill group, there are substantial differences in states posting net inflows versus those with net positive or negative shifts. Positive shifts are seen for New York, Massachusetts, Connecticut, New Jersey, Illinois, and Wisconsin. Negative shifts, in comparison occurred in North Dakota, Idaho, Delaware, Tennessee, North Carolina, South Carolina, Florida, Missouri, Arizona, and Nevada. Again, the shifting measure shows where, considering all occupational flows, this skilled category did comparatively worse or better. And in this category, the highest intensity of positive shifting is California.

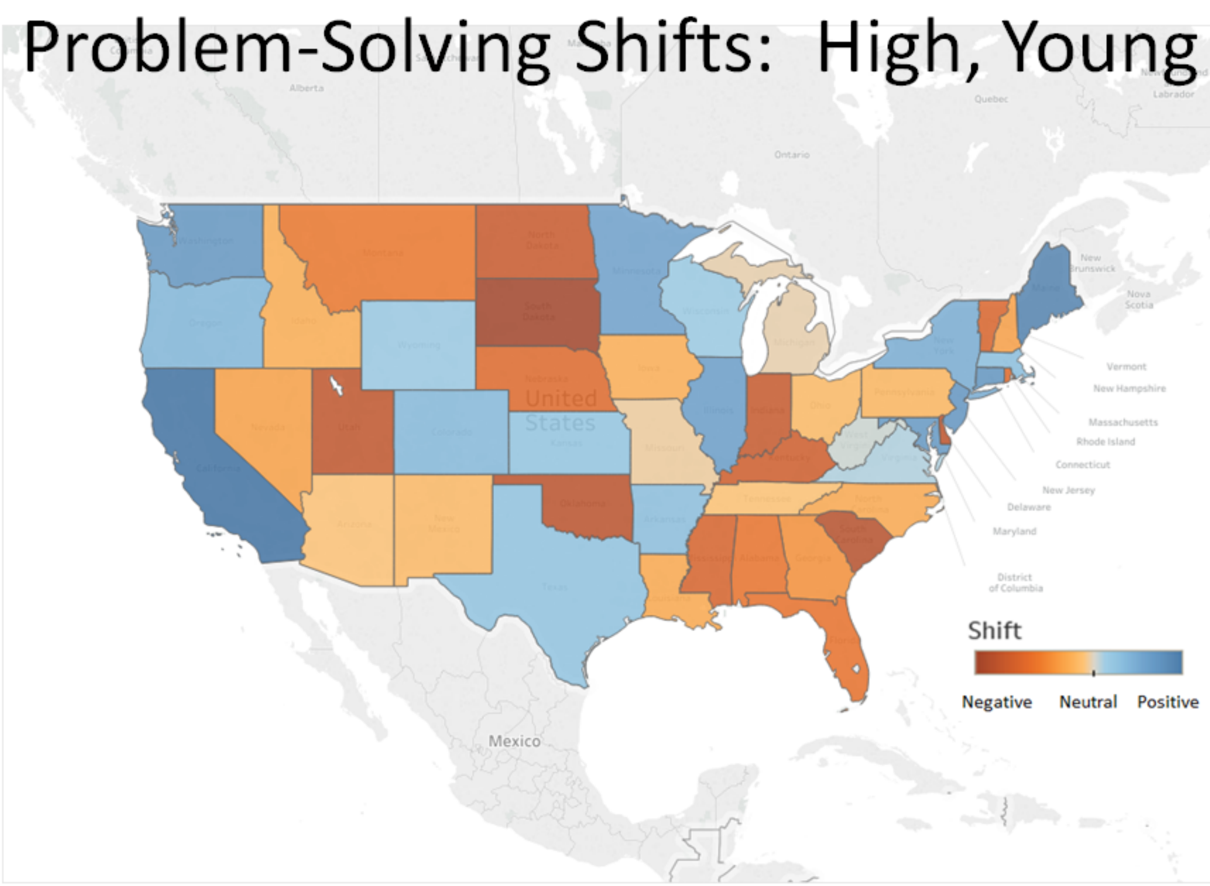

Figure 8

The high level technical skills group involved the specific skills of operations analysis, programming, and quality control analysis. As the scoring for this occupational group was skewed sharply towards the lower end, we therefore chose a smaller subset of occupations (z-scores > 1.0) to designate as the "high" group.

Net inflows of the workers with the highest scoring occupations were not evident among nearly all of the Plains states and the Great Lakes region of the Midwest. Relative greater gain intensities were evident in Colorado, Nevada, and Oregon. Strong relative outflows were evident in North Dakota and South Dakota, Indiana, New York, New Jersey, West Virginia, and Rhode Island.

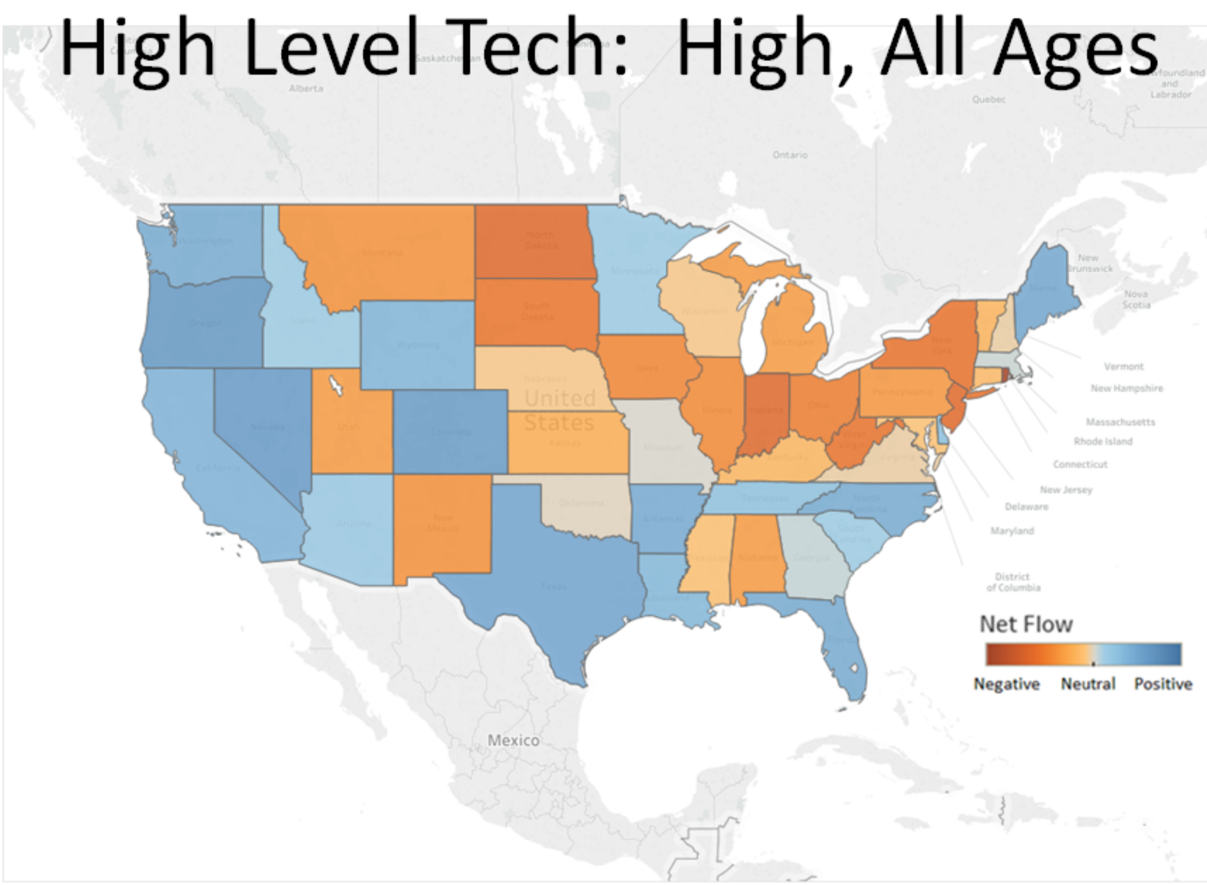

Figure 9

Controlling for the younger migrants (Figure 10) in this group, only minor differences in inflows and outflows are evident. Delaware, South Carolina, and Arizona move into the net outflow category.

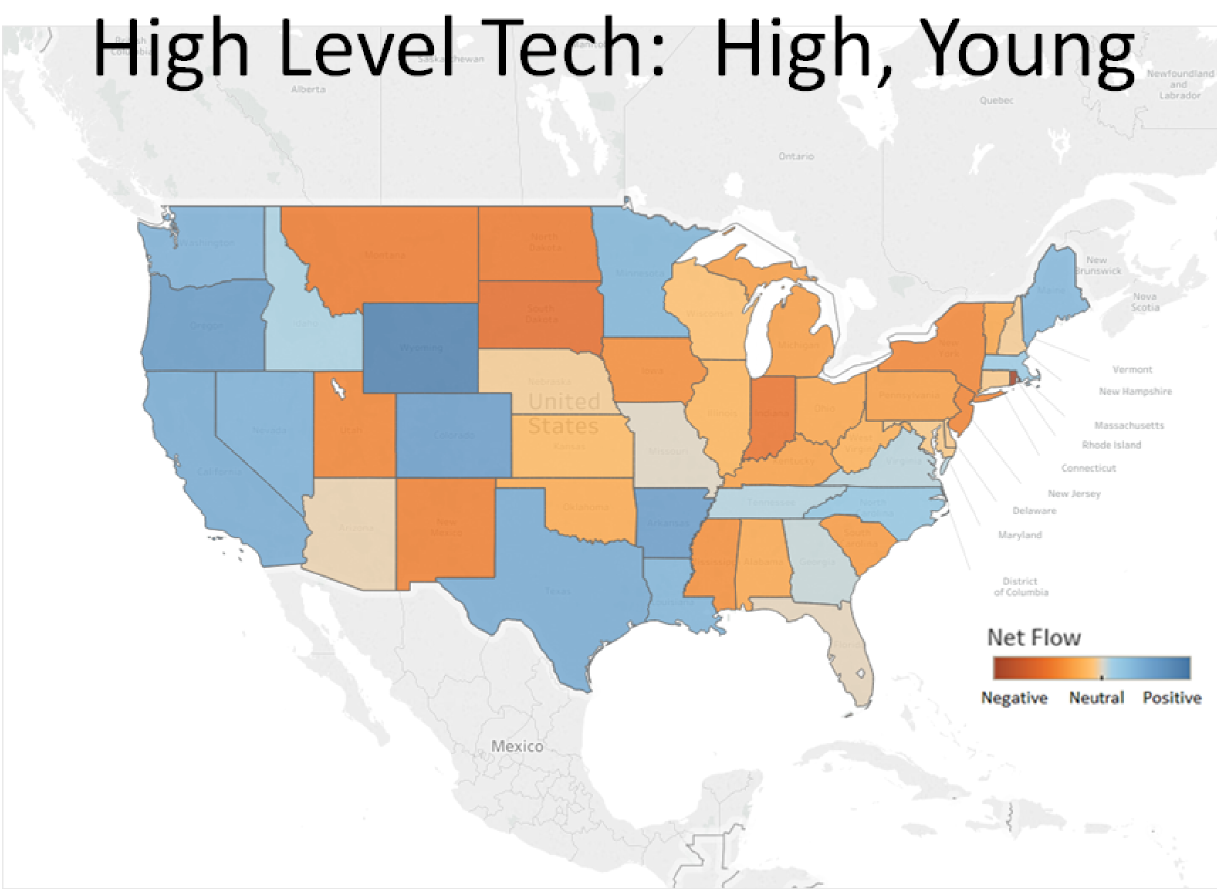

Figure 10

Shifting of young workers across this high skill group yielded some differences from just the net overall flow of young workers above. New York, Connecticut, New Jersey, North and South Carolina, and Illinois showed positive competitive shifts compared to overall change in their occupational migration flows. Florida moved from close to neutral to negative

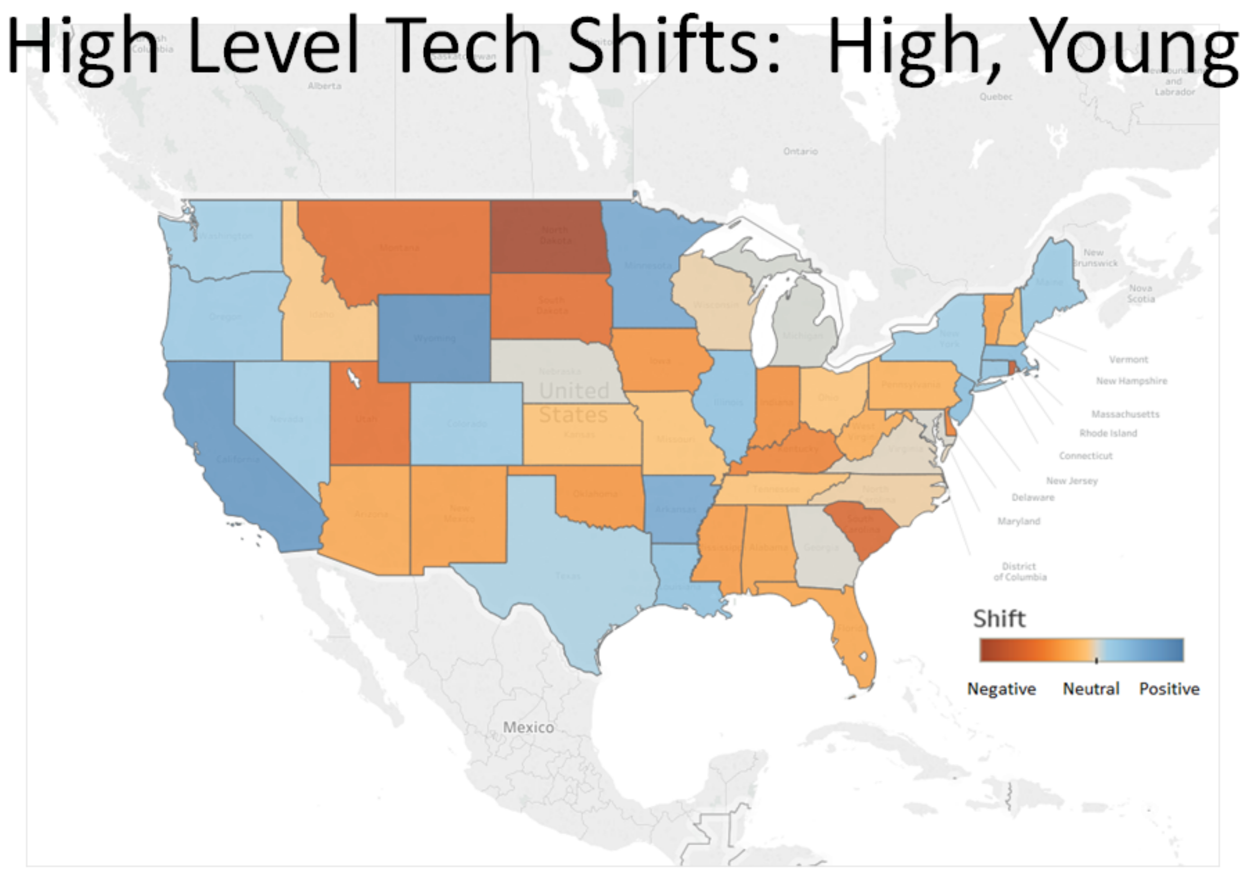

Figure 11

The remaining measures will display the net migration flows of higher and lower skilled occupations as measured by zone and next by the highest level of education held by the sampled person.

Figure 12 shows the flow of workers by preparation zones four and five, those that required considerable-to-extensive preparation. Like many of the previous graphs, the geographic contrasts are stark. Much of the Great Plains, the Great Lakes, and the Deep South demonstrate net negative flows of workers with these higher scored occupations. The comparatively strongest outflow rates are in South Dakota, Illinois, Michigan, Ohio, New York, and New Jersey. Stronger inflow rates are in Maine, North and South Carolina, Florida, Texas, Colorado, Oregon, and Washington.

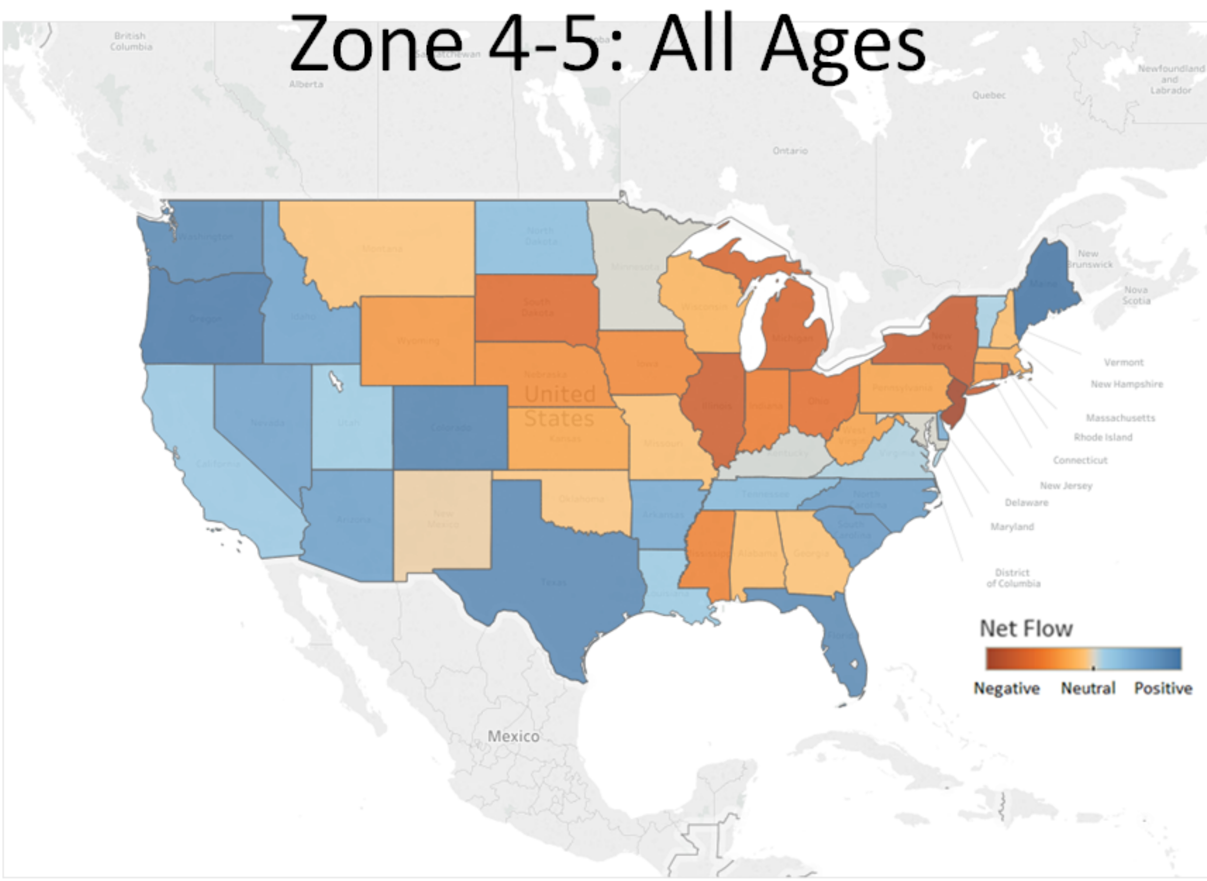

Figure 12

Figure 13 displays the relative flows of workers with lower to middle levels of skill and knowledge preparation, according to the O*NET ordinal scale. Overall just 10 of the states realized net losses in this category, with New York, New Jersey, and Illinois showing the highest outflow rates. North Dakota had the strongest inflow rate, again, owing to the shale oil boom.

