Patterns and Determinants of Stretch Commuting Across the Rural-Urban Continuum

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Abstract

Residential and employment locational decisions for working households frequently are commingled. Numerous economic and social factors such as job accessibility, wage differentials, demographics, housing markets, travel time, trip-chaining opportunities, dual employment and other quality of life considerations influence where a household ultimately chooses to locate. These choices in turn shape commuting and migration patterns within a region. The rising availability of origin-destination employment data has allowed for increasingly textured analyses of these joint residential-employment decisions across the rural-urban continuum. Our analysis adds to this literature by considering the phenomenon of long-distance commuting, or those individuals who travel 50 miles or more between their place of residence and place of employment (i.e. “stretch commuters”). Specifically, we consider the feasibility of using the Census Bureau’s LEHD Origin-Destination Employment Statistics (LODES) at the sub-county level using network analysis to examine changes in the patterns and determinants of long distance commuting across the rural-urban continuum. Our analysis is largely exploratory.

Introduction

Commuting patterns, or the spatial connections between an individual's place of work and place of residence, have long been an area of interest among regional scientists. Indeed, the body of literature on commuting has grown dramatically over the past few decades with lines of inquiry originating from a variety of environmental, sociological and economic perspectives. Accordingly, we do not attempt a comprehensive review of this literature for this paper. Instead we consider selected studies on commuting patterns that inform some of the socio-economic, spatial and methodological considerations that should be considered in our exploratory analysis of long distance commuting.

Commuting creates costs and benefits at a variety of societal and geographic scales. These costs and benefits also vary across space and time. From an individual's perspective, commuters are assumed to select their residential locations and workplaces in a manner that maximizes the positive benefits to his or her household (Renkow and Hoover, 2000; Cho, Rodriguez and Song, 2008; So, Orazem and Otto, 2001; Partridge, Ali and Olfert, 2010). Accordingly, an individual may weigh many costs associated with living in one place and working in another including housing prices, housing characteristics, quality of life considerations and wage differentials.

However, the costs and benefits arising from commuting are by no means uniform. Cho, Rodriquez and Song (2008) suggest that the exact influence of commuting length/time (i.e. employment accessibility) on locational decisions is neither definitive nor consistent. For instance, several studies suggest that workplace accessibility is either significant or a critical determinant for individuals who are deciding where to live (Abraham and Hunt, 1997; Levinson, 1998; Bhat and Guo, 2004). Yet other research places a higher importance on a location's demographic composition, its housing characteristics and its neighborhood attributes (Molin and Timmermans, 2003; Zondag and Pieters, 2005).

Variations in commuting patterns are also attributed to workers' socio-economic characteristics (Ma and Banister, 2007; Prashker, 2008). Some groups may face mobility constraints that create longer commuting times. Often these barriers may impact low income or low skilled workers who face a spatial mismatch in access to jobs that provide substantial economic opportunities (Immergluck, 1998; Carroll and Blair, 2007). Furthermore, commuting characteristics vary by occupation, gender, income, and household structure (Kim, Sang, Chun and Lee, 2012; Wyly, 1998; Rapino and Fields, 2012).

In addition to variations in commuting patterns by individual characteristics, yet other studies consider how regional/local labor markets, population changes and industry structure influence commuting flows from both inter and intra-regional perspectives (Mitchelson and Fisher, 1987; Renkow and Hoover, 2000; Boschmann and Kwan, 2010; Partridge, Ali and Olfert, 2010; Chen, Zhan and Wu, 2012). These studies highlight how the economic and spatial characteristics of a regional economy can influence the flow of labor across the rural-urban hierarchy beyond the considerations of an individual commuter.

While the absolute influence of commuting time and commuting distance may vary by time and space, the influence of distance on commuting patterns nonetheless remains an important consideration. If shorter commuting times or distances are to be viewed as amenities to an individual (or a region), the values of these amenities must diminish as commuting times or distances increase. Indeed, several studies have identified distance thresholds where the returns associated with commuting become negligible. That is, at some distance the costs of commuting outweigh any additional benefits gained by living in one place and working in another. For instance, Mitchelson and Fisher (1987) suggest that the maximum extent of commuting into metropolitan areas lies around 50 to 60 miles between a community of residence and the community of employment. Beyond this distance, individuals become less likely to benefit from a metropolitan labor market. Similarly, an analysis of Canadian rural-urban economic structure also finds a travel distance of 118 kilometers (~73 miles) as a critical threshold where rural areas become less likely to benefit from rural-to-urban integration through commuting (Partridge, Ali and Olfert, 2010).