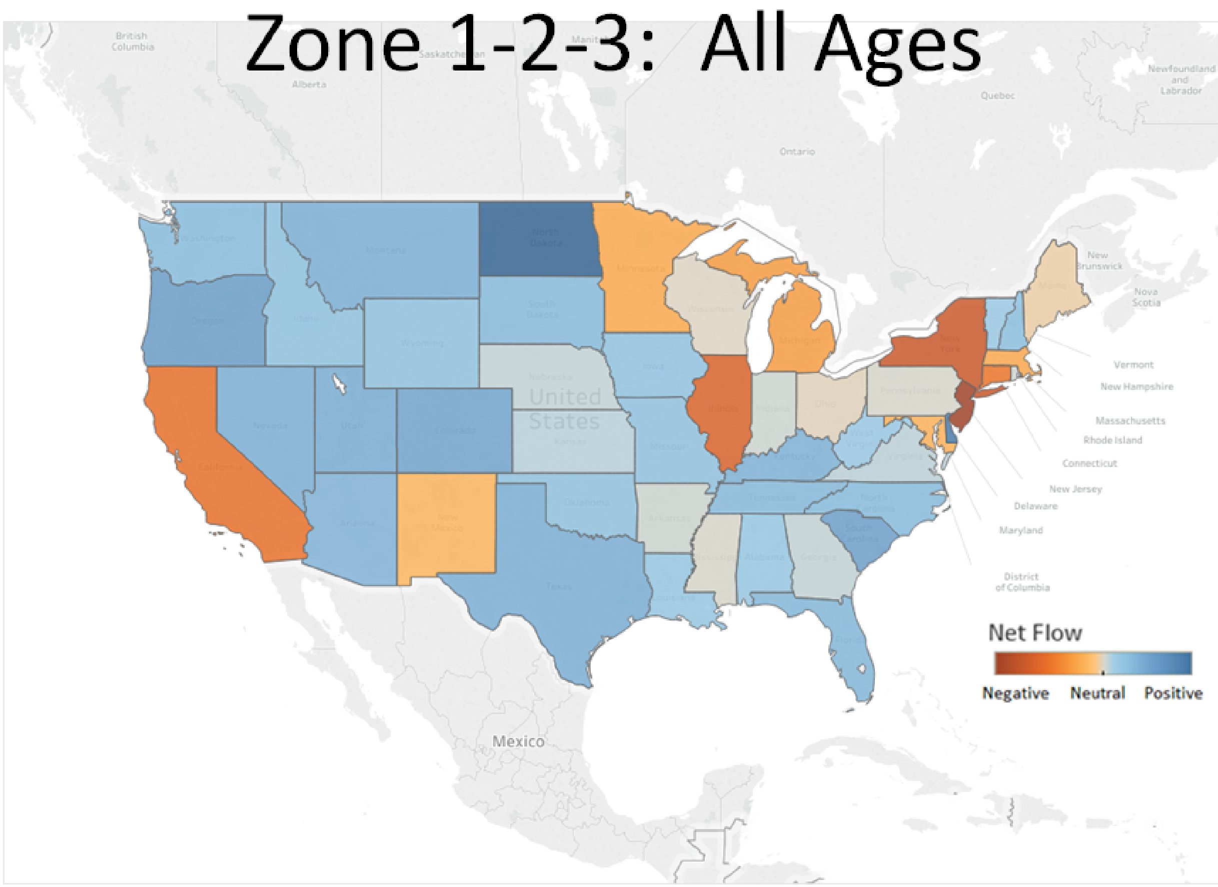

Figure 13

Net flows of persons with bachelor's degrees or higher displayed in Figure 14. Using this measure, the higher rate of outflow states include South Dakota, Iowa, Illinois, Ohio, Michigan, West Virginia, New Jersey, Rhode Island, and Mississippi. Strong inflow rates are evident in Texas, Colorado, Nevada, Oregon, and Washington.

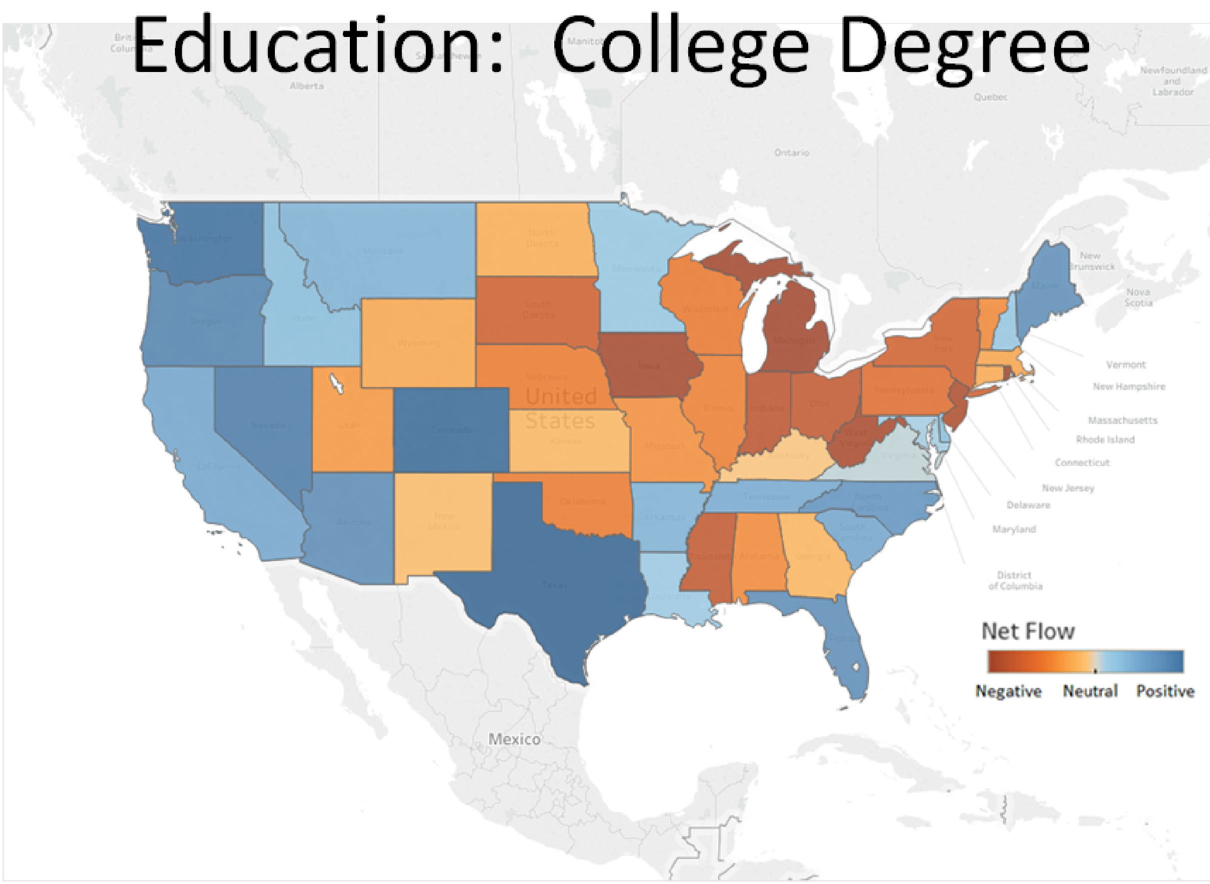

Figure 14

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Last, Figure 15 shows the net positive and negative migration flows of persons with at least a high school diploma, but without a bachelor's degree or higher. Though it differs in intensity, the pattern matches the results for Figure 13 where zones one through three were measured. Of the lower 48 states, ten posted outflows of what would generally be classified as persons who would be likely to work in middle skill positions.

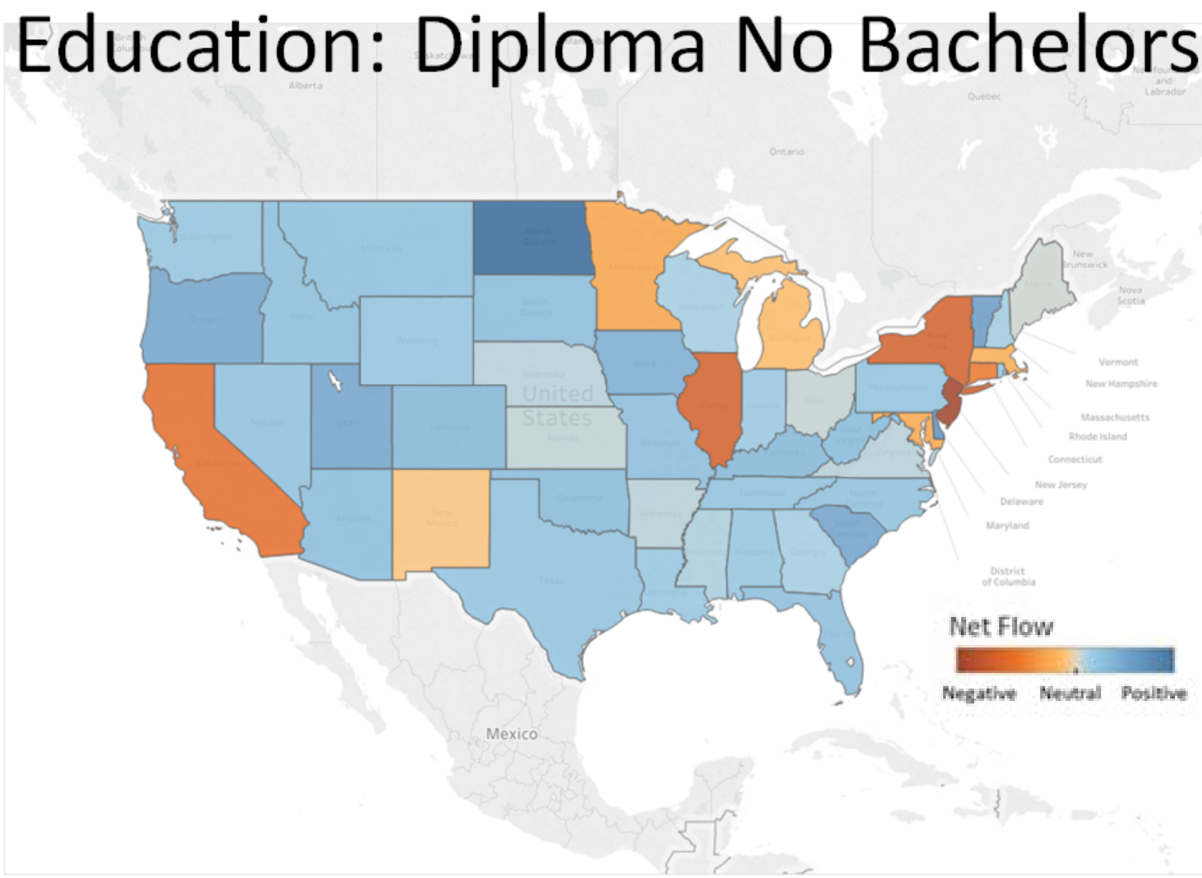

Figure 15

5. Conclusions

This evaluation considered three skill dimensions of U.S. occupations: critical basic skills, problems solving skills, and high level technical skills. This evaluation also considered job preparation levels of occupations. Skills scores from the O*NET database were summed for each subset and standardized using z-scores. Next, "high" skill occupations were selected based on z-score cutoffs. The occupation scores were matched with the Standard Occupational Codes attached to respondents in the U.S. PUMS, 2011 – 2015 rolling sample who indicated that they had moved from one state to another over that time period. This allowed for a calculation of the gross inflows and outflows of specific occupations among the states and the District of Columbia with an eye towards isolating the set of higher skill occupational flows.

The purpose of the analysis was to initially test the utility of the O*NET measures of higher skills as determined by the researchers in order to score and display the variation of the measures across the states. The analysis found that there were generally high correlations among the higher-skill occupational measures, but that there were unique variations as well across all the variables assessed. While most of the absolute state level variations were displayed in **Error! Reference source not found.** and **Error! Reference source not found.**, magnitudes of change were also calculated and mapped to demonstrate the relative intensity of change by the skill categories, as well as the preparation zone values and the overall education level of the migrating sample.

There has been widespread discussion of middle skills gaps or shortages as well as expressed concerns that some areas of the U.S., especially in much of the Midwest, are realizing noticeable skill or workforce capacity losses, or more accurately, negative exchanges when looking at the kinds of workers who flow into these areas as measured by their occupation scores versus the kinds that flow out. This analysis allowed us to generalize the characteristics of migrants across multiple dimensions and to describe migration flows in absolute terms and in relative terms. Though these are simple measures, they do allow us to quantify the states' abilities to attract workers considering different skill types, preparation zones, or education levels. The analysis also controlled for younger versus older migrants to further assist in compiling the states' competitive advantages in that desirable demographic subgroup.

This analysis is exploratory and preliminary. Because the data are sample based, there are measurement parameters to the results that allow us to state with more or less confidence whether differences between in-migrants versus out-migrants among the states are statistically significant. We have not done those calculations. That means that differences declared in this analysis may not in fact be the case, especially where the differences by the variables measured are relatively small or the number of migrants in the sample categories themselves are relatively small.

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MID-CONTINENT
REGIONAL
SCIENCE
ASSOCIATION

2017 MCRSA Conference Proceedings

Credit Unions, Business Lending, and State-level Economic Growth

Bienvenido S. Cortes
Pittsburg State University

Abstract

According to the Credit Union National Association (CUNA, 2016), bankers have argued erroneously that credit unions have been growing dramatically and gaining significant market share over the past two decades. The statistics show, however, that U.S. banks have $16.9 trillion in total assets compared to $1.3 trillion for credit unions. Large banks account for 75% of financial institution assets and small banks account for roughly 18%. On the other hand, the market share of credit unions has been steady at 7%. Credit unions are not-for-profit institutions and are exempt from federal taxation. Thus, commercial banks consider this tax-exempt status of credit unions as an unfair competitive advantage. The objective of this study is to examine the lending activity of credit unions to its members, particularly to member business owners. Moreover, the study will analyze whether credit union business lending activity has any impact on regional economic growth. It uses a pooled sample of U.S. states and quarterly time-series data for 2011-2016. Following Jeong *et al.* (2006), this study applies a two-equation model: the first equation identifies the state-level banking and economic conditions that determine credit union member business lending, and the second tests the effect of business loans on state economic growth. After adjusting for simultaneity and control variables, the findings show that credit union business lending has a positive and significant impact on state-level economic growth.

1. Introduction

This paper examines the impact of credit unions on the local economy. In spite of its long history in the U.S. (Mook *et al*., 2015), credit unions have not been in the limelight as much as their larger for-profit commercial and savings bank counterparts. However, interest on the credit union's economic role and influence has increased recently due to the 2007-09 Great Recession when regular banks reduced small business lending while credit unions stepped up to extend loans to member borrowers. Moreover, the closing of many bank branches due to the recession underscores the issue of access to financial capital and other banking services especially in rural and small communities ("banking deserts," St. Louis Fed *Regional Economist* 2017).

Credit unions are not-for-profit banks owned by their depositors or members. There is a common bond among the members such as employees of a company (ex., teachers of a school or university), labor union members, or military service members. The original credit unions started in Germany, spread throughout Europe, and then began in the U.S. in the early 1900s. These institutions are currently in more than 100 countries with more than 217 million members. More important, they are tax-exempt organizations; a credit union's surplus income is used to improve services, to reduce operating costs, and to provide dividends to its members. (Mook *et al*., 2015)

In 2016, there were 5,966 credit unions in the U.S. with over 108 million members (or a third of the U.S. population) and 20,622 branches (CUNA, US Credit Union Profile 2016). Although credit unions account for a very small share of the U.S. financial market, their contribution is not trivial. Their total assets were valued at $1.3 trillion, or 7.1% of the financial market in 2016, a slight but steady increase from 5.6% market share in 1992, and total savings deposits rose from $797 billion in 2010 to $1.1 trillion in 2016. Most credit unions are small with assets of less than $100 million; in 2016, the average size of credit unions was $217 million while the average size of commercial banks was $2,790 million (CUNA). By comparison, the 100 largest U.S. banks dominate the financial market with its asset market share rising from 41.1% in 1992 to 75.1% in 2016 (with total assets of $13.64 trillion in 2016); on the other hand, the market share of smaller banking institutions has declined dramatically from 53.3% in 1992 to 17.8% in 2016 (total assets of $3.22 trillion in 2016). (CUNA, Credit Unions & Banks Fallacies: Facts and Recent Trends, 2016)

Credit unions have historically concentrated on providing high returns on deposits and low interest cost on consumer loans to their members. They also have been extending member business loans (MBL) but regulatory burdens such as caps as a percentage of assets have limited credit union lending to businesses and thereby limited business and local economic growth. Ely and Robinson (2009) stated that the increase in small business lending activity by credit unions is due to: (a) efforts by the National Credit Union Administration to relax the definition of "common bond" to include various employer groups and larger communities; (b) Small Business Administration including credit unions in its business loan program starting in 2003 as well as other legislation increasing the caps on credit union business loans from 12.25% to 20% of assets. In 2011, the total value of MBL outstanding was $40.5 billion or 4.16% of total assets. As of end-2016, the total member business lending of all credit unions in the U.S. amounted to over $68.6 billion or

5.24% of total combined credit union assets. CUNA estimates that if the lending cap is raised from the current 12.25% of assets to 27.5%, then MBLs would increase by $6.2 billion in the first year with a projected employment effect of 54,103 persons.

As a component of the credit union's portfolio, member business loans account for only 7.8% of total loans of U.S. credit unions in 2016 (compared to 6.7% in 2010). The proportion of credit unions that offer MBL is 37.8% in 2016, up from 30.2 in 2010. Moreover, and not surprisingly, the percentage of credit unions extending MBL is also directly related to credit union asset size. Seven to 31% of smaller credit unions with assets of less than $50 million extend MBL while 75% or more of larger credit unions (with assets of $100 or greater) offer MBL. Nevertheless, member business loans have been increasing significantly from 6.2% in 2010 to 14.4% in 2016. In fact, with the exception of new automobiles, MBLs grew faster in 2016 than loans for first and second mortgages, credit cards, used autos, and unsecured loans. (CUNA, U.S. Credit Union Profile 2016)

The main objective of this study is to analyze the impact of credit union business lending activity on state-level economic growth. It contributes to the growth-financial development nexus by examining the effect of credit union member business loans using pooled cross-sectional and time-series data for 48 states and quarterly data for 2011-16. The method of two-stage least squares (2SLS) is applied to adjust for simultaneity or endogeneity issues. The following section discusses some past studies, followed by the econometric model, variables, and data sources. Analysis of the empirical results, conclusions, and implications are then presented.

2. Review of Past Studies

There has been a good deal of research on the competitive relationship between non-profit credit unions and for-profit banks (Feinberg, 2001; Feinberg and Ataur Rahman, 2006; Mook, Maiorano, and Quarter, 2015) The focus of this present study, however, is on the business lending decision of credit unions and whether the presence of credit unions and their lending activity have any significant impact on state economic growth. The following relatively recent articles analyze the credit union's lending and locational patterns.

In their study, Ely and Robinson (2009) empirically tested whether business lending activity by credit unions is caused by: (a) bank acquisition or consolidation activity ("relationship lending hypothesis" which hypothesizes that a credit union is more likely to offer business loans if it is located in a market with few community banks), and/or (b) by the average size of establishments in the geographic area ("endogenous banking structure hypothesis" which states that the more small businesses exist in an area, the higher the demand for small business loans, and the greater the probability of credit union business lending). In their logit model, the authors included various measures of acquisition activity and average establishment size as well as control variables such as the Herfindahl concentration index, bank deposits, assets, net worth, age of a credit union, and charter-type and time dummy variables. Ely and Robinson found evidence to support both hypotheses. For the 2002-06 period, their findings indicated that in large and small urban markets, credit union lending activity is directly related to mergers and acquisition activity, and is negatively correlated with average size of establishments in the area.

Wheelock and Wilson (2011) stated that credit unions are similar to community banks in terms of their small-scale operations and dependence on relationship lending. Just like banks and savings institutions, the number of credit unions has dropped dramatically from a peak of 23,866 in 1969 to 8,662 in 2006 (to 5,966 in 2016) due to merger and acquisition activity. The authors found that despite the rapid growth in membership, deposits, and loans during their year of study (2006), credit unions have not fully taken advantage of economies of scale and predicted that more acquisition and consolidation will occur.

Deller and Sundaram-Stukel (2012) analyzed various socioeconomic variables that influence the spatial location decision of credit unions vis-à-vis banks. Using county data and the central place theory, the authors regressed credit union concentration (i.e., number of credit unions per 10,000 persons) on bank concentration, population density, metro and non-metro county dummies plus three variable groups: socio-demographic (ex., Hispanic, poverty rate, unemployment rate), economic structure (population-employment ratio, population-proprietor ratio), and organizations of common bond (ex., civic organizations, labor unions, professional associations per 10,000 population). They found that credit union concentration is negatively related to bank concentration, thus indicating segmented markets. Deller and Sundaram-Stukel concluded that members want to stay with their credit unions due to organizational benefits such as ownership and governance structure, despite similar services and prices offered by banks and savings and loans. Their results also indicated that credit union concentration is lower in metropolitan counties and adjacent non-metro counties. Finally, the location of credit unions is positively correlated with socioeconomic variables such as Hispanic population share and number of civic organizations and labor unions; it is negatively related to unemployment rate, growth of number of households, and the population-employment ratio.

Similar to Deller and Sundaram-Stukel's earlier study, Mook *et al.* (2015) were also interested in the location or "representation" of credit unions in rural vs. urban communities and in low-income areas. The Mook study differed in two important ways: (1) the unit of analysis used was the branch instead of the head office; (2) it only examined three states (Arizona, New Hampshire, and Wisconsin) instead of the entire country. The authors classified community size by population and zip code. Mook and colleagues found that credit union branches in the three states are represented or concentrated more in larger urban communities; they partly explained this on the fact that 80% of U.S. credit unions have an "occupational bond of association" via manufacturing firms which are more located in bigger cities. Unlike Deller and Sundaram-Stukel, the authors found that credit union branches are mainly located in the same geographic communities as banks, i.e., credit unions are not spatially different from banks. Lastly, credit unions are located more in low-income areas than banks. Mook and others concluded that "our data suggest that credit unions and banks cluster in relation to population concentrations, but within that broad area, credit unions are more likely to situate within lower income areas than bank branches." (p. 826)

3. Method, Data, and Analysis

This current study derives much of its theoretical framework from earlier studies of state-level economic growth such as Abrams, Clarke, and Settle (1999), Jeong, Kymn, Kymn, and Cushing (2006), and Bruce, Deskins, Hill, and Rork (2009). In particular, it applies Jeong *et al.*'s method of testing the credit view which hypothesizes that banking sector health influences real economic growth. Jeong and colleagues estimated a two-equation model via 2SLS technique on panel data consisting of 48 states and ten years (1984-93). The first equation shows growth rate of investment-oriented bank loans (IOBL) as a function of bank health variables (ratio of bank capital to assets, ratio of net income to assets, ratio of nonperforming loans to total loans, and growth rate of loan loss reserves, all lagged one year), lagged IOBL growth rate, and year dummy variables to represent three banking laws. In the second equation, the difference between state-level Gross State Product and U.S. GDP growth rate is regressed on its own lagged value, the current growth rate of IOBL, and the three year dummy variables. Unlike Jeong *et al.*, this current study uses: (a) credit union member business loans rather than IOBL as a function of credit union financial health variables; (b) quarterly data for 2011-16, the period after the Great recession, and; (c) more control variables such as industry employment shares, unemployment rate, and population density to explain the growth of state GSP relative to the nation.

The general state-level econometric model to be estimated is:

$$GRGSP\text{-}GRUSGDP = b_1 + b_2GRMBL + b_3GRBANKLOAN + b_4UR + b_5MFTG + b_6SERV + b_7DENSITY + e$$

where GRGSP-GRUSGDP is the growth rate of Gross State Product minus the growth of U.S. GDP; GRMBL, the key variable of interest, is the growth of credit union member business loans; GRBANKLOAN is the growth of commercial bank lending; UR is state unemployment rate; MFTG is the share of manufacturing in total state employment; SERV is the service employment share; DENSITY is the population density or number of persons per square mile; e is the error term. All explanatory variables, except the unemployment rate, for the state-level growth equation are expected to have a positive sign.

Since GRMBL may be endogenous, it is regressed on a number of instrumental variables including the growth of credit union assets, credit union net worth ratio, credit union return on assets, and credit union delinquency rate, following Jeong *et al*. Also, following Ely and Robinson (2009), average establishment size for both goods-producing sector and service sector are included as instruments. Lastly, to account for any spatial effects, a dummy variable for interstate branching by credit unions is added; BRANCHING is equal to one if the state is Alabama, Georgia, Florida, Missouri, Mississippi, North Carolina, or Tennessee, zero otherwise (in 2008, these southeastern states mutually agreed to allow setting up branches across state lines).

Data on credit unions were kindly provided by Mr. Paul Ledin of the Credit Union National Association. Other variables were gathered from the BEA, Census Bureau, and the FDIC. Using EViews statistical package, pooled 2SLS method was applied to a balanced panel data set consisting of 48 states and quarterly data for the 2011Q2-2016Q3 period. Autoregressive procedure AR(1) to account for autocorrelation as well as state fixed effects were also applied.

The results of estimating the two-equation model are shown in the table below.

POOLED 2SLS WITH GROWTH OF GSP MINUS GROWTH OF USGDP AS DEPENDENT

Variable	Coefficient	t-Statistic
Constant	1.03	3.66***
GRMBL	0.26	3.09***
GRBANKLOAN	0.05	0.57
UR	-0.002	-1.94*
MFTG	-0.63	-2.03**
SERV	-1.61	-4.07***
DENSITY	0.001	1.85*
LAGGED DEPENDENT	-0.10	-2.91***

Note: ***Significant at the 1% level; **5%; *1%.

After accounting for simultaneity and control variables, the main finding is that the key variable of interest, credit union MBL growth rate, has a positive and statistically significant impact on the growth of state-level output relative to that of the nation. Although growth of bank loans has a positive estimated coefficient, it is not significant; replacing bank loans with bank assets or deposits gives the same results. Confirming past studies, the unemployment rate has the expected negative sign and the positive population density coefficient indicates agglomeration effects. The negative effects of the manufacturing and service sectors reflect current national trends. Finally, the initial or lagged state-to-U.S. growth indicates convergence.

4. Conclusion

This study is an initial attempt at measuring the differential effect of credit union business lending activity on local economic growth. Although credit union share of the U.S. financial market is small compared to commercial banks and savings and loans, the strong growth of the number of credit unions, their membership, and the variety of customer services bode well for local economic growth especially as it pertains to small businesses. The empirical results of the study support the positive and significant impact of credit union business loans. The important economic role of credit unions was underscored when the U.S. Small Business Administration (SBA) partnered with the Credit Union National Association (in 2015) as well as with the regulatory agency, the National Credit Union Administration (in 2017), to encourage and promote small business commercial lending. Given that small businesses in the country generate two out of three jobs, that half of U.S. workers are employed by small firms, and that almost a third of the U.S. population are members of a credit union, this partnership expects to dramatically improve financial conditions and stimulate overall growth. Critics argue that the size of SBA loans, say $5,000 to $50,000, may not be helpful and may even restrict the type of firm borrowers. The SBA and its credit union partners are more optimistic and believe that new or growing small operations need only a little push to get moving. This remains to be seen and is the subject of future study.

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South Dakota Migration Patterns Between 2000 and 2015

Ronald Gunderson
Northern Arizona University
David Sorenson
Augustana University

Abstract:

This paper presents an analysis of migration patterns for South Dakota and its counties since 2005 using Internal Revenue Service and Census Bureau data. The paper will compare the results to those of an earlier study of the nature of migration in the state which preceded the severe recession of 2008. The study includes reconciliation of the IRS and Census Bureau American Community Survey datasets and an assessment of the effects of the imputation process. Migration tendencies will also be examined for their association with counties' niches in the urban hierarchy and the proximity of origins and destinations.

1. Introduction

Migration is of great concern for many states and cities in the U.S. Of special concern for more rural Midwestern states are the sustainability of smaller towns and the often-countervailing need for new workers in growing urban areas. An earlier study (Sorenson, 2008) examined county-to-county flows in 1995-2000 and 2000-2005 to assess the relative performance of South Dakota's counties and investigate migration patterns within the urban hierarchy. The study revealed dramatically different outcomes for different counties and documented a pattern of migration up the urban hierarchy.

The present study seeks to extend the examination to more recent years. In doing so, we combine broad, aggregated data and much more detailed county-to-county flows to assess more current trends. In addition to looking at more recent data, we also compare our finding to earlier years to see whether the "Great Recession" altered migration flows. The remainder of the paper includes a literature review, comparison of more recent county gross and net flows to those of earlier years, an examination of known county-to-county flows in the two time periods to assess migration within the urban hierarchy, a methodological section on imputing values for the suppressed flows of the IRS migration data, and assessments of more current South Dakota migration among counties and within the urban hierarchy.

2. Literature Review

Migration analysis has been a popular topic for research for several decades, and outputs have ranged from basic descriptive reports from State Data Centers and various state level offices and departments which report and analyze population and migration activities, to more sophisticated analyses of migration patterns including projected current and future impacts based on these trends, as well as more formal migration models which can be employed to predict and understand the forces which underlie migration decisions.

The more descriptive types of research typically rely upon data which originate from the Bureau of the Census and the Internal Revenue Service (IRS) regarding migration activity for a particular state or small area such as a county. As an example, Cicha (2017) utilizes IRS data to show how common it is for residents in all of North Dakota's counties to move and where the exchange of residents was most likely to occur. A more comprehensive look at county migration patterns was undertaken by the Ohio Research Office (2016), a state affiliate with the U.S. Census Bureau. This report used county-to-county migration flow estimates from the 2013 American Community Survey to produce a detailed set of migration data for each of Ohio's counties including the top origin and destination regions of the migrants along with the place of birth and ability to speak English for all inmigrants in each county.

More detailed studies of migration are found in reports documenting various population and migration trends and which offer greater analysis of the effects of migration activities. In a study released by the Federal Reserve Bank of St. Louis, Bandyopadhyay and Vermann (2013) examine migration into the major cities of the Federal Reserve Eighth District and found that new residents migrating into these metro areas comprised a relatively small percentage of total movers, instead finding that high levels of intracity migration accounted for much of the activity, implying that these metro regions were undergoing spatial growth.

In a study completed at the Texas Demographic Center, White et al. (2017) found that while all of Texas counties are impacted by migration, the major metropolitan counties not only experience the largest amounts of inmigration, but had people moving there are culturally and demographically more heterogeneous, leading the authors to conclude that "the state's geographical differences in opportunities and challenges" will sharpen in future years.

Finally, the uppermost level of relevant migration literature often develops formal measures of migration in order to understand migration trends. In a significant work, Plane, Henrie, and Perry (2005) examined recent migration in light of Ravenstein's (1885) laws of migration, in particular, the predisposition toward step migration along the urban hierarchy.

Benetsky and Fields (2015) developed several models that address the issue pertaining to how much the Great Recession affected the migration of millennials over the three years encompassing 2010-2012. Their findings showed significant declines in migration rates for young adults this period.

Molloy, Smith, and Wozniak (2014) adopted a longer timeframe, concluding that there has been a secular decline in interstate migration since the 1980s which they attribute to downward trends in labor market transitions as a result of declining returns to job-changing in recent decades (e.g. the wage gains associated with job changes have declined over the period). This change has led to reductions in the percentages of workers who move from job-to-job or change occupations entirely.

In a study specific to South Dakota, Fogg and Harrington (2014) assessed the growth and change in South Dakota labor markets during the time of the recent weak national economy, concluding that the state weathered the recession much better than most states, resulting in a reversal of the state's long-term slow growth in population and bringing a sharp increase in the number of new migrants into the state. Our analysis in the current paper appears to confirm the findings of Fogg and Harrington.

3. Statewide Flows

As an initial summary of South Dakota migration, the total in- and out-migration between 2001 and 2014 is shown in Figure 1. Over the five-year period spanning 2001-2006, an average of 20,153 persons per year migrated from a South Dakota county to a county elsewhere in the U.S. while an average of 20,451 persons per year migrated to a South Dakota county. These numbers produced a net inmigration of 298 persons per year; however, the net migration rate was essentially flat at less than 0.04% of the 2001 State population. This is not unexpected for states similar to South Dakota; however, the slightly positive net migration rate does represent a turnaround from a negative net migration figure in the previous five-year period covering 1995-2000.

From 2006 to 2013 a persistent gap between inmigration and outmigration developed, leading to positive net migration. The gap is was fairly consistent through the Great Recession, so at least for the gross flows at the state level, little deviation was evident during or immediately after the recession. The increase in both in- and out-migration between 2011 and 2013 most likely reflect advances in the IRS data-matching procedure than actual changes in migration.

Migration exchanges with the ten top sending and receiving states are shown in Figure 2. Most of the state flows are fairly consistent over time, but there does appear to be a dampening of migration of inmigration from several states, including Minnesota, immediately after the recession. The uptick due to the IRS matching improvement is also evident in the state data, especially for Florida. The outmigration patterns are similarly fairly stable over time.

Overall, the statewide pattern and exchanges with other states paint a fairly static picture. However, the aggregate pattern could well hide significant changes in the underlying county patterns, to which we not turn.

Annual County Net Migration and Demographic Efficiency 2001-2006

Although net migration in South Dakota overall during the 2001-2006 timeframe was slightly positive with the annual average of 298 per year, a review of the individual counties tells quite a different story (Table 1). Over this five year period, only twelve of the sixty-six counties experienced positive net migration, while the remaining 54 counties lost population as a result of net negative migration.

Lincoln County, which includes the southern portion of the City of Sioux Falls, and is one of four counties in the Sioux Falls Metropolitan Statistical Area (MSA) experienced the largest increase with an average of 1,490 net new migrants annually over this five-year period, and it also had the highest annual net migration rate of 5.8 percent per year. However, a portion of this increase is due to an ongoing shift in the movement of Sioux Falls residents from Minnehaha County to the southern part of the city which is located in Lincoln County, and therefore some of Lincoln's growth is a reflection of the movement of population within the same MSA. Minnehaha County also continued to see net positive migration, but at a much lower rate than what occurred in Lincoln County (0.3% vs. 5.8%).

Hanson (3.2%), Custer (2.0%), and Union (1.0%) counties were the only other counties which experienced net positive migration rates at or above 1.0%. Pennington County, the second largest county in South Dakota and the home of Rapid City, experienced a small increase of 42 net new migrants per year, or a migration rate of 0.1%.

On the other hand, the percentage losses as a result of net outmigration varied from a loss of one person per year (essentially 0%) in Davison County to a negative 2.2% in Haakon County. Net migration losses on a numerical basis were highest in Beadle and Brookings counties, which saw annual losses of 208 and 200 persons respectively each year.

Regional differences in net migration and the net migration rate can be seen in Figure 3, which indicates that the counties with the highest levels of net immigration primarily were clustered in the southeast and southwest regions of the state, while much of the northeast, north-central, and south-central regions of the state experienced net outmigration in many counties.

We also examined the demographic efficiency of the migration flows. Demographic efficiency, or the ratio of net migration to gross migration multiplied by 100, is used to assess the degree to which counter flows offset or negate what would otherwise represent a more efficient migration movement. Demographic efficiency is calculated as:

$$e_{ij} = 100(m_{ij}-m_{ji})/(m_{ij}+m_{ji})$$

where e_{ij} is the efficiency measure and m_{ij} is the amount of migration between location i and location j. The measure can have values which range from +100 to – 100, and apply to any pairing of origin and destination locations. In the analysis, for this paper, these refer to migration flows in one county relative to all other counties. Migration streams whose demographic efficiency measure is close to +100 or to -100 are assumed to be "effective". In the extreme case, a value of +100 indicates that only immigration occurred, while a value of -100 indicates that only outmigration occurred. Alternatively, a value closer to zero indicates an approximate balance between the amount of in- and outmigration in a county, and is considered to be "ineffective" since it does not redistribute population.

Over the 2001-2006 period, the demographic efficiencies of the South Dakota counties ranged from -45.5 in Campbell County to +27.6 in Lincoln County. Fifty-three of the sixty-six counties had negative measures, and the absolute values on the negative measures generally exceeded those with positive measures, indicating a substantial dominance of outmigration in many counties. Generally, demographic efficiencies will closely mirror net migration rates; however, the relatively lower absolute values for the net inmigration counties are the result of the relatively large gross flows which underlie the high net flows.

4. Net Migration and Demographic Efficiency in 2009-2013 Compared with 2001-2006

The annual county net migration and demographic efficiency measures for the post-recessionary period between 2009 and 2013 show considerable changes when compared with numbers from the earlier period prior to the recession. As previously shown in Figure 1, net migration into South Dakota was considerably higher over this four-year period when compared to the 2001-2006 period, and the magnitude of the flows was also larger in the later period.

For the four-year period from 2009-2013, an average of 22,068 persons per year migrated from a South Dakota county to counties elsewhere in the U.S., and an average of 24,544 persons per year migrated from counties in other states to a South Dakota county. The difference in these flows resulted in a net annual inmigration of 2,476 persons over this period, compared to only 298 net new annual inmigrants in the pre-recessionary period. Statewide, the net migration rate rose from 0.04% in the earlier period to 0.4% of the state population in the more recent period, which indicates that a substantial change in net migration patterns occurred between the first and second time periods under consideration.

When we examine the migration streams from 2009-2013 in the individual counties, it is unmistakable that several changes in the migration pattern occurred over large portions of the state (Table 2). In this period, forty-one of the sixty-six counties experienced average annual positive net migration, compared with only twelve in the earlier period, and only twenty-three counties lost population due to net negative migration in the more recent years. Numbers for Buffalo and Haakon Counties were unavailable for some years, and were not included in this comparison.

In both time periods Lincoln County recorded the largest increases in net migration, although annual net migration rate in Lincoln County did decline somewhat from the earlier 5.8 percent to 3.0 percent more recently. Once again, a substantial portion of the net migration influx in this county can be attributed to the movement of Sioux Falls residents across county lines from Minnehaha to Lincoln County. In addition, Custer County (2.1%) extended its trend as a leader among South Dakota counties in attracting net additional migrants, and it was joined by Lake County (2.0%) as the counties with the second and third highest net positive migration rates in the state.

For the twenty-three counties which experienced net outmigration between 2009 and 2013, only four incurred losses of -1% or greater. Net outmigration rates were highest in Clay and Hyde Counties where each experienced a -1.4% rate of net annual outflow; however, on a numerical basis, the largest loss occurred in Brookings County which experienced annual losses of 149 persons each year.

Although the majority of South Dakota counties experienced a turnaround in net migration rates, regional differences in net migration patterns were still evident, as can be seen in Figure 4. The counties with the highest levels of net immigration primarily are again clustered in the southeast and southwest regions of the state, while much of the northeast and south-central regions of the state continued to experience net outmigration in many counties, or at a minimum their net inmigration rates were smaller compared with the remainder of the state's counties.

Finally, the demographic efficiencies for the South Dakota counties in 2009-2013 also differ considerably from the earlier period, ranging from -14.8 in Beadle County to +23.0 in Harding County. Lincoln County, which had the highest demographic efficiency in the previous period, still continued to perform well with an efficiency value of +15.5, which was second highest behind Harding. Overall, forty-six of the sixty-six counties had negative values on the demographic efficiency measure, although the fact that the absolute values were lower than they were prior to the recession suggests that migration streams were generally less efficient in the post-recessionary years.

Analyzing County-to-County Flows

In order to assess the county-to-county flows, the severe suppression problem in the IRS data needed to be addressed. Since the IRS reports only the flows where at least ten returns were found, increasing to twenty in 2013-14, the majority of migration flows are suppressed in the public dataset. One means of assessing changes in the nature of the gross migration flows is to only focus on the reported flows, while the other is to impute the suppressed values using additional information and an algorithm to estimate individual flows consistent with the reported county total inmigration and outmigration flows. A portion of the 2010-2011 IRS county data set is shown in Table 3 to illustrate typical data available.

Comparing Reported Flows

Reported county-to-county flows in the IRS data were calculated for the periods 2001-2006 and 2009-2014. Once all flows for all years in each of the time periods were merged, averages were computed for use in the comparison. Only flows that occurred in at least three of the five years in the early period were used. Flows with two or more years were used for the later time period, since the change in threshold to twenty returns led to much more suppression in 2013-2014.

The inmigration and outmigration flows are summarized in Table 4 according to levels of the urban hierarchy as indicated in the USDA ERS Rural-Urban Continuum codes (RUCC) for 2003. The RUCC codes increase from the largest MSAs with code 1 to completely rural counties with code 9. The Sioux Falls MSA is in the third grouping and South Dakota has no counties in the code 4 group, so the list of categories is abbreviated for South Dakota. Most notable in comparing the migration counts for outmigration are the higher values in the latter time period. This most likely reflects 1) the IRS methodology changes that increased reported gross flows nationwide in 2011-2013 and suppressed flows with less than twenty returns in 2013-2014, and 2) the decision to use flows that occurred in only two years in the latter time period.

When we examine the percentage distribution of outmigration flows, it is clear that the general scaling up of the numbers does not appreciably affect the distribution of flows among categories: the percentages are remarkably stable from 2001-2006 to 2009-2014. The percentage tables for inmigration are also fairly stable, but they do illustrate some interesting shifts, including increases in the percentage of inmigrants from the largest MSAs, which are only out-of-state, into the top four categories of South Dakota counties. We also see an interesting decline in the percentage of inmigrants to category 5, urban population of 20,000 or more and not adjacent to an MSA, from more rural counties.

The inmigration figures reveal more changes between the earlier and later time periods. The South Dakota MSA counties had positive net migration with large metros out-of-states in the latter period, turning around net outmigration from the earlier period. However, net migration exchanges with more rural counties were much smaller than they were in the earlier time period. The more rural categories (7 through 9) generally had more favorable, although still negative in cases, exchanges.

Imputation of Suppressed Flows

The imputation procedure was performed separately for in-state and out-of-state migration. For the in-state migration flows, the reported in- and out-migration totals by county can be used in a fairly straightforward bi-proportional, often referred to as RAS, fitting procedure. The reported flows are subtracted from the totals by county to form the margins for the fitting procedure. We chose 2010-2011 as the year of analysis since it is the most recent year with the lower suppression cutoff of ten that does not suffer from the "inflated" numbers for 2011-2013. For 2010-11 the known flows capture the majority of the migration (about 17,000 of 23,000) within the state of South Dakota, but a much smaller portion (only about 4,000 of the 22,000 inmigrants, for example) of out-of-state flows is reported. The remaining flows must be estimated through the RAS procedure using the residual, unknown flows.