Undoubtedly, long commuting distances reduce the interchange of commuters within or between regions. Nonetheless, several analyses have found that the number of individuals willing to commute more than 50 miles each way is notable. These long distance commuters, or so-called "stretch commuters", totaled more than 3.3 million individuals between 2001 and 2002 (Bureau of Transportation Statistics, 2004)[1]. Furthermore, Rapino and Fields (2012) find that five percent of all full-time workers traveled 50 miles or more from their place of residence to place of employment during the 2006-2010 period. As these individuals likely incur some of the greatest commuting costs, it is not surprising that these individuals tend to be higher wage workers over the age of 30 (Rapino and Fields, 2012).

These snapshots of long distance commuters confirm that some segment of the U.S. population is willing to travel distances either at or beyond the thresholds where individuals or regions experience diminished returns. These travel distances are probably not overly surprising given that average commuting times and distances have gradually increased over time. However, we do not necessarily know how place-based factors or individual motivations influence an individual's decision to commute beyond 50 miles (Rapino and Fields, 2012). Furthermore, we do not know whether patterns of stretch commuters vary across time and space similar to other socio-economic categories of commuters.

Methodological Concerns with Measuring Commuting Patterns

From the perspective of travel potential, commuting can be measured in terms of accessibility between residential locations and employment centers. Variations of these measures are employed in both metro and non-metro contexts. From a metropolitan perspective, studies may consider the number of jobs accessible within some distance of a given residential location (Cho, Rodriguez and Song, 2008; Borschman and Kwan, 2010). Similarly, job accessibility between urban and rural regions may rely on

[1] See: http://nhts.ornl.gov/2001/pub/ec071.pdf

the distance decay between enumeration units (such as counties) containing potential employment opportunities and population centers (Partridge, Ali and Olfert, 2010).

Other perspectives on commuting patterns concern the exchange of commuters between specific geographic pairs using measures of net, gross, in or out commuting. For instance, Mitchelson and Fisher (1987) use the distances between minor civil divisions (MCDs) and urban centers with a population of more than 5,000 residents to calculate commuter flows in New York State. Goetz, Han, Findeis and Brasier (2010) use county-level commuting data to explore commuting networks in terms of in and out-entropy. Similarly, Renkow and Hoover (2000) use the Census Bureau's Journey to Work data at the county level to examine inter-county commuting flows.

For purposes of measuring long distance commuters, we also must rely on estimating commuting flows between geographic pairs. Traditionally, several data sets have been used to measure distance and commuting flows among geographic areas including county-to-county and MCD-to-MCD datasets produced by the U.S. Census Bureau and the Census Transportation Planning Package; which is a product jointly produced by the American Association of State Highway and Transportation Officials (AASHTO) and the Census Bureau. While these datasets provide the ability to measure commuting flows at a number of geographic levels and across socio-economic conditions, they are limited to several time periods which may not adequately capture temporal changes in commuting patterns.

The ability to capture changes in commuting flows across time periods is desirable as the relationship between regional economic characteristics and commuting patterns may vary across time frames. For instance, Shearmur and Polese (2007) suggest that job growth should elicit a somewhat immediate commuting response. Recently, the dramatic changes in population and employment attributed to the Great Recession provide opportunities to model these types of responses. More broadly, understanding change in commuting patterns across and within economic periods offers both insights to the evolving factors that influence the substitution of commuting for migration as well as the changing geographic extents of regional economic influence.

As suggested earlier, many analyses of commuting patterns rely on counties or similar enumeration units as their unit of analysis. Indeed, counties allow for relatively easy calculations between origins and destinations. Counties are also the enumeration unit for a multitude of other economic and demographic information. However, using counties to calculate distance is somewhat problematic as these distances are influenced by a county's geographic size. In fact, Goetz et al (2010) suggest that ignoring the influence of county size on commuting patterns could lead to biased regression estimates.