The key concern with this method is to populate the flow matrix with initial values. For this we employ the American Community Survey (ACS) data gathered from 2009 to 2014. The county-to-county flows in the ACS are considered unreliable as estimates given the sampling procedure and sample size (about 2.5% of the population per year), so they cannot be used as the estimates of migration. For example, as shown in Table 5, the margins of error are quite large, in some cases larger than the estimated flow itself. Other caveats to bear in mind include the increased coverage of the ACS estimates, especially college students and low-income populations, and the multi-year nature of the sampling, which together mean that we would expect approximate conformance at best. We also expect some deviation due to the suppression handling techniques used by the IRS, which moves the unreported small flows into other counties in some cases.

While the ACS flows have too high of a margin of error to stand alone as estimates, they are still unbiased estimators of the flows among counties, given the caveats above, so they are arguably suitable as a starting point for bi-proportional fitting using additional county margin information to restrict values to known, non-sampled values. Before running the procedure, some initial estimation of a few counties' margins was necessary, since the flows were too small for the IRS to even report the split between in-state and out-of-state migration. In those cases, five counties for inmigration and four counties for outmigration, the split of the total migration was based on the proportions reported in the closest available year.

Given the marginal in- and outflow totals, the in-state RAS algorithm alternated between adjustments forced to reconcile to the inmigration total and then to the outmigration total. The first round of adjustment involved inmigration county adjustment ratios ranging from 0.165 to 4.875, i.e., ACS totals ranged from about one-fifth of the IRS margin to more than five times the IRS margin, and the first round of outmigration adjustment ratios ranged from 0.28 to 13.2. Following these large initial adjustments, convergence for most flows happened fairly quickly, with fourth-round ratios between 0.92 and 1.03 for inmigration and between 0.98 and 1.07 for outmigration, although significant adjustment persisted in a couple of cases. Upon closer examination, we found that the combination of county margins and ACS cases generated a situation where it would be impossible to reconcile the values. In this case, we averaged the final two iterations of the procedure to arrive at a final value.

For the out-of-state flows, no attempt was made to reconcile county-to-county flows throughout the nation, but we still had two sets of constraints to satisfy: the county total migration (in and out done separately) and the total flows to and from the state of South Dakota to different states. In addition, for several counties the suppressed flow totals are reported for the four major census regions of the U.S., so adding up to the county level was performed by region for those counties. The reconciliation process began with the summing to the county residual totals and then to the state residual totals. The process converged to minimal change after fifty iterations.

Several exceptions were needed to account for suppressed IRS migration flows that did not have any corresponding flows in the ACS dataset. For two counties, the IRS migration data reported that there were flows to and from the Northeast Region, but no individual flows were reported in the ACS data. In these cases "dummy" counties were created for the four northeastern states with the highest migration exchanges with South Dakota. A dummy flow was also created between Minnehaha County and Delaware to account for the reported state migration exchange with Delaware which was not matched by any record in the ACS data. After processing, we also discovered that there were no reported ACS flows to Hyde County. Rather than assign a dummy flow to any particular state, we simply allowed the missing value to persist through the processing, which did not affect reconciliation for other counties.

Convergence was fairly quick with the out-of-state data. For example, the first-round inmigration adjustment ratios (to reconcile summed ACS flows with the margins) for counties without a regional breakdown of flows ranged from 0.15 to 9.75, i.e., almost a ten-fold increase, but the fourth-round adjustments ranged between 0.965 and 1.052. The counties with a regional breakdown of flows behaved similarly, with the exception of the single flow between Lincoln County and Rhode Island, which was irreconcilable between the county and state margins. The first-round state ratios ranged from 0.51 to a whopping 28, but they converged to a range of roughly 0.96 to 1.05 by the fourth round, with the exception of the persistent Lincoln County/Rhode Island case at 0.51. All RAS methods had converged to essentially no change, with the exception of the cases noted above, by the time the fifty-round procedure ended.

The imputation procedure worked satisfactorily, but some concerns remain.

The substantial differences between the ACS and IRS county totals are an indication that the different coverage and years prevent the two datasets from being completely compatible. The lack of any matching flows in selected cases is also of some concern. In addition, several flows in the final imputed results were well above forty, which would be a reasonable cap for a county that had nine or fewer tax returns filed. A further refinement to the imputation might introduce a constraint on the size of an imputed flow.

Imputed Pattern v. Known-only Pattern

Comparing the imputed results to those using only known values for the South Dakota county flows provides and initial assessment of the impact of incorporating imputed flows. As shown in Table 6, which compares the 2010-2011 imputed results to the 2009-2014 known-only results, several differences are readily apparent. Initially, we see the obvious addition of RUCC code 4 counties in the imputed outmigration data, a category which did not show up in the known flows. Of more importance are the shifts among the reported RUCC categories, including the notable increase in the percentage of outmigration to larger MSAs, which don't exist in South Dakota. Given the small proportion of the out-of-state migration flow reporting in the IRS data, we are not surprised to see this increase. The increase to large MSAs in accompanied by decreases to other categories, most notably the decreased importance of smaller MSAs and RUCC 5, smaller urban areas, as destinations. The inmigration findings are similar, although beyond the MSA percentages, decreases in importance as source counties are most evident in urban areas between 2,500 and 20,000 population (RUCC 7).

5. Imputed Pattern Compared to Earlier Period

Outmigration from Counties

The 2010-2011 outmigration destination percentages appear in Table 7a. Counties are classified by an altered county typology that better reflects South Dakota's urban hierarchy. In this classification scheme, out-of-state flows are lumped into aggregated metro and nonmetro categories. In-state categories are central MSA, other MSA, central micropolitan, several less urban categories, and, finally, the two counties which host the state's largest universities. A map of the typology is shown in Figure A2.

When we look at the three "Central MSA" counties, we find some similarities in destination patterns, as well as substantial differences. About forty percent of the outmigrants from Minnehaha and Pennington counties moved to metropolitan areas out of state, while approximately fifteen percent relocated to out-of-state nonmetropolitan areas. However, in Lincoln County over half of the outmigrants simply moved across the county line to Minnehaha County (or, far less likely, to Pennington County) while only twenty percent of Lincoln's outmigrants moved to metropolitan areas out of state, and just over ten percent relocated to out-of-state nonmetropolitan areas.

The movement of residents from Lincoln to Minnehaha was partially offset by a concurrent movement of residents in the opposite direction. About twenty-six percent of the outmigration from Minnehaha was directed to Lincoln (or, again to a much lesser extent, Pennington). A similar pattern occurred in the western portion of the state where almost twenty-seven percent of Pennington County's outmigrants moved to other Central MSA counties, mostly across the county line to Meade County. When we observe the remaining outmigrants from each of the three Central MSA counties, no other in-state group of counties at the micropolitan-or-smaller classifications received even seven percent of the outmigration.

The "Other MSA" counties (McCook, Meade, Turner, and Union) also experienced quite different outmigration patterns among the four counties. Union County sent half of its outmigrants to out-of-state MSAs, which was expected since it is part of the Sioux City MSA adjacent to the state's border. Meade's outmigrants were essentially split between moving to out-of-state MSAs and South Dakota Central MSAs (largely to Pennington), while McCook and Turner counties sent only fifteen and ten percent of outmigrants to out-of-state non-metro regions, respectively, while sending approximately half of their outmigrants to South Dakota Central MSAs. These two counties also sent around fifteen percent to central micropolitan counties, and very little of the outmigration was distributed to the semi-rural or rural counties of the state.

The outmigration patterns from the seven "Central Micropolitan" counties are more consistent across these counties. In all but Lawrence, about one-quarter to one-third of their outmigration went to out-of-state metro areas, while another one-third of the migration was directed to out-of-state non-metro areas or South Dakota Central MSA counties. However, a striking difference occurs among this group of counties when compared to South Dakota's larger counties. In each of these six counties, outmigration to entirely rural counties (rural-non-MSA-adjacent counties) varied between ten and twenty-five percent of total outmigration. These percentages are substantially higher than what occurred in any of the larger counties, and instead are similar to what has occurred in many of the semi-rural not-adjacent counties. It is not clear that a common rationale explains this pattern across these counties. Lawrence County's pattern reveals a comparable percentage of out-of-state outmigration, although favoring non-metro areas, and it sends a much smaller percentage to rural non-adjacent counties.

The outmigration patterns which existed for most of the semi-rural and rural counties in the urban hierarchy varied considerably from county to county; however, in many of these counties a third to one-half of the outmigrants moved to out-of-state metropolitan and non-metro areas. Much of the remaining movement went to the Central MSA and Central Micropolitan areas, although in a few instances (Brule, Buffalo, Lyman, and others) a substantial percentage of the outmigrants moved to completely rural non-MSA adjacent counties as well.

Inmigration to Counties

Turning to inmigration, the percentages for each county for 2010-2011 appear in Table 7b, and again are sorted by county type. The patterns reflecting inmigration to the Central MSA counties are similar to those occurring with outmigration. The highest percentages of immigrants to Minnehaha and Pennington counties arrive from out-of-state metropolitan areas, while Lincoln's inmigrants predominantly come from Minnehaha County. Inmigration from out-of-state nonmetropolitan areas accounts for the second largest percentage in

Pennington County, although in Minnehaha the percentage of inmigrants from the central MSAs in the state barely edges out the percentage arriving from the out-of-state metropolitan areas.

Inmigration to the other MSAs in South Dakota follows a similar pattern to what occurred with outmigration. In the four Other MSAs only Union County received the majority of its new migrants from out-of-state MSAs, while the other three counties received approximately half of their inmigration from the Central MSAs within South Dakota. Very little inmigration occurred from the rural regions of the state into these counties, although Turner County received twelve percent of its migrants from college counties, which is not surprising since it is located next to Clay County, which hosts the University of South Dakota.

The seven Central Micropolitan counties also saw significant percentages of new migrants arriving from the out-of-state metropolitan areas as well as from out-of-state nonmetro areas and from the central MSAs in South Dakota. In addition, the entirely rural not-MSA adjacent counties were significant contributors to this inmigration, and in the case of Hughes County, home of the state capital, these rural counties accounted for the largest percentage of new inmigrants into this county for this time period. Lawrence again stands out relative to the other counties in that it has a much smaller contribution from the most rural counties.

There are only two semi-rural MSA-adjacent counties in the state: Butte, bordering Wyoming and the western metro- and micropolitan areas, and Lake, situated between the Sioux Falls MSA and Brookings. The inmigration patterns for these two counties differ considerably. Out-of-state nonmetro and semi-rural MSA-adjacent counties each account for about one-third of all new inmigrants to Butte. Alternatively, inmigration to Lake County was dominated by out-of-state flows, especially metro. These variances could likely impact future resettlement patterns with Lake County perhaps becoming the home to more residents from large-city environments, while Butte's growth may result from primarily more rural residents from out-of-state.

Inmigration to the semi-rural non-adjacent and all other counties lower in the hierarchy was generally small; however, the sources of the new migrants to these counties varied considerably over this period. Inmigration from out-of-state MSAs accounted for the largest percentage of recent migrants for about half of these counties (25 of 49 counties), while the remaining counties, with few exceptions, saw the largest numbers of new migrants arriving from out-of-state nonmetro and central South Dakota MSA counties. Interestingly, a group of counties near the center of the state (Buffalo, Dewey, Hyde, and Sully) received the highest number of new inmigrants from the rural-not-MSA adjacent counties. This is the same pattern that occurred in Hughes County, home to the capital and located next door to most of these counties.

Finally, and not surprisingly, the two college counties (Brookings and Clay) received about half of their new migrants from out-of-state metro and nonmetro counties, which largely reflect students from other states who were enrolled in the state's largest universities located in these counties.

The migration flows can be further summarized as demographic efficiencies relative to other county types. The patterns relative to out-of-state metropolitan areas and in-state central metro counties are shown in Figure 5, with comparable figures from 1995-2000, the last interval with decennial census migration flow figures, shown in Figure 6. Relative to the out-of-state metros, the large number of positive values stands out, including for many rural counties. While the Rapid City MSA and most of the Sioux Falls MSA had positive values, Minnehaha did not. The lowest negative values were for more rural counties, but almost all of the highest values were also more rural. The recent map is quite different from the corresponding map for 1995-2000, which was overwhelmingly negative except for the southeastern part of the state.

Relative to the central in-state metro counties the pattern is more balanced between positive and negative flows for the more rural counties, while all of the central micropolitan counties except for Lawrence had negative exchanges. Many of the rural county values were in the most extreme category, indicating more efficient exchanges. This pattern was also quite different from the 1995-2000 pattern, in which a substantial majority of counties had negative efficiencies relative to the central MSA counties. In addition to the large number of counties changing from negative to positive, many of the counties that previously had a positive balance with the central MSAs turned negative in the later time period.

6. Migration Exchanges in the Urban Hierarchy

In addition to looking at individual counties, we gathered together the groupings of counties to examine the broad exchange between levels of the urban hierarchy. This information is displayed in Table 8. There is significant movement in both directions for most categories, although imbalance is clear. The net migration totals indicate that the Central MSA counties have large negative net migrations with out-of-state metros and other in-state metro counties, while having substantial positive net migration with most of the other urbanization categories and the college counties. The Other MSA counties had large positive net migration from both in- and out-of-state metros, driven largely by Meade County, which experienced an expansion in military personnel at Ellsworth AFB. Central Micropolitan counties as a whole had positive net migration relative to other states and negative net migration relative to central MSA counties in South Dakota. Several of the less-urban groups had positive net migration with other states.

Most of the demographic efficiencies were under 20, capturing the two-way nature of the migration exchanges. The most efficient, or lopsided if one prefers, exchange was from semi-rural non-adjacent counties with college counties. In addition, the net flows from other MSA counties to semi-rural non-adjacent and rural MSA-adjacent counties accounted for between thirty and fifty percent of the total of the gross flows.

The mix of positive and negative flows as one moves up the urban hierarchy contrasts with the findings from the 1995-2000 data. In the earlier time period Sorenson (2008) found an entirely positive set of flows above the diagonal, suggestive of a step-migration pattern that does not appear as significant in the more recent time period.

7. Conclusion

The examination of migration illustrated some significant changes in migration patterns in South Dakota over time, with greater success of less urban counties and a diminished sense of step migration. Combining IRS and ACS data provided a data set that proved useful in performing the analysis, but is should be kept in mind that the county-to-county flows used in the latter part of the paper were based on estimates subject to a degree of error. Some of the findings may be attributable to the assignment of migration flows through the imputation process. However, given the aggregate findings based only on total county inmigration and outmigration as actually reported, it seems safe to conclude that we have seen a change in migration patterns.

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Table 1. County Migration Gross Flows, 2001-2006

	In-state Out-migration	In-state In-migration	From Other States	To Other States	Net In State	Net Out-of-State	Total Net Migration	Net Migration Percentage	Demographic Efficiency With SD	Demographic Efficiency Out-of-State
State	23208	23208	20451	20153	0	298	298	0.0	0.0	0.7
Aurora	111	97	29	27	-14	2	-13	-0.4	-6.9	3.2
Beadle	502	347	272	324	-155	-53	-208	-1.4	-18.3	-8.9
Bennett	87	91	48	68	4	-20	-16	-0.6	2.4	-17.2
Bon Homme	185	152	99	85	-33	14	-19	-0.4	-9.8	7.5
Brookings	828	729	675	776	-98	-101	-200	-0.9	-6.3	-7.0
Brown	733	714	644	777	-19	-133	-152	-0.5	-1.3	-9.4
Brule	191	168	75	69	-23	6	-17	-0.4	-6.4	4.0
Buffalo	62	73	19	27	11	-8	2	0.2	7.9	-18.0
Butte	340	354	304	299	14	5	19	0.2	2.0	0.8
Campbell	37	14	25	38	-23	-14	-37	-2.0	-45.5	-22.1
Charles Mix	223	194	120	137	-29	-17	-46	-0.6	-7.1	-6.6
Clark	124	76	47	51	-48	-4	-52	-1.6	-24.0	-4.3
Clay	526	432	427	524	-94	-97	-191	-2.0	-9.8	-10.2
Codington	751	754	536	565	3	-29	-26	-0.1	0.2	-2.6
Corson	117	94	101	96	-23	5	-18	-0.6	-10.9	2.3
Custer	259	294	342	263	35	78	113	2.0	6.3	13.0
Davison	679	706	376	403	27	-27	-1	0.0	1.9	-3.5
Day	185	153	99	90	-33	9	-23	-0.5	-9.6	4.9
Deuel	149	135	89	88	-14	2	-12	-0.3	-5.0	1.0
Dewey	212	186	81	108	-26	-26	-52	-1.0	-6.6	-13.9
Douglas	93	60	34	32	-33	2	-31	-1.0	-21.5	2.9
Edmunds	133	105	46	63	-28	-16	-44	-1.2	-11.7	-15.0
Fall River	189	176	294	234	-13	60	47	0.8	-3.6	11.4
Faulk	76	51	26	22	-25	4	-21	-1.0	-19.6	9.2
Grant	173	131	151	161	-42	-11	-52	-0.7	-13.7	-3.4
Gregory	107	79	58	65	-28	-6	-34	-0.8	-14.9	-5.2
Haakon	82	43	31	38	-38	-7	-46	-2.2	-30.7	-10.7
Hamlin	195	184	85	88	-11	-4	-15	-0.3	-3.0	-2.1
Hand	103	71	41	43	-32	-2	-34	-1.0	-18.3	-2.9
Hanson	110	99	167	53	-10	114	104	3.2	-5.0	51.8
Harding	28	22	33	37	-6	-3	-10	-0.8	-12.1	-4.8
Hughes	638	666	327	349	28	-22	7	0.0	2.2	-3.2
Hutchinson	232	171	83	81	-61	2	-59	-0.9	-15.2	1.2
Hyde	64	53	22	19	-11	3	-8	-0.6	-9.5	7.3
Jackson	85	68	40	35	-17	5	-12	-0.6	-11.2	7.0
Jerauld	86	71	26	23	-15	3	-12	-0.7	-9.7	6.1
Jones	42	38	17	20	-4	-3	-7	-0.7	-4.6	-9.1
Kingsbury	163	137	71	70	-26	1	-24	-0.5	-8.5	1.0
Lake	366	342	186	181	-24	5	-20	-0.2	-3.4	1.3
Lawrence	724	733	883	792	9	91	100	0.6	0.6	5.4
Lincoln	1576	2777	994	705	1201	289	1490	5.8	27.6	17.0
Lyman	146	107	52	49	-39	3	-36	-1.1	-15.3	2.8
McCook	230	207	72	71	-23	1	-22	-0.4	-5.2	0.8
McPherson	60	39	40	38	-21	3	-18	-0.9	-20.7	3.3
Marshall	96	101	76	81	6	-5	1	0.0	2.8	-3.2
Meade	1527	1481	1451	1527	-47	-76	-122	-0.5	-1.5	-2.5
Mellette	74	65	30	32	-9	-2	-11	-0.7	-6.3	-3.6
Miner	101	61	35	21	-40	13	-27	-1.4	-24.9	23.7
Minnehaha	4045	3949	5113	4570	-96	544	448	0.3	-1.2	5.6
Moody	221	210	105	116	-12	-11	-23	-0.4	-2.7	-5.2
Pennington	2335	2665	3082	3370	330	-288	42	0.1	6.6	-4.5
Perkins	72	50	73	85	-22	-12	-34	-1.1	-17.8	-7.8
Potter	81	57	35	34	-24	1	-23	-1.0	-17.3	1.4
Roberts	222	198	207	206	-24	2	-22	-0.3	-5.7	0.4
Sanborn	91	75	34	26	-17	8	-9	-0.4	-10.1	13.3
Shannon	230	212	208	203	-18	5	-13	-0.2	-4.0	1.2
Spink	196	143	81	77	-54	4	-50	-0.9	-15.8	2.4
Stanley	218	228	42	54	9	-12	-3	-0.1	2.1	-12.4
Sully	54	44	24	19	-10	5	-5	-0.4	-10.3	11.1
Todd	177	151	182	172	-27	10	-17	-0.3	-8.1	2.7
Tripp	164	128	80	85	-36	-5	-41	-0.8	-12.4	-3.2
Turner	340	318	117	112	-22	5	-17	-0.2	-3.3	2.3
Union	223	239	842	744	15	98	113	1.0	3.3	6.2
Walworth	178	160	119	138	-18	-19	-36	-0.7	-5.2	-7.2
Yankton	474	433	478	506	-41	-29	-70	-0.4	-4.5	-2.9
Ziebach	79	67	20	24	-12	-4	-16	-1.7	-8.2	-9.7

Table 2. County Migration Gross Flows, 2009-2013

	In-state Out-migration	In-state In-migration	From Other States	To Other States	Net In State	Net Out-of-State	Total Net Migration	Net Migration Percentag	Demographic Efficiency With SD	Demographic Efficiency Out-of-State
State	24921	24921	24,544	22068	0	2476	2476	0.4	0.0	5.3
Aurora	91	83	40	28	-8	12	4	0.2	-4.5	17.6
Beadle	452	336	539	430	-117	109	-8	-0.1	-14.8	11.2
Bennett	88	69	60	53	-20	7	-13	-0.5	-12.6	6.2
Bon Homme	174	172	104	85	-3	19	16	0.3	-0.7	9.9
Brookings	872	762	824	863	-111	-39	-149	-0.7	-6.8	-2.3
Brown	740	790	981	874	49	108	157	0.5	3.2	5.8
Brule	188	183	115	103	-5	11	6	0.1	-1.3	5.2
Buffalo										
Butte	346	392	307	286	46	21	67	0.8	6.2	3.6
Campbell	29	28	52	39	-1	14	13	1.0	-2.2	15.2
Charles Mix	222	206	125	103	-16	23	7	0.1	-3.7	10.0
Clark	116	101	64	50	-15	14	-1	0.0	-6.8	11.8
Clay	492	404	472	506	-88	-35	-122	-1.4	-9.8	-3.6
Codington	761	730	551	546	-31	5	-26	-0.1	-2.1	0.5
Corson	76	75	107	94	-2	13	11	0.4	-1.2	6.2
Custer	265	287	362	256	22	107	129	2.1	3.9	17.3
Davison	644	630	403	427	-14	-25	-38	-0.2	-1.1	-3.0
Day	177	167	113	99	-11	14	3	0.1	-3.1	6.6
Deuel	140	117	98	87	-24	11	-12	-0.3	-9.1	6.1
Dewey	154	174	114	83	20	31	50	1.0	6.0	15.5
Douglas	77	66	47	27	-11	20	9	0.3	-7.9	26.8
Edmunds	145	141	68	53	-5	14	10	0.3	-1.6	11.8
Fall River	190	170	319	268	-20	52	32	0.6	-5.4	8.8
Faulk	59	57	26	27	-3	-1	-4	-0.2	-2.2	-2.3
Grant	166	143	155	159	-24	-4	-28	-0.4	-7.6	-1.4
Gregory	97	83	68	65	-14	3	-12	-0.3	-7.8	1.9
Haakon										
Hamlin	219	181	113	90	-38	23	-15	-0.3	-9.4	11.5
Hand	92	89	44	39	-3	5	2	0.1	-1.4	5.5
Hanson	91	103	149	185	11	-36	-24	-0.6	5.8	-10.6
Harding	20	33	38	61	12	-23	-11	-1.0	23.0	-23.5
Hughes	668	664	466	464	-3	1	-2	0.0	-0.2	0.1
Hutchinson	210	192	123	82	-17	41	24	0.4	-4.3	20.1
Hyde	63	48	15	17	-14	-2	-16	-1.4	-12.9	-5.2
Jackson	84	101	39	33	17	7	24	1.2	9.2	9.0
Jerauld	89	80	49	28	-8	21	13	0.8	-5.0	27.0
Jones	35	40	19	23	5	-4	1	0.2	6.7	-8.7
Kingsbury	205	169	84	70	-36	14	-22	-0.5	-9.6	9.3
Lake	349	334	524	316	-15	208	194	2.0	-2.1	24.7
Lawrence	759	783	939	825	24	115	138	0.7	1.5	6.5
Lincoln	2430	3322	1,378	1094	893	284	1177	3.0	15.5	11.5
Lyman	130	118	65	45	-11	20	9	0.3	-4.5	17.9
McCook	240	215	90	78	-25	11	-14	-0.3	-5.4	6.7
McPherson	53	54	50	40	1	9	10	0.5	0.7	10.3
Marshall	111	113	123	95	2	29	31	0.9	0.9	13.1
Meade	1686	1742	1,728	1360	57	368	425	1.8	1.7	11.9
Mellette	81	63	20	19	-18	1	-17	-1.2	-12.7	2.5
Miner	77	68	28	32	-8	-4	-13	-0.6	-5.7	-7.1
Minnehaha	4633	4269	5,613	5221	-365	393	28	0.0	-4.1	3.6
Moody	228	200	123	118	-28	6	-22	-0.4	-6.5	2.4
Pennington	2723	2781	4,111	4083	58	28	86	0.1	1.1	0.3
Perkins	54	52	97	66	-3	31	29	1.2	-2.4	19.1
Potter	57	65	51	32	8	18	26	1.3	6.4	22.1
Roberts	208	207	232	206	-2	26	24	0.3	-0.4	5.9
Sanborn	94	95	31	21	1	9	10	0.5	0.5	17.9
Shannon	269	260	222	182	-9	40	31	0.3	-1.7	9.8
Spink	172	168	106	84	-4	23	19	0.4	-1.1	12.0
Stanley	211	208	57	48	-3	10	7	0.3	-0.7	9.0
Sully	66	58	43	29	-8	14	6	0.5	-6.5	19.9
Todd	184	165	130	142	-19	-12	-31	-0.5	-5.4	-4.4
Tripp	138	120	94	78	-18	16	-2	0.0	-7.0	9.3
Turner	322	325	124	119	4	5	9	0.1	0.6	2.0
Union	276	267	954	759	-9	195	186	1.4	-1.7	11.4
Walworth	172	157	157	119	-14	38	24	0.5	-4.3	13.9
Yankton	517	475	583	533	-42	50	8	0.0	-4.2	4.5
Ziebach	54	65	28	21	11	7	18	1.8	9.4	14.9

Table 3. Sample of IRS County Migration Data

SOUTH DAKOTA INFLOW

Individual Income Tax Returns: County-to-County Migration Inflow for Selected Income Items, Calendar Years 2010-2011

[Money amounts are in thousands of dollars]

Destination into South Dakota		Origin from				Number of returns	Number of exemptions	Aggregate adjusted gross income (AGI)
State Code	County Code	State Code	County Code	State	County Name	(1)	(2)	(3)
46	000	96	000	SD	Total Mig - US & For	25,521	45,858	1,007,667
46	000	97	000	SD	Total Mig - US	25,307	45,379	998,705
46	000	97	001	SD	Total Mig - US Same St	13,267	23,319	460,740
46	000	97	003	SD	Total Mig - US Diff St	12,040	22,060	537,964
46	000	98	000	SD	Total Mig - Foreign	214	479	8,962
46	003	96	000	SD	Aurora County Tot Mig-US & For	63	111	1,864
46	003	97	000	SD	Aurora County Tot Mig-US	63	111	1,864
46	003	97	001	SD	Aurora County Tot Mig-Same St	42	73	1,229
46	003	97	003	SD	Aurora County Tot Mig-Diff St	21	38	635
46	003	98	000	SD	Aurora County Tot Mig-Foreign	d	d	d
46	003	46	003	SD	Aurora County Non-Migrants	1,002	2,295	50,944
46	003	46	035	SD	Davison County	21	35	559
46	003	58	000	SS	Other Flows - Same State	21	38	670
46	003	59	000	DS	Other Flows - Diff State	21	38	635
46	005	96	000	SD	Beadle County Tot Mig-US & For	422	871	13,440
46	005	97	000	SD	Beadle County Tot Mig-US	422	871	13,440
46	005	97	001	SD	Beadle County Tot Mig-Same St	182	334	5,530
46	005	97	003	SD	Beadle County Tot Mig-Diff St	240	537	7,910
46	005	98	000	SD	Beadle County Tot Mig-Foreign	d	d	d
46	005	46	005	SD	Beadle County Non-Migrants	6,363	13,643	324,531
46	005	46	099	SD	Minnehaha County	34	57	1,058
46	005	46	115	SD	Spink County	12	20	619
46	005	46	011	SD	Brookings County	11	13	270
46	005	46	073	SD	Jerauld County	11	29	339
46	005	46	111	SD	Sanborn County	10	21	461
46	005	58	000	SS	Other Flows - Same State	104	194	2,785
46	005	59	000	DS	Other Flows - Diff State	240	537	7,910
46	005	59	001	DS	Other Flows - Northeast	10	18	287
46	005	59	003	DS	Other Flows - Midwest	107	241	3,872
46	005	59	005	DS	Other Flows - South	69	159	1,877
46	005	59	007	DS	Other Flows - West	54	119	1,874

Table 4. Migration Patterns Using Only Known Flows

4a. Outmigration

2001-2006		Receiving County RUCC Code							
Numbers		1	2	3	5	6	7	8	9
	3	1453	730	7424	262	1002	1061	401	208
Sending	5	34		264		23	161	81	279
SD County	6	37	18	1041	72	295	109	23	23
RUCC Code	7	112	21	1707	254	118	540	147	738
	8			425		26	156		
	9			397	186		897		154

2009-2014		Receiving County RUCC Code							
Numbers		1	2	3	5	6	7	8	9
	3	2210	900	9194	390	1116	1407	446	357
Sending	5	56		231		21	234		262
SD County	6	24	23	1020	76	345	181		27
RUCC Code	7	144	26	1725	304	140	566	183	947
	8			342		19	194		22
	9			374	181	27	963		248

2001-2006		Receiving County RUCC Code							
Percentages		1	2	3	5	6	7	8	9
	3	11.6%	5.8%	59.2%	2.1%	8.0%	8.5%	3.2%	1.7%
Sending	5	4.0%	0.0%	31.4%	0.0%	2.7%	19.1%	9.6%	33.1%
SD County	6	2.3%	1.1%	64.3%	4.4%	18.2%	6.7%	1.4%	1.4%
RUCC Code	7	3.1%	0.6%	46.9%	7.0%	3.2%	14.8%	4.0%	20.3%
	8	0.0%	0.0%	70.0%	0.0%	4.3%	25.7%	0.0%	0.0%
	9	0.0%	0.0%	24.3%	11.4%	0.0%	54.9%	0.0%	9.4%

2009-2014		Receiving County RUCC Code							
Percentages		1	2	3	5	6	7	8	9
	3	13.8%	5.6%	57.4%	2.4%	7.0%	8.8%	2.8%	2.2%
Sending	5	7.0%	0.0%	28.7%	0.0%	2.6%	29.1%	0.0%	32.6%
SD County	6	1.4%	1.4%	60.1%	4.5%	20.3%	10.7%	0.0%	1.6%
RUCC Code	7	3.6%	0.6%	42.8%	7.5%	3.5%	14.0%	4.5%	23.5%
	8	0.0%	0.0%	59.3%	0.0%	3.3%	33.6%	0.0%	3.8%
	9	0.0%	0.0%	20.9%	10.1%	1.5%	53.7%	0.0%	13.8%

4b. Inmigration

2001-2006		Sending County RUCC Code								
Numbers		1	2	3	4	5	6	7	8	9
	3	1321	551	7823	23	352	1398	2037	562	432
Receiving	5	16		117				254		209
SD County	6	20		839		64	295	118	26	26
RUCC Code	7	45		954		184	109	561	156	967
	8			302			23	150		
	9			208		81	21	681	32	190

2009-2014		Sending County RUCC Code								
Numbers		1	2	3	4	5	6	7	8	9
	3	2304	766	9392	19	408	1377	2000	444	369
Receiving	5	46		253				279		212
SD County	6	74		903		96	345	164	19	30
RUCC Code	7	96		1308		265	163	591	194	1088
	8			345				183		
	9			335		241		801	22	220

2001-2006		Sending County RUCC Code								
Percentages		1	2	3	4	5	6	7	8	9
	3	9.1%	3.8%	54.0%	0.2%	2.4%	9.6%	14.0%	3.9%	3.0%
Receiving	5	2.7%	0.0%	19.6%	0.0%	0.0%	0.0%	42.6%	0.0%	35.1%
SD County	6	1.4%	0.0%	60.4%	0.0%	4.6%	21.3%	8.5%	1.9%	1.9%
RUCC Code	7	1.5%	0.0%	32.1%	0.0%	6.2%	3.7%	18.9%	5.2%	32.5%
	8	0.0%	0.0%	63.6%	0.0%	0.0%	4.8%	31.6%	0.0%	0.0%
	9	0.0%	0.0%	17.1%	0.0%	6.7%	1.7%	56.1%	2.6%	15.7%

2009-2014		Sending County RUCC Code								
Percentages		1	2	3	4	5	6	7	8	9
	3	13.5%	4.5%	55.0%	0.1%	2.4%	8.1%	11.7%	2.6%	2.2%
Receiving	5	5.8%	0.0%	32.0%	0.0%	0.0%	0.0%	35.3%	0.0%	26.8%
SD County	6	4.5%	0.0%	55.4%	0.0%	5.9%	21.2%	10.1%	1.2%	1.8%
RUCC Code	7	2.6%	0.0%	35.3%	0.0%	7.2%	4.4%	16.0%	5.2%	29.4%
	8	0.0%	0.0%	65.3%	0.0%	0.0%	0.0%	34.7%	0.0%	0.0%
	9	0.0%	0.0%	20.7%	0.0%	14.9%	0.0%	49.5%	1.4%	13.6%

4c. Net Migration

2001-2006		Sending County RUCC Code								
Numbers		1	2	3	4	5	6	7	8	9
	3	-132	-179	399	23	90	396	976	161	224
Receiving	5	-18	0	-147	0	0	-23	93	-81	-70
SD County	6	-17	-18	-202	0	-8	0	9	3	3
RUCC Code	7	-67	-21	-753	0	-70	-9	21	9	229
	8	0	0	-123	0	0	-3	-6	0	0
	9	0	0	-189	0	-105	21	-216	32	36
2009-2014		Sending County RUCC Code								
Numbers		1	2	3	4	5	6	7	8	9
	3	94	-134	198	19	18	261	593	-2	12
Receiving	5	-10	0	22	0	0	-21	45	0	-50
SD County	6	50	-23	-117	0	20	0	-17	19	3
RUCC Code	7	-48	-26	-417	0	-39	23	25	11	141
	8	0	0	3	0	0	-19	-11	0	-22
	9	0	0	-39	0	60	-27	-162	22	-28

Table 5. Sample of ACS Data

State Code of Geography A	FIPS County Code of Geography A	Island Area/Foreign Region Code of Geography	FIPS County Code of Geography B	County Name of Geography A	State/U.S. Island Area/Foreign Region of Geography B	County Name of Geography B	Flow from Geography B to Geography A		Counterflow from Geography A to Geography B[1]		Net Migration from Geography B to Geography A[1]		Gross Migration between Geography A and Geography B[1]	
							Estimate	MOE	Estimate	MOE	Estimate	MOE	Estimate	MOE
046	003	004	013	Aurora C	Arizona	Maricopa Coun	5	7	0	30	5	7	5	7
046	003	004	019	Aurora C	Arizona	Pima County	2	5	0	30	2	5	2	5
046	003	027	053	Aurora C	Minnesota	Hennepin Coun	2	5	0	20	2	5	2	5
046	003	027	067	Aurora C	Minnesota	Kandiyohi Cou	2	3	0	18	2	3	2	3
046	003	029	189	Aurora C	Missouri	St. Louis Coun	0	9	3	6	-3	6	3	6
046	003	031	055	Aurora C	Nebraska	Douglas Count	3	4	0	22	3	4	3	4
046	003	046	005	Aurora C	South Dakota	Beadle County	2	6	0	15	2	6	2	6
046	003	046	009	Aurora C	South Dakota	Bon Homme C	0	9	15	20	-15	20	15	20
046	003	046	011	Aurora C	South Dakota	Brookings Cou	5	8	16	23	-11	25	21	25
046	003	046	013	Aurora C	South Dakota	Brown County	11	12	117	163	-106	168	128	160
046	003	046	023	Aurora C	South Dakota	Charles Mix Co	0	9	29	33	-29	33	29	33
046	003	046	027	Aurora C	South Dakota	Clay County	0	9	24	34	-24	34	24	34
046	003	046	033	Aurora C	South Dakota	Custer County	3	6	25	30	-22	30	28	30
046	003	046	035	Aurora C	South Dakota	Davison Count	22	14	77	121	-55	124	99	119

Table 6. Comparison of Patterns: Imputed Flows v. Known-only

2009-2010 Outmigration Percentage Using Known and Imputed Flows

		Receiving County RUCC Code								
		1	2	3	4	5	6	7	8	9
	3	17.5%	10.1%	42.5%	3.6%	3.8%	6.0%	9.6%	2.8%	4.1%
Sending	5	18.8%	6.1%	21.8%	4.8%	1.9%	5.8%	21.3%	0.7%	18.8%
SD County	6	12.3%	7.1%	32.5%	5.7%	7.8%	12.0%	14.3%	1.0%	7.3%
RUCC Code	7	11.9%	12.1%	27.0%	1.4%	5.2%	6.8%	13.6%	3.6%	18.4%
	8	18.9%	15.7%	24.6%	0.1%	2.2%	7.1%	18.1%	2.6%	10.8%
	9	12.2%	5.1%	19.8%	1.1%	6.0%	7.9%	26.6%	2.7%	18.6%

2009-2014 Outmigration Percentage Using Known Flows Only

		Receiving County RUCC Code							
		1	2	3	5	6	7	8	9
	3	13.8%	5.6%	57.4%	2.4%	7.0%	8.8%	2.8%	2.2%
Sending	5	7.0%	0.0%	28.7%	0.0%	2.6%	29.1%	0.0%	32.6%
SD County	6	1.4%	1.4%	60.1%	4.5%	20.3%	10.7%	0.0%	1.6%
RUCC Code	7	3.6%	0.6%	42.8%	7.5%	3.5%	14.0%	4.5%	23.5%
	8	0.0%	0.0%	59.3%	0.0%	3.3%	33.6%	0.0%	3.8%
	9	0.0%	0.0%	20.9%	10.1%	1.5%	53.7%	0.0%	13.8%

2009-2010 Inmigration Percentage Using Known and Imputed Flows

		Sending County RUCC Code								
		1	2	3	4	5	6	7	8	9
	3	15.7%	9.4%	42.9%	2.2%	3.4%	7.7%	11.4%	2.2%	5.1%
Receiving	5	12.8%	9.6%	20.8%	0.4%	8.8%	1.4%	21.2%	1.3%	23.8%
SD County	6	14.3%	10.3%	30.0%	1.1%	3.3%	11.3%	16.0%	2.1%	11.7%
RUCC Code	7	13.7%	9.5%	23.3%	2.9%	6.4%	6.8%	13.0%	4.1%	20.2%
	8	13.7%	11.4%	30.0%	0.0%	4.0%	5.7%	23.7%	3.0%	8.5%
	9	12.8%	5.4%	16.5%	2.5%	6.1%	5.8%	26.5%	3.3%	21.1%

2009-2014 Inmigration Percentage Using Known Flows Only

		Sending County RUCC Code								
		1	2	3	4	5	6	7	8	9
	3	13.5%	4.5%	55.0%	0.1%	2.4%	8.1%	11.7%	2.6%	2.2%
Receiving	5	5.8%	0.0%	32.0%	0.0%	0.0%	0.0%	35.3%	0.0%	26.8%
SD County	6	4.5%	0.0%	55.4%	0.0%	5.9%	21.2%	10.1%	1.2%	1.8%
RUCC Code	7	2.6%	0.0%	35.3%	0.0%	7.2%	4.4%	16.0%	5.2%	29.4%
	8	0.0%	0.0%	65.3%	0.0%	0.0%	0.0%	34.7%	0.0%	0.0%
	9	0.0%	0.0%	20.7%	0.0%	14.9%	0.0%	49.5%	1.4%	13.6%