Furthermore, simply measuring point-to-point distances using a straight-line approach is also somewhat problematic as it assumes the presence of optimal transportation networks. Both rural and urban areas may face a number of travel barriers and network inefficienes that are not reflected in straight distance measures. Distance measures based on a travel optimization of the transportation network provides an opportunity to address this issue. While they are more ideal, it should be noted that network analyses do indeed create a cost in terms of the computational time needed to calculate distances.

When considering the opportunity and desirability to calculate commuting distances across numerous time periods, ideally using sub-county data, we explore the potential of examining spatial-temporal patterns in stretch commuters using a dataset of census tract-to-census tract commuting distances based on the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES). We calculate distances based on optimized network analysis procedures rather than relying on straight line distance measures. Our study area includes six upper Midwestern states including Illinois, Indiana, Iowa, Michigan, Minnesota and Wisconsin. This region contains a mix of 535 counties that fall along the rural-urban continuum. Importantly, this region has also experienced a number of significant socio-economic changes since 2000 that provides a foundation for future modeling. In fact, these changes have received considerable attention in postmortems of the 2016 presidential election given their potential role in influencing the election of Donald Trump.

Data Assembly and Description

The Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics dataset is produced annually with data currently available the years between 2002 and 2015. Its enumeration units start with census blocks, which can be further aggregated to other geographic areas. As a product of the LEHD program at the U.S. Census Bureau, LODES data are comprised of administrative records, census and survey data focused on the labor market, worker, and firm statistics. State unemployment insurance reporting and account information and federal worker earnings records provide information on employment location for covered jobs and residential information for workers, which form the basis of the LODES data product (Graham, Kutzbach, and McKenzie, 2014). The LODES data also includes some limited information on the origins and destinations of individuals by their earnings, age and industry of employment, which will eventually help us to consider several specific characteristics of commuters.

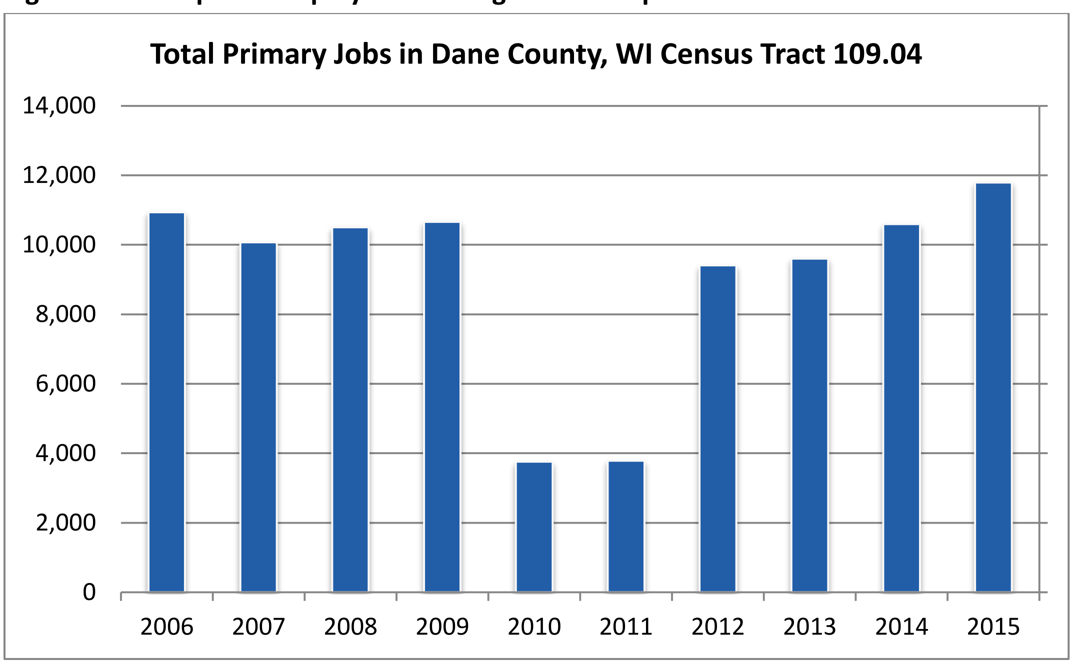
As noted by the Census Bureau, workplace information is protected by combining confidential employment data with noise in a manner that ensures that the published data, while not exact, become increasingly more accurate as the number of businesses in an enumeration unit (such as a census block) gets large. No actual data for a given employer are used for any workplace reports. The employment data for private employers are controlled to state-level totals provided by the Bureau of Labor Statistics.

LODES data are split into two different datasets: main and auxiliary. The main data include information on individuals who are located in the same state for both their place of residence and place of work. Auxiliary files consider those individuals who work in a given state, but live in a different state. Accordingly, we must consider both files to calculate stretch commuting. For purposes of this analysis, we limit the pair of origins and destinations to individuals who live in one of the six aforementioned states and places of work in either the study area states, or in states that are adjacent to the study area. As we are using network analysis rather than straight-line distances, these limitations are made primarily due to the diminishing returns of individuals who commute to other more distant states and to minimize the notable computation requirements for these measurements. Even with these geographic restrictions, the analysis results in more than 300 million potential tract-to-tract origin-destination pairs. As we repeat these calculations for six different years (2004, 2006, 2008, 2010, 2012, and 2014), the total analysis results in more than 1.8 billion tract-to-tract distance measurements.

Despite its ability to address a number of traditional methodological concerns, LODES data face a number of potential limitations and challenges. While the use of census tracts allows for smaller geographic areas and greater texture in the analysis, the use of tracts does not necessarily ameliorate the modifiable areal unit problem. Indeed, tracts can vary significantly in size and shape which in turn influence the location of the census tract centroid.

Furthermore, the LODES dataset uses synthetic data methods to protect confidential information about workplace information and the residential locations of workers. Consequently, these methods may result in place-based data variations from year-to-year. While some of the variations are subtle at the census tract level, others may be more significant. For instance, consider the number of employees in census tract 109.04 located in Dane County, Wisconsin. The number of employees in this tract varies dramatically between 2009 and 2012 despite remaining largely consistent in other time periods. While the employment numbers likely changed somewhat across these years, it is doubtful that these changes occurred in such a significant manner. As 20 percent of the workers in this census tract traveled at least 50 miles, these types of changes have the potential to impact the stretch commuting calculations.