Table 7a. County Outmigration Patterns, 2010-2011, Using Imputed Data

Classification	County	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	Lincoln	20.0%	10.8%	54.5%	5.4%	2.9%	1.0%	1.0%	0.6%	1.7%	1.9%
	Minnehaha	40.7%	13.7%	25.7%	3.3%	6.3%	1.2%	1.0%	2.0%	3.3%	2.8%
	Pennington	37.6%	16.4%	3.5%	26.7%	6.0%	0.8%	3.2%	2.3%	3.0%	0.7%
Other MSA	McCook	15.9%	8.5%	44.0%	1.7%	14.2%	0.0%	2.0%	8.5%	1.4%	3.7%
	Meade	31.8%	15.3%	38.0%	0.5%	6.2%	2.4%	0.9%	1.6%	2.2%	1.1%
	Turner	10.4%	10.4%	53.2%	0.8%	12.2%	1.5%	0.0%	6.1%	0.0%	5.6%
	Union	50.8%	24.1%	12.5%	0.1%	2.5%	0.4%	2.1%	0.0%	0.7%	6.9%
Central Micropolitan	Beadle	26.8%	16.5%	19.0%	4.2%	9.0%	0.5%	3.2%	0.2%	15.4%	5.1%
	Brown	32.6%	14.3%	13.7%	0.4%	10.5%	0.5%	7.8%	0.6%	15.6%	4.0%
	Codington	27.3%	14.8%	14.6%	0.2%	6.5%	1.8%	4.2%	0.5%	25.9%	4.2%
	Davison	33.4%	7.3%	22.0%	2.1%	8.9%	2.1%	1.2%	5.7%	14.2%	3.1%
	Hughes	31.5%	7.4%	16.3%	3.0%	9.6%	0.7%	0.0%	3.9%	23.9%	3.8%
	Lawrence	19.2%	33.1%	14.6%	9.0%	2.5%	15.0%	0.4%	1.5%	4.4%	0.4%
	Yankton	27.7%	19.7%	19.3%	5.7%	5.8%	0.1%	0.4%	2.8%	10.4%	8.0%
Semi-rural MSA-adjacent	Butte	14.0%	31.4%	12.2%	8.3%	29.4%	0.0%	0.4%	0.0%	3.2%	1.1%
	Lake	34.9%	12.7%	35.4%	0.0%	5.9%	0.0%	0.0%	2.5%	2.7%	5.9%
Semi-rural Not MSA-adjacent	Fall River	26.3%	32.2%	20.0%	3.7%	4.2%	0.0%	0.0%	10.3%	3.0%	0.2%
	Grant	18.8%	29.0%	8.3%	0.0%	18.0%	0.0%	9.9%	1.6%	10.2%	4.3%
	Shannon	19.5%	18.7%	34.0%	1.6%	3.6%	0.0%	0.5%	8.6%	12.7%	0.8%
	Spink	27.0%	1.5%	10.3%	0.0%	31.9%	0.0%	0.0%	0.0%	23.0%	6.4%
	Tripp	13.6%	13.1%	47.6%	1.0%	7.3%	0.0%	0.0%	1.0%	12.0%	4.2%
	Walworth	27.8%	12.8%	9.3%	0.9%	16.7%	0.0%	0.9%	0.0%	29.5%	2.2%
Rural MSA-adjacent	Custer	39.0%	11.0%	29.5%	0.9%	8.3%	0.0%	7.4%	2.3%	1.1%	0.5%
	Haakon	0.0%	35.9%	56.3%	0.0%	0.0%	0.0%	0.0%	7.8%	0.0%	0.0%
	Hanson	68.7%	4.0%	0.0%	0.0%	14.2%	2.9%	0.0%	5.5%	2.5%	2.2%
	Hutchinson	17.9%	5.1%	12.5%	5.5%	23.1%	2.2%	0.0%	0.0%	16.5%	17.2%
	Jackson	30.3%	2.0%	28.3%	0.0%	0.0%	0.0%	0.0%	0.0%	39.4%	0.0%
	Miner	0.0%	19.3%	13.8%	0.0%	22.9%	6.4%	0.0%	0.0%	30.3%	7.3%
	Moody	15.2%	23.1%	32.3%	5.0%	0.7%	1.7%	4.6%	0.7%	1.3%	15.5%
Rural Not MSA-adjacent	Aurora	22.7%	0.0%	31.1%	5.0%	31.1%	0.0%	0.0%	1.7%	6.7%	1.7%
	Bennett	3.4%	29.5%	30.7%	0.0%	2.8%	0.0%	3.4%	1.7%	28.4%	0.0%
	Bon Homm	16.8%	15.7%	17.2%	0.0%	25.5%	2.2%	0.0%	7.3%	11.3%	4.0%
	Brule	16.9%	14.3%	14.3%	0.0%	13.0%	2.2%	0.0%	0.4%	35.9%	3.0%
	Buffalo	17.7%	6.3%	13.9%	0.0%	16.5%	0.0%	0.0%	0.0%	45.6%	0.0%
	Campbell	0.0%	54.8%	0.0%	0.0%	32.9%	0.0%	0.0%	0.0%	12.3%	0.0%
	Charles Mi	18.5%	10.6%	27.2%	0.0%	20.8%	0.0%	1.9%	0.8%	17.0%	3.4%
	Clark	12.3%	14.0%	31.8%	0.0%	25.7%	4.5%	1.7%	3.4%	1.1%	5.6%
	Corson	30.1%	30.6%	9.1%	0.0%	0.0%	0.0%	19.4%	0.0%	8.1%	2.7%
	Day	21.5%	14.2%	2.7%	0.0%	32.2%	0.0%	7.3%	0.0%	20.7%	1.5%
	Deuel	21.2%	10.4%	9.0%	0.0%	29.3%	1.8%	0.5%	0.0%	10.4%	17.6%
	Dewey	13.8%	27.1%	14.7%	0.0%	21.6%	0.9%	14.7%	0.0%	6.4%	0.9%
	Douglas	17.9%	1.3%	11.5%	0.0%	20.5%	16.7%	0.0%	3.8%	28.2%	0.0%
	Edmunds	26.6%	8.3%	0.0%	0.0%	45.3%	6.8%	1.6%	5.7%	4.2%	1.6%
	Faulk	14.4%	10.0%	0.0%	0.0%	7.8%	0.0%	6.7%	14.4%	46.7%	0.0%
	Gregory	30.1%	11.8%	13.1%	7.8%	15.7%	0.0%	0.0%	0.0%	20.3%	1.3%
	Hamlin	24.8%	0.7%	15.3%	0.0%	26.3%	1.1%	0.0%	0.0%	21.2%	10.6%
	Hand	6.0%	24.8%	10.3%	0.0%	55.6%	0.9%	1.7%	0.0%	0.0%	0.9%
	Harding	58.1%	12.9%	19.4%	0.0%	9.7%	0.0%	0.0%	0.0%	0.0%	0.0%
	Hyde	0.0%	0.0%	67.8%	0.0%	0.0%	0.0%	0.0%	0.0%	28.8%	3.4%
	Jerauld	14.8%	11.5%	5.7%	0.0%	43.4%	0.0%	13.1%	0.0%	11.5%	0.0%
	Jones	0.0%	42.6%	2.1%	0.0%	31.9%	0.0%	0.0%	23.4%	0.0%	0.0%
	Kingsbury	10.5%	12.0%	16.7%	0.0%	22.0%	13.9%	0.0%	0.0%	5.7%	19.1%
	Lyman	21.9%	4.4%	5.0%	5.0%	14.4%	0.0%	0.0%	0.6%	48.1%	0.6%
	McPherson	22.5%	26.8%	0.0%	0.0%	17.7%	0.0%	0.5%	0.0%	29.7%	2.9%
	Marshall	55.4%	0.0%	0.0%	0.0%	25.9%	0.0%	18.8%	0.0%	0.0%	0.0%
	Mellette	0.0%	28.8%	0.0%	0.0%	0.0%	0.0%	71.2%	0.0%	0.0%	0.0%
	Perkins	6.9%	47.2%	0.0%	30.6%	9.7%	0.0%	0.0%	0.0%	4.2%	1.4%
	Potter	31.9%	5.6%	9.7%	15.3%	18.1%	0.0%	8.3%	0.0%	11.1%	0.0%
	Roberts	16.2%	31.3%	13.0%	0.0%	19.2%	0.3%	9.1%	0.0%	10.0%	0.9%
	Sanborn	0.0%	14.3%	0.0%	0.0%	49.3%	0.0%	0.0%	13.6%	22.9%	0.0%
	Stanley	13.4%	6.5%	0.0%	0.0%	60.3%	12.5%	0.0%	0.0%	6.9%	0.4%
	Sully	0.0%	36.6%	15.9%	0.0%	31.7%	0.0%	0.0%	0.0%	15.9%	0.0%
	Todd	25.7%	20.9%	16.0%	0.0%	1.5%	0.0%	14.2%	3.7%	17.9%	0.0%
	Ziebach	28.3%	5.0%	38.3%	13.3%	3.3%	0.0%	0.0%	0.0%	11.7%	0.0%
College County	Brookings	33.8%	16.0%	23.2%	2.5%	9.6%	2.3%	0.1%	3.3%	9.1%	0.2%
	Clay	32.3%	15.7%	21.9%	10.0%	15.4%	0.0%	0.4%	0.0%	2.2%	2.1%

Table 7b. County Inmigration Patterns, 2010-2011, Using Imputed Data

Classification	County	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	Lincoln	22.5%	7.9%	54.3%	3.6%	4.3%	0.5%	1.4%	0.7%	1.4%	3.4%
	Minnehaha	32.7%	20.4%	21.3%	4.3%	8.3%	1.9%	0.7%	1.5%	4.6%	4.2%
	Pennington	44.2%	15.4%	4.2%	15.1%	6.7%	1.6%	4.4%	3.0%	4.0%	1.5%
Other MSA	McCook	25.6%	1.6%	41.7%	6.7%	8.7%	0.4%	0.8%	8.7%	5.1%	0.8%
	Meade	32.5%	10.8%	48.9%	0.2%	4.5%	1.2%	0.5%	0.1%	1.3%	0.1%
	Turner	18.4%	5.8%	54.0%	0.0%	7.9%	0.0%	0.0%	1.6%	0.2%	12.1%
	Union	65.5%	15.7%	6.5%	0.0%	4.2%	0.0%	0.5%	0.0%	0.4%	7.2%
Central Micropolitan	Beadle	35.5%	25.8%	9.1%	0.6%	12.5%	0.0%	3.7%	2.3%	8.2%	2.3%
	Brown	34.7%	21.3%	7.4%	1.0%	10.1%	0.5%	4.7%	1.2%	17.0%	2.1%
	Codington	29.3%	10.8%	14.0%	1.0%	6.8%	0.9%	5.6%	1.1%	26.0%	4.4%
	Davison	27.5%	8.6%	11.9%	3.2%	10.3%	6.7%	3.1%	8.9%	16.3%	3.4%
	Hughes	20.8%	16.4%	18.9%	5.1%	6.5%	0.3%	0.6%	0.6%	27.5%	3.3%
	Lawrence	34.3%	18.8%	16.4%	8.8%	3.8%	8.6%	0.7%	1.2%	4.8%	2.6%
	Yankton	31.6%	22.1%	17.7%	3.7%	1.6%	0.0%	0.2%	0.7%	12.9%	9.6%
Semi-rural MSA-adjacent	Butte	12.6%	31.6%	6.5%	9.1%	32.5%	0.0%	0.0%	0.0%	7.3%	0.5%
	Lake	38.1%	22.3%	17.3%	1.2%	6.3%	0.0%	0.0%	3.0%	7.7%	4.1%
Semi-rural Not MSA-adjacent	Fall River	24.3%	42.8%	11.9%	0.0%	5.6%	0.0%	3.0%	5.3%	7.1%	0.0%
	Grant	15.3%	39.8%	20.1%	0.0%	8.0%	0.0%	0.0%	4.7%	11.7%	0.4%
	Shannon	23.8%	19.2%	37.9%	1.4%	0.8%	0.0%	4.4%	2.4%	10.1%	0.0%
	Spink	28.8%	2.5%	7.7%	14.4%	27.4%	0.7%	1.8%	0.4%	16.5%	0.0%
	Tripp	44.4%	17.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	38.4%	0.0%
	Walworth	25.0%	19.5%	10.1%	0.0%	27.9%	0.0%	0.6%	0.0%	15.6%	1.3%
Rural MSA-adjacent	Custer	23.6%	30.8%	25.4%	7.2%	4.3%	0.0%	5.6%	0.0%	3.2%	0.0%
	Haakon	10.4%	6.3%	25.0%	0.0%	6.3%	0.0%	6.3%	20.8%	25.0%	0.0%
	Hanson	53.3%	7.4%	8.3%	5.0%	13.6%	0.0%	3.7%	0.0%	2.5%	6.2%
	Hutchinson	17.9%	11.7%	18.7%	9.3%	24.5%	0.0%	1.6%	5.8%	10.1%	0.4%
	Jackson	22.5%	9.4%	29.7%	0.0%	6.5%	0.0%	22.5%	5.1%	4.3%	0.0%
	Miner	2.4%	19.3%	16.9%	18.1%	2.4%	18.1%	0.0%	0.0%	22.9%	0.0%
	Moody	29.7%	7.7%	30.4%	1.0%	9.1%	0.0%	2.8%	0.0%	5.6%	13.6%
Rural Not MSA-adjacent	Aurora	29.7%	4.5%	2.7%	0.0%	44.1%	0.0%	0.9%	7.2%	9.9%	0.9%
	Bennett	31.1%	20.9%	0.7%	0.0%	10.8%	0.0%	19.6%	0.7%	8.8%	7.4%
	Bon Homm	29.2%	8.2%	17.1%	0.4%	27.8%	0.4%	1.4%	7.1%	7.8%	0.7%
	Brule	39.1%	4.0%	14.6%	0.0%	9.5%	0.0%	7.9%	0.0%	24.9%	0.0%
	Buffalo	12.8%	19.8%	0.0%	0.0%	22.1%	0.0%	0.0%	0.0%	45.3%	0.0%
	Campbell	63.4%	0.0%	0.0%	0.0%	7.3%	0.0%	14.6%	0.0%	14.6%	0.0%
	Charles Mi	30.2%	10.4%	24.5%	0.0%	13.1%	0.0%	0.3%	0.3%	18.1%	3.0%
	Clark	23.1%	16.2%	15.4%	3.1%	23.8%	0.0%	0.8%	0.0%	5.4%	12.3%
	Corson	39.4%	27.3%	0.6%	0.0%	4.8%	1.2%	19.4%	0.0%	5.5%	1.8%
	Day	6.3%	26.3%	7.0%	0.0%	36.8%	0.0%	3.9%	0.4%	19.3%	0.0%
	Deuel	23.0%	21.6%	6.1%	0.0%	16.9%	0.0%	3.8%	0.0%	17.4%	11.3%
	Dewey	29.6%	13.8%	0.4%	1.7%	7.5%	0.0%	7.9%	0.0%	35.4%	3.8%
	Douglas	37.0%	11.0%	0.0%	0.0%	15.0%	0.0%	0.0%	10.0%	27.0%	0.0%
	Edmunds	13.0%	19.0%	4.9%	0.0%	53.8%	1.6%	4.3%	0.0%	3.3%	0.0%
	Faulk	26.9%	1.3%	19.2%	0.0%	15.4%	0.0%	20.5%	9.0%	0.0%	7.7%
	Gregory	32.7%	10.9%	7.3%	10.9%	15.5%	0.0%	12.7%	6.4%	2.7%	0.9%
	Hamlin	30.4%	10.6%	5.5%	0.0%	28.6%	0.0%	1.8%	0.0%	15.4%	7.7%
	Hand	15.8%	12.0%	1.5%	22.6%	25.6%	0.0%	0.0%	0.0%	17.3%	5.3%
	Harding	23.8%	34.9%	14.3%	0.0%	0.0%	22.2%	1.6%	0.0%	3.2%	0.0%
	Hyde	0.0%	23.1%	5.8%	0.0%	9.6%	0.0%	7.7%	0.0%	48.1%	5.8%
	Jerauld	22.1%	15.4%	4.8%	0.0%	38.5%	0.0%	17.3%	0.0%	0.0%	1.9%
	Jones	0.0%	23.3%	76.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Kingsbury	3.5%	29.5%	11.0%	0.0%	25.2%	2.8%	0.0%	3.5%	7.1%	17.3%
	Lyman	7.7%	31.7%	9.8%	0.0%	31.7%	0.0%	0.0%	0.0%	13.7%	5.5%
	McPherson	52.1%	2.8%	8.3%	0.0%	25.7%	0.0%	1.4%	0.0%	9.7%	0.0%
	Marshall	33.3%	12.0%	14.5%	0.0%	29.1%	0.0%	1.7%	0.0%	9.4%	0.0%
	Mellette	7.8%	27.3%	37.7%	0.0%	0.0%	0.0%	1.3%	0.0%	26.0%	0.0%
	Perkins	48.6%	22.1%	14.3%	0.0%	3.6%	0.0%	0.0%	2.1%	9.3%	0.0%
	Potter	13.0%	31.0%	0.0%	0.0%	20.0%	0.0%	0.0%	0.0%	36.0%	0.0%
	Roberts	16.5%	40.5%	5.6%	0.0%	9.6%	1.8%	0.8%	1.0%	24.1%	0.3%
	Sanborn	18.6%	14.5%	4.8%	3.4%	29.7%	0.0%	0.0%	16.6%	11.7%	0.7%
	Stanley	0.0%	18.6%	1.9%	0.0%	67.9%	0.0%	7.9%	0.0%	3.7%	0.0%
	Sully	40.5%	0.0%	1.4%	8.1%	1.4%	0.0%	0.0%	0.0%	48.6%	0.0%
	Todd	24.5%	17.7%	27.4%	0.0%	2.5%	0.0%	0.4%	13.7%	13.7%	0.0%
	Ziebach	29.6%	1.2%	8.6%	4.9%	18.5%	0.0%	16.0%	0.0%	21.0%	0.0%
College County	Brookings	29.9%	16.6%	15.3%	4.1%	11.0%	2.5%	2.6%	6.0%	10.5%	1.4%
	Clay	40.0%	12.4%	16.1%	7.7%	15.8%	0.6%	1.0%	2.8%	3.3%	0.3%

Table 8. Migration Within the Urban Hierarchy, 2010-2011

Outmigration	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	6888	2697	4291	2299	1074	192	343	359	557	365
Other MSA	1374	683	1422	23	274	70	48	93	66	129
Central Micropolitan	2200	1312	1299	274	580	268	212	159	1194	302
Semi-rural MSA-adjacent	285	252	278	47	201	0	2	15	34	41
Semi-rural Not MSA-adjacent	402	375	381	26	216	0	41	85	237	46
Rural MSA-adjacent	487	190	342	34	166	26	47	32	133	110
Rural Not MSA-adjacent	993	886	697	67	1279	114	263	102	874	178
College County	865	413	592	137	304	38	5	55	171	23

Inmigration	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	6402	3019	4291	1422	1299	278	381	342	697	592
Other MSA	2125	622	2299	23	274	47	26	34	67	137
Central Micropolitan	2459	1420	1074	274	580	201	216	166	1279	304
Semi-rural MSA-adjacent	411	400	192	70	268	0	0	26	114	38
Semi-rural Not MSA-adjacent	482	466	343	48	212	2	41	47	263	5
Rural MSA-adjacent	425	268	359	93	159	15	85	32	102	55
Rural Not MSA-adjacent	1318	1006	557	66	1194	34	237	133	877	171
College County	793	348	365	129	302	41	46	110	178	23

Net Migration	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	-486	322	0	-877	225	86	38	-17	140	227
Other MSA	751	-61	877	0	0	-23	-22	-59	1	8
Central Micropolitan	259	108	-225	0	0	-67	4	7	85	2
Semi-rural MSA-adjacent	126	148	-86	23	67	0	-2	11	80	-3
Semi-rural Not MSA-adjacent	80	91	-38	22	-4	2	0	-38	26	-41
Rural MSA-adjacent	-62	78	17	59	-7	-11	38	0	-31	-55
Rural Not MSA-adjacent	325	120	-140	-1	-85	-80	-26	31	3	-7
College County	-72	-65	-227	-8	-2	3	41	55	7	0

Demographic Efficiency	Out-of-State Metro	Out-of-State Non-Metro	Central MSA	Other MSA	Central Micropolitan	Semi-rural MSA-adjacent	Semi-rural Not MSA-adjacent	Rural MSA-adjacent	Rural Not MSA-adjacent	College County
Central MSA	-3.66	5.63	0.00	-23.57	9.48	18.30	5.25	-2.43	11.16	23.72
Other MSA	21.46	-4.67	23.57	0.00	0.00	-19.66	-29.73	-46.46	0.75	3.01
Central Micropolitan	5.56	3.95	-9.48	0.00	0.00	-14.29	0.93	2.15	3.44	0.33
Semi-rural MSA-adjacent	18.10	22.70	-18.30	19.66	14.29	0.00	-100.00	26.83	54.05	-3.80
Semi-rural Not MSA-adjacent	9.05	10.82	-5.25	29.73	-0.93	100.00	0.00	-28.79	5.20	-80.39
Rural MSA-adjacent	-6.80	17.03	2.43	46.46	-2.15	-26.83	28.79	0.00	-13.19	-33.33
Rural Not MSA-adjacent	14.06	6.34	-11.16	-0.75	-3.44	-54.05	-5.20	13.19	0.17	-2.01
College County	-4.34	-8.54	-23.72	-3.01	-0.33	3.80	80.39	33.33	2.01	0.00