Figure 1 – Example of employment changes in a Sample Census Tract

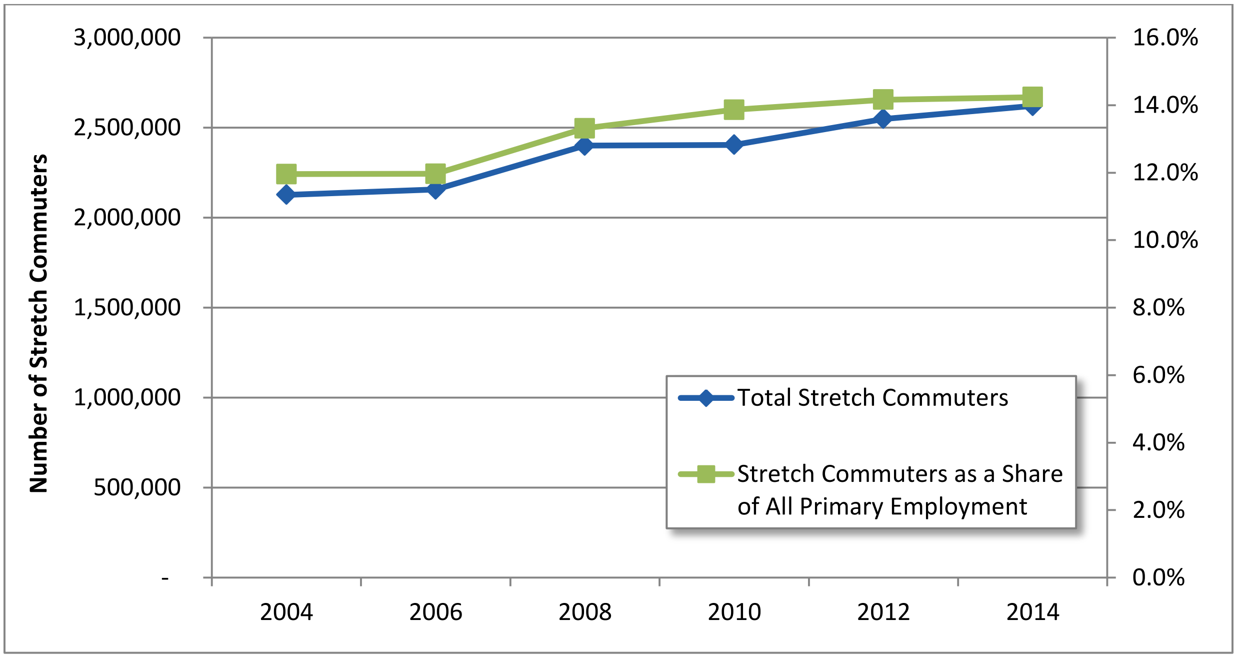


Source: LODES and Authors' Calculations

Descriptive Analysis and Discussion

As previously mentioned, our analysis is simply exploratory in nature. From a broad perspective, the data suggest a somewhat consistent growth in the number of stretch commuters in the six state study area (Figure 2). Between 2004 and 2014, the total number of stretch commuters increased from 2.13 million to 2.72 million. Stretch commuters as a share of all workers also increased from 12.0% to 14.2% over the same period. Note that stretch commuters as a share of total commuters are also influenced by overall employment levels that varied across this period, partially due to effects stemming from the Great Recession. While these numbers are somewhat larger than the national figures previously reported, these differences may reflect variations in the time periods, data sources, geographic extent, and methodologies used for measuring distance.

Figure 2 – Change in Study Area Stretch Commuting (2004-2014)



Source: LODES and Authors' Calculations

Similar to the aforementioned characteristics of long distance commuters, we also find that individuals between the ages of 30 to 54 comprise the greatest share of stretch commuters in the study area (Figure 3). As this age group also accounts for the largest share of total study area workers, this finding should not be surprising. However, we do see that individuals age 29 or younger appear to be more likely to be stretch commuters than the overall workforce within this age group. We also find that older individuals comprise a greater share of stretch commuters in 2014 than in 2004. In contrast, the share of stretch commuters, under the age of 30 has declined. These differences are expected given shifts in age structure throughout the study area (i.e. the region is growing older). From an earnings perspective, individuals making more than $3,333 per month currently account for the greatest number of stretch commuters (although this finding varies by year). However, individuals making less than $1,250 per month are more likely to be stretch commuters than the overall workforce in the study area.

Figure 3 – Distribution of Stretch Commuters vs. All Employees by Age and Earnings

Percent of Total	2004	2006	2008	2010	2012	2014
Age 29 or Younger						
Stretch Commuters	31.3%	31.3%	30.6%	27.9%	27.0%	27.6%
All Employees	25.9%	25.9%	25.5%	23.3%	22.6%	22.8%
Age 30 to 54						
Stretch Commuters	54.1%	53.1%	52.5%	53.6%	52.5%	51.1%
All Employees	58.8%	57.5%	56.5%	57.3%	56.0%	54.8%
Age 55 or Older						
Stretch Commuters	14.7%	15.6%	17.0%	18.4%	20.5%	21.4%
All Employees	15.3%	16.7%	18.0%	19.4%	21.3%	22.4%
Earnings of $1250/month or less						
Stretch Commuters	32.3%	30.7%	28.8%	28.4%	27.5%	27.1%
All Employees	25.6%	24.4%	23.0%	22.1%	21.6%	21.2%
Earnings between $1251 and $3333/month						
Stretch Commuters	37.7%	36.8%	36.9%	36.5%	35.8%	34.5%
All Employees	40.8%	39.2%	37.9%	37.0%	35.9%	34.8%
Earnings greater than $3333/month						
Stretch Commuters	30.0%	32.5%	34.3%	35.1%	36.8%	38.3%
All Employees	33.6%	36.4%	39.1%	40.9%	42.4%	44.1%

Source: LODES and Authors' Calculations

For purposes of illustration and preliminary modeling, we aggregate the census tract data to the county level. From a spatial perspective, it is not surprising that counties with large shares of stretch commuters are found in rural areas around large metropolitan centers (Figure 4). The drawing powers of metro areas such as Chicago, Twin Cities, Milwaukee and Detroit are apparent. We also see similar patterns around mid-sized metro areas such as Des Moines, Iowa and Madison, Wisconsin.