Figure 1. Total Domestic Migration Gross Flows, 2001-2014

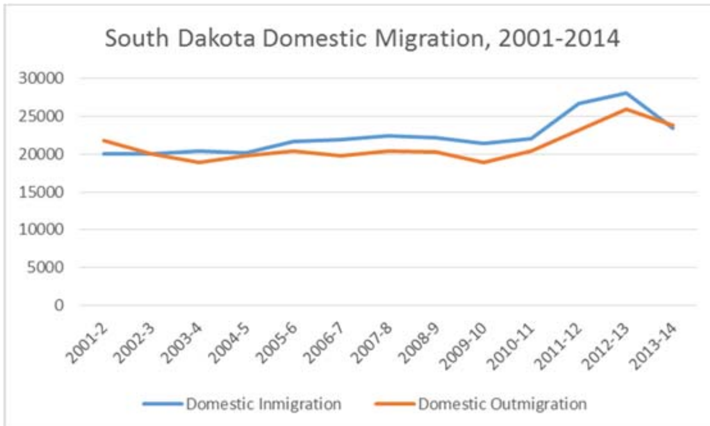


Figure 2a. Inmigration from Top Origin States, 2001-2014

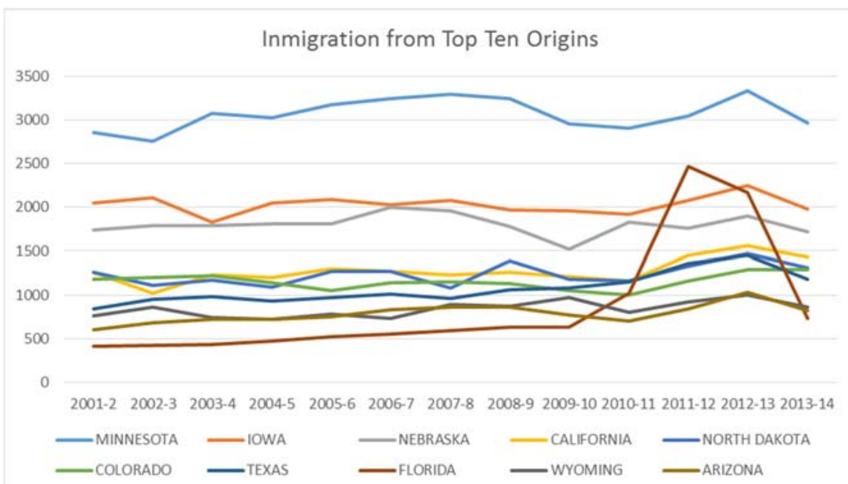


Figure 2b. Outmigration to Top Destination States, 2001-2014

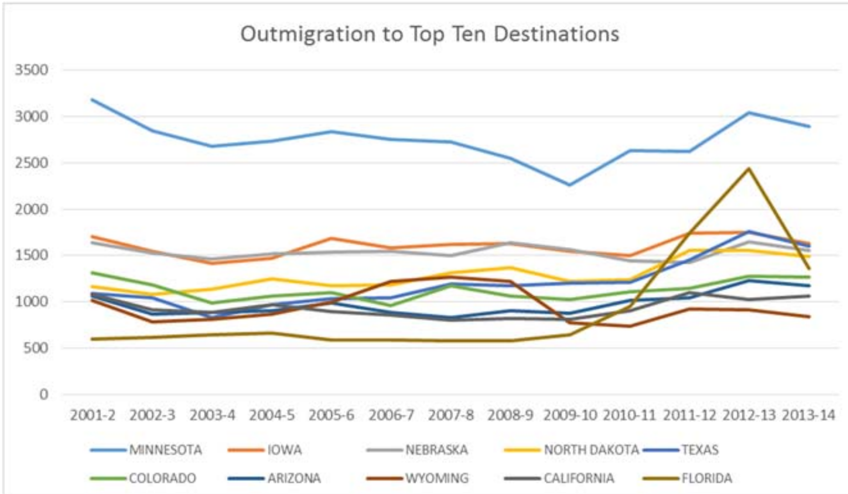
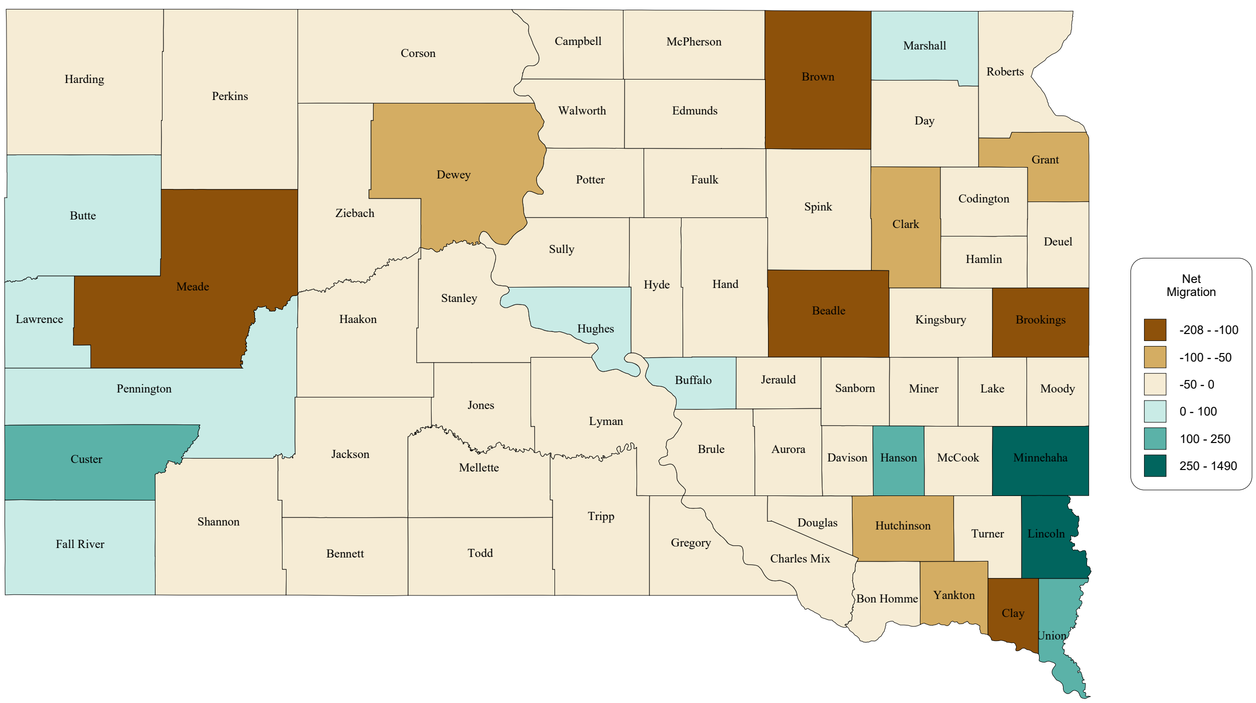
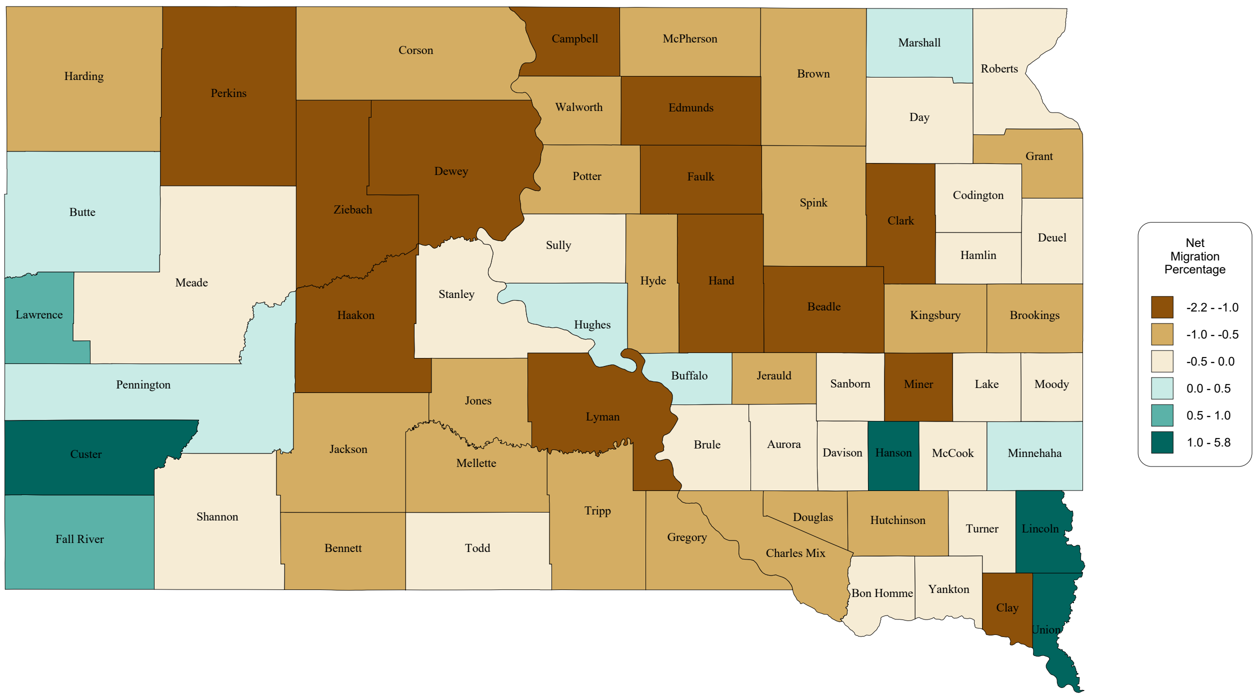


Figure 3. Net Migration, Migration Rate, and Demographic Efficiency, 2001-2006

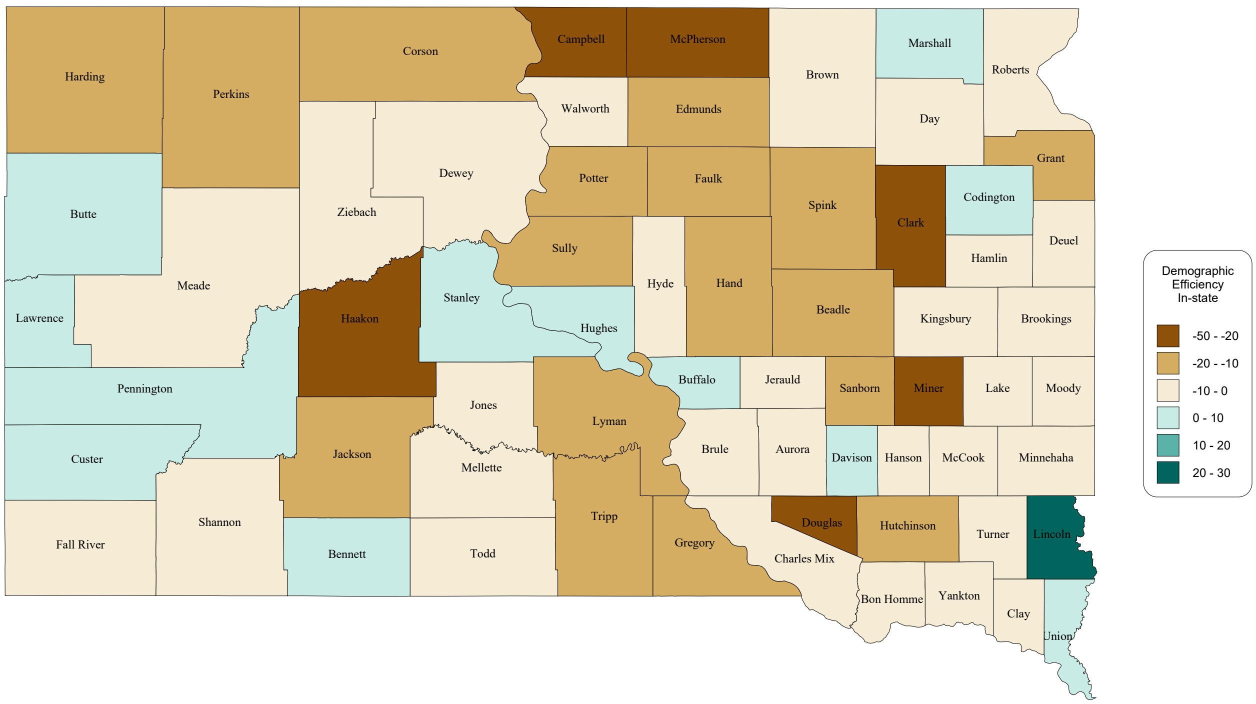
Net Migration 2001-2006



Net Migration Percentage 2001-2006



Demographic Efficiency with SD 2001-2006



Demographic Efficiency with Other States 2001-2006

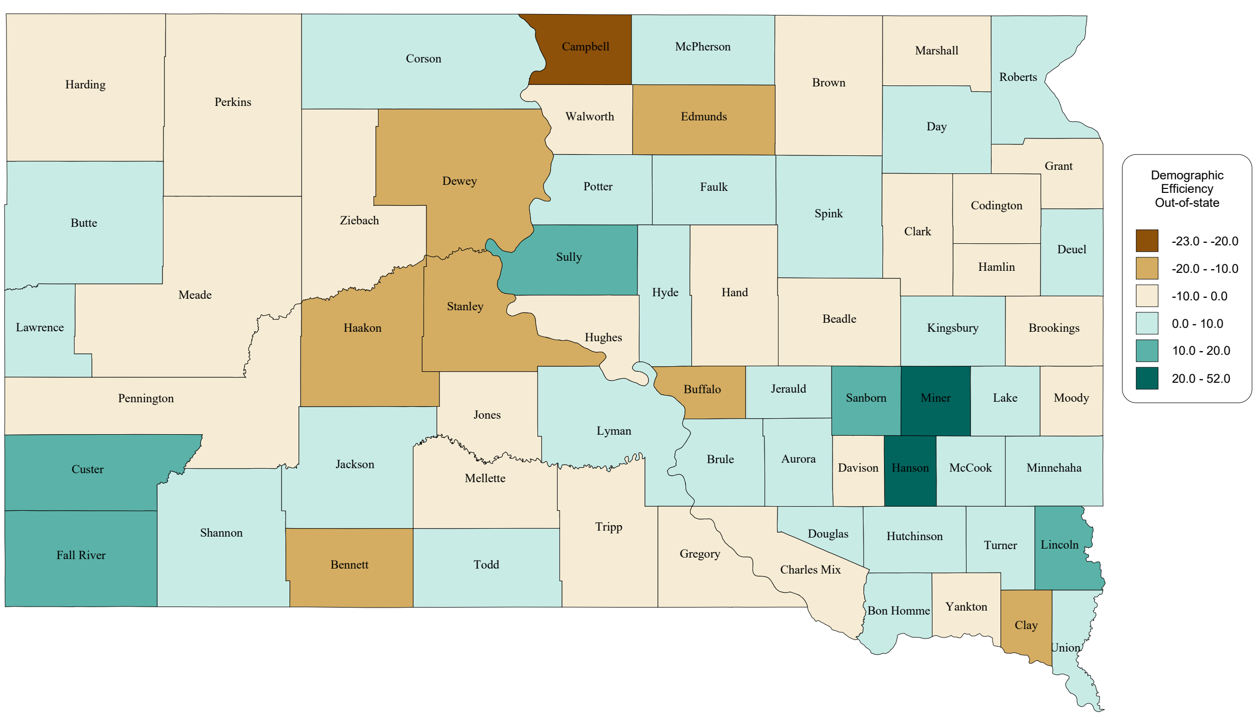
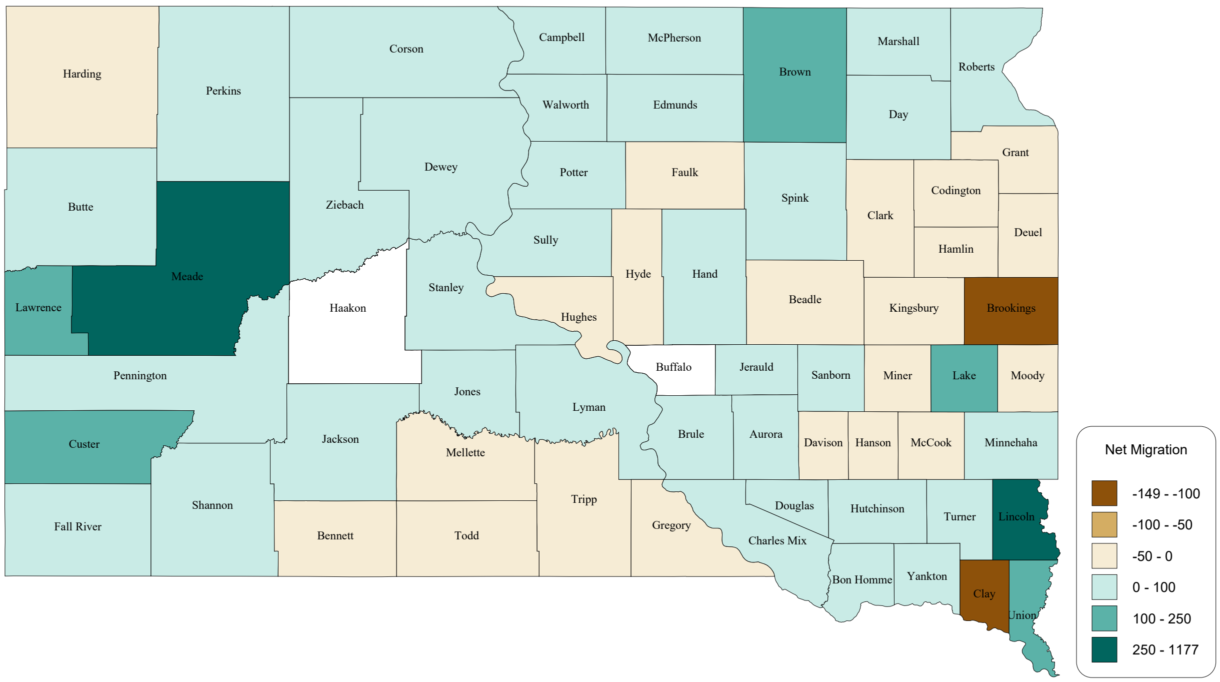
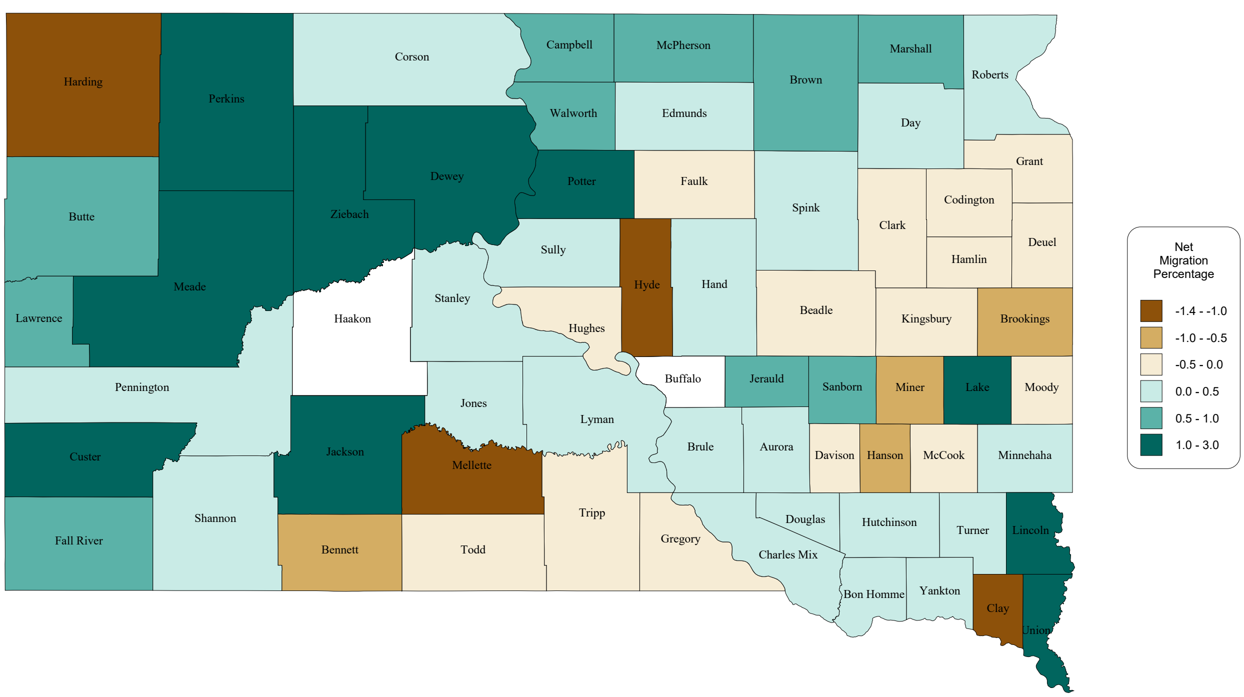


Figure 4. Net Migration, Migration Rate, and Demographic Efficiency, 2009-2014

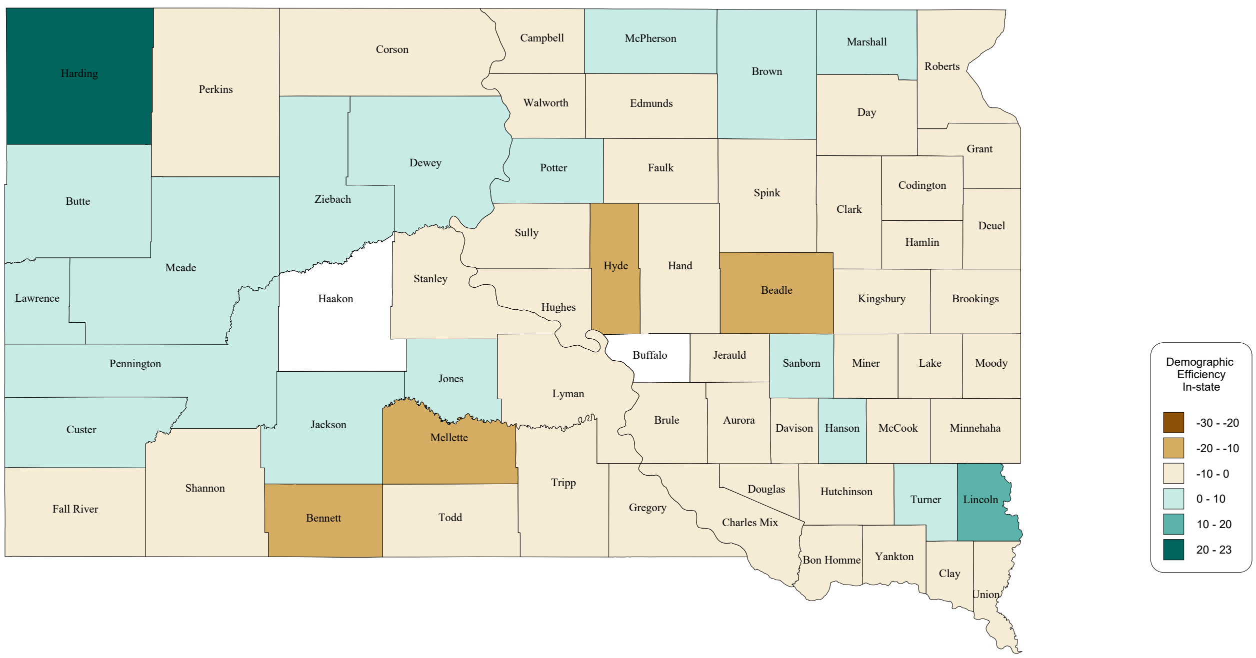
Net Migration 2009-2014



Net Migration Percentage 2009-2014



Demographic Efficiency with SD 2009-2014



Demographic Efficiency with Other States 2009-2014

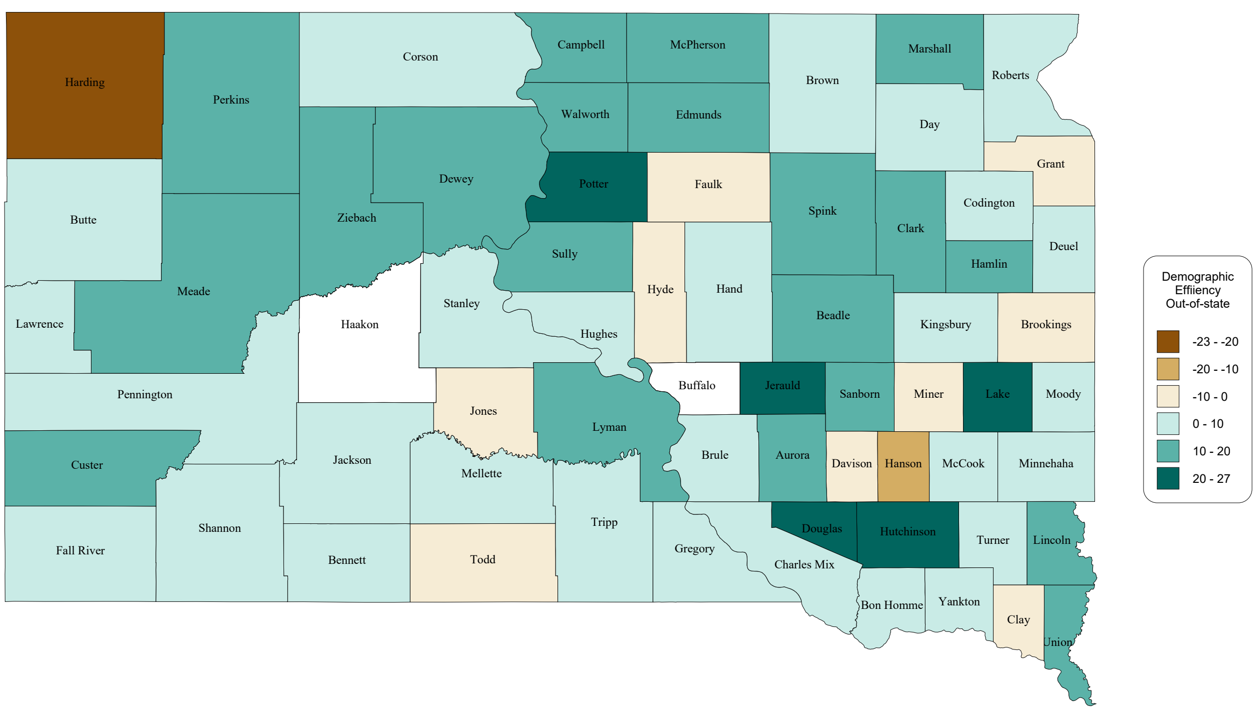
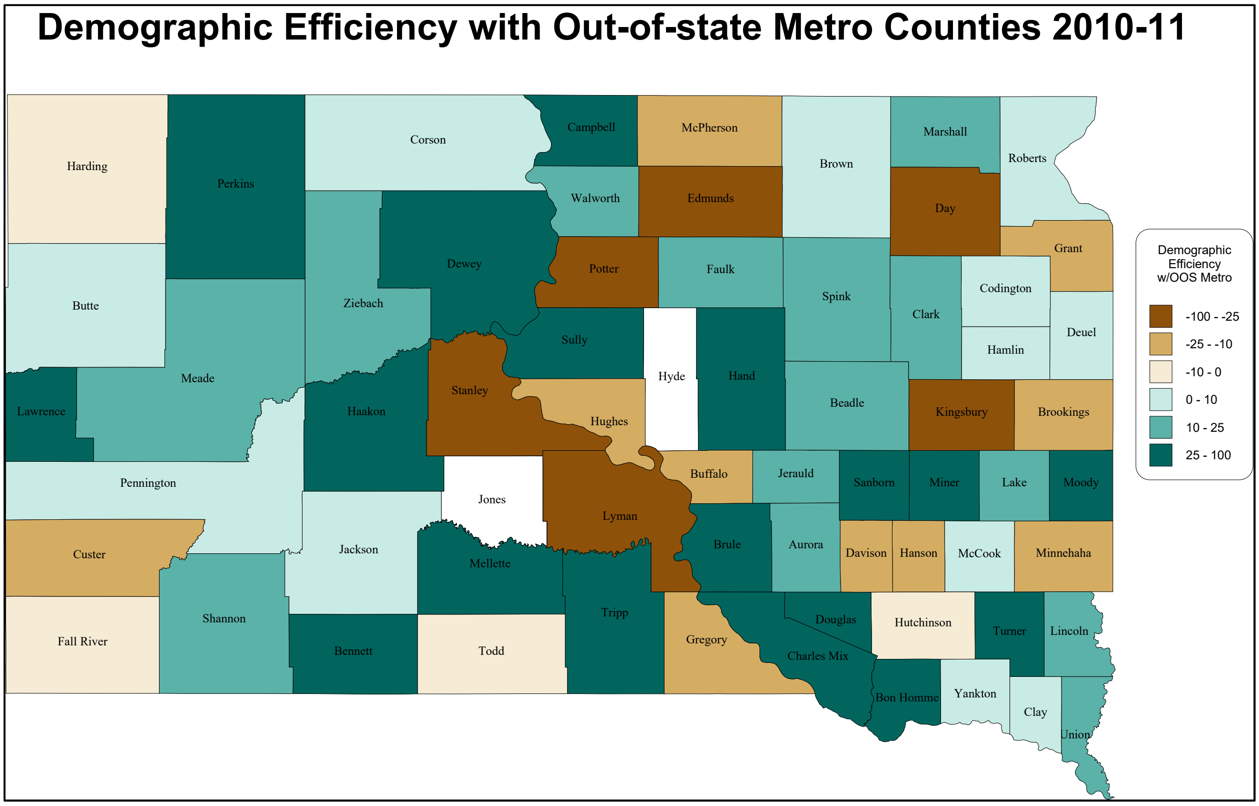


Figure 5. Demographic Efficiency with County Types, 2010-11



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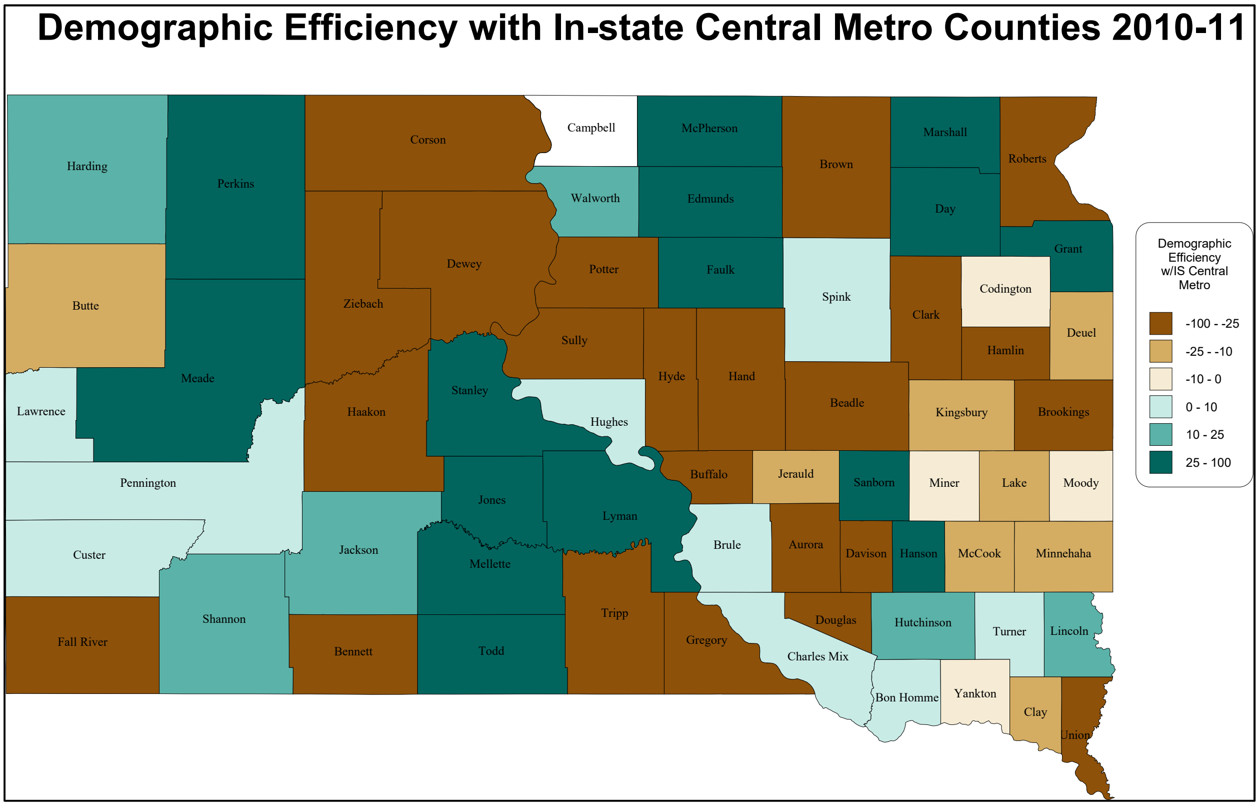
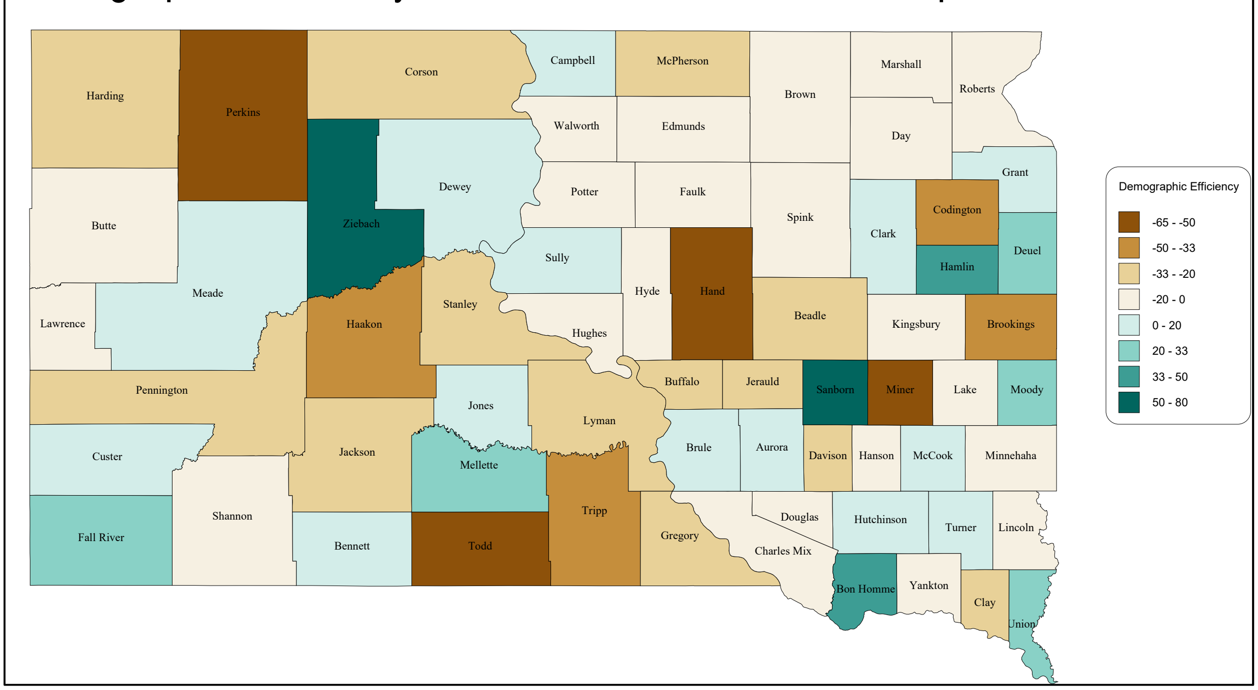
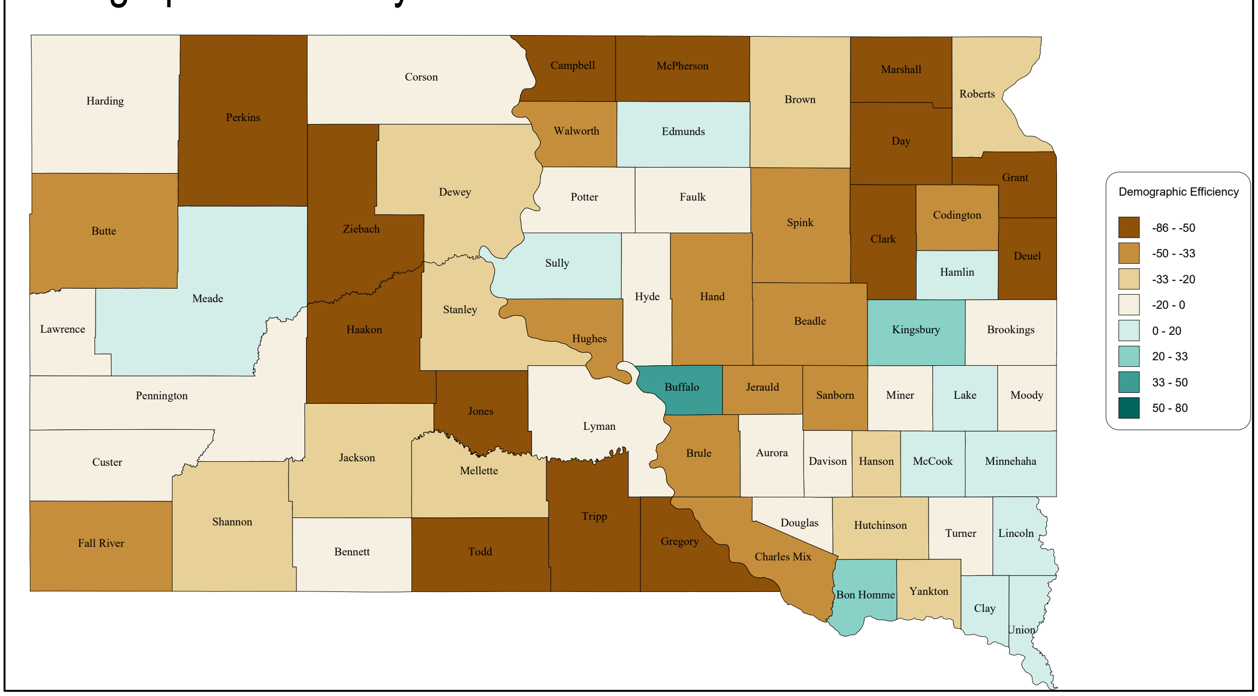


Figure 6. Demographic Efficiency with County Types, 1995-2000

Demographic Efficiency Relative to Out-of-State Metropolitan Counties



Demographic Efficiency Relative to Central MSA Counties



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Appendix.

Figure A1. Census Metropolitan/Micropolitan Designation of South Dakota Counties.

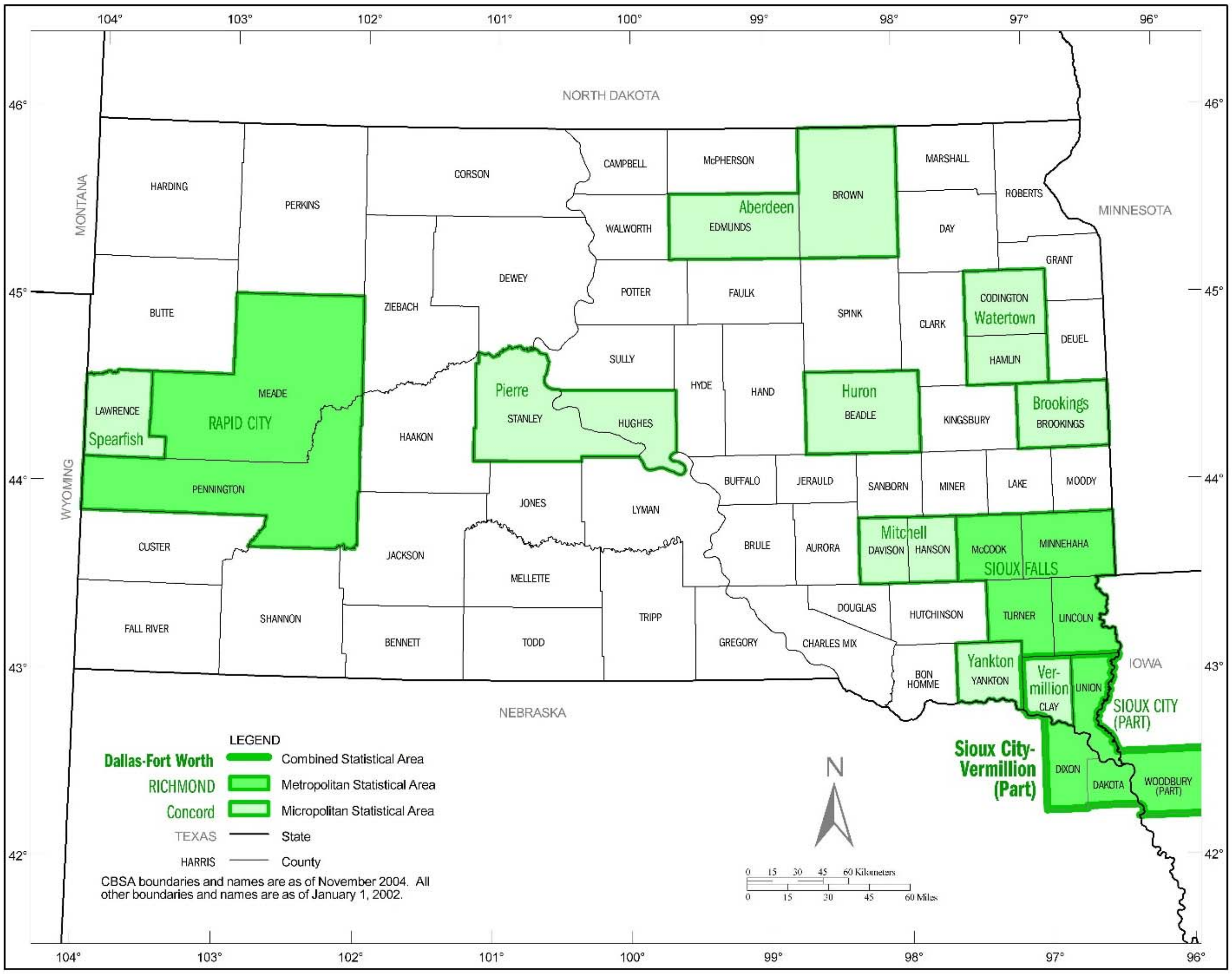

Figure A2. South Dakota County Group Designations.