We also see how concentrations of stretch commuting vary over time across rural areas of Minnesota, Southern Illinois, Michigan and Wisconsin. Stretch commuting concentrations in Northwest Wisconsin remained somewhat consistently high over this period. In contrast, portions of Michigan's Lower Peninsula increased as did regions in southern Illinois. These increases are partially a reflection of significant job losses in these areas, and not always a large net growth in stretch commuters (Figure 5). Interestingly, we notice a relatively high share of stretch commuters in the core of the Indianapolis metro area. This pattern is also supported by employment growth patterns in this region.

Figure 4 – Changes in Stretch Commuters by County

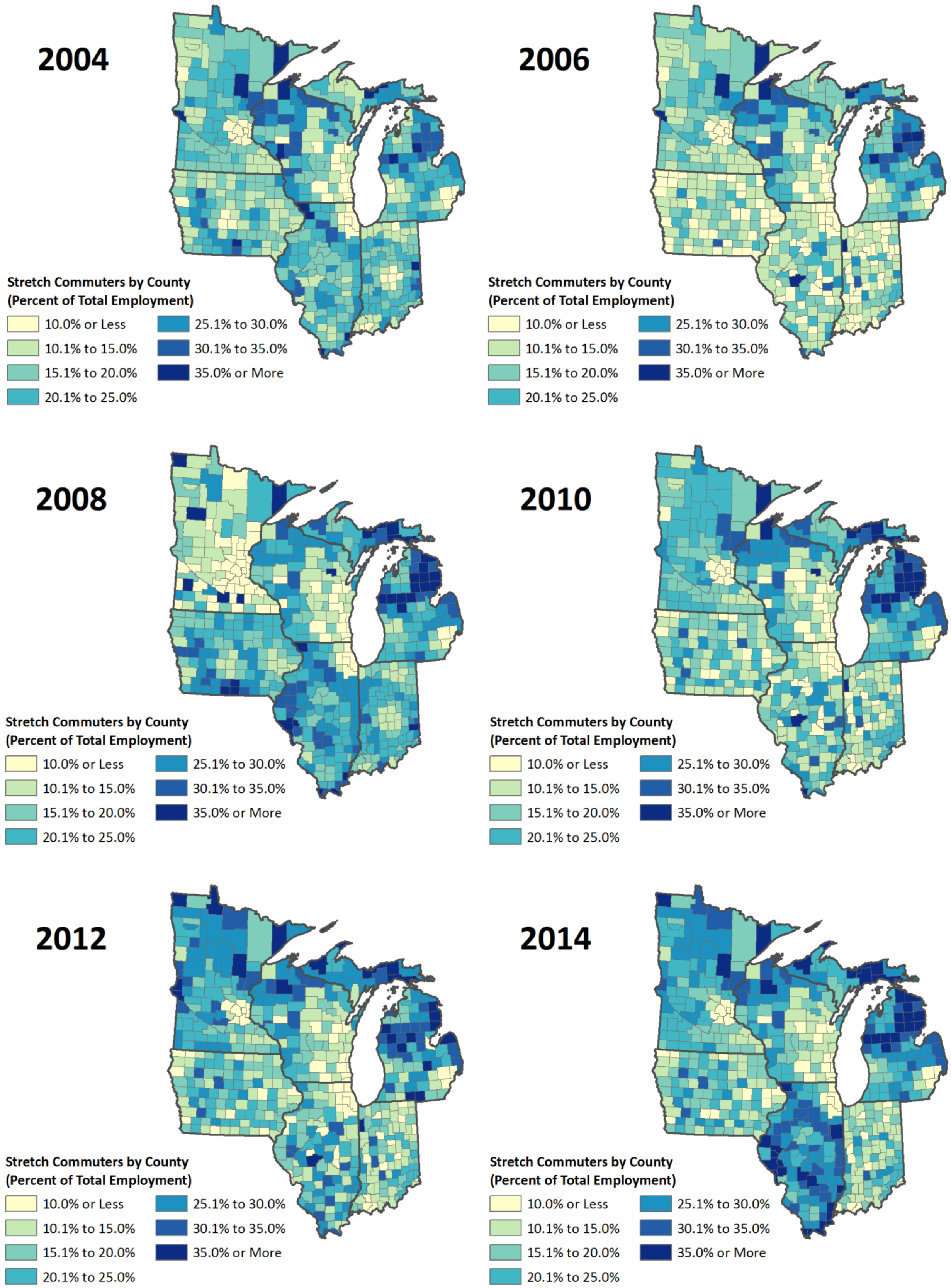
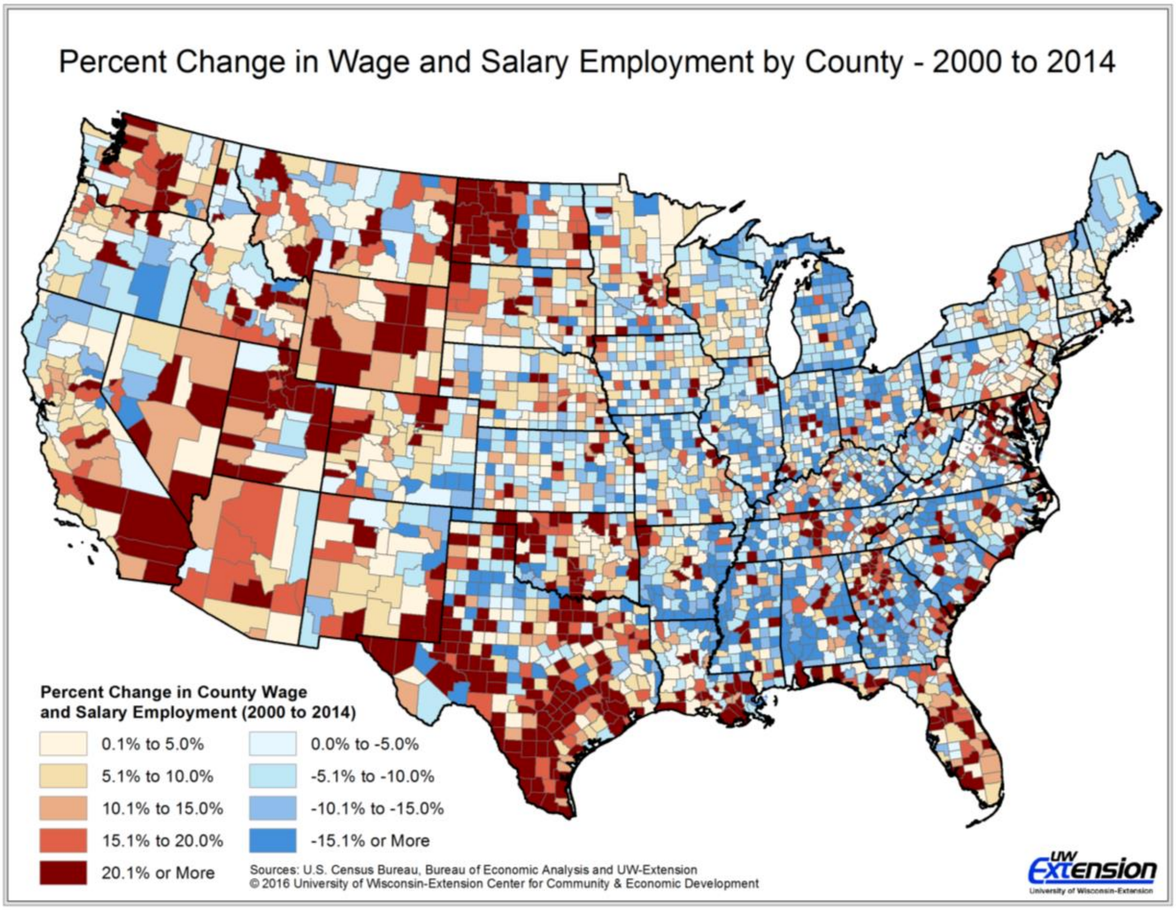


Figure 5 – Percent Change in Wage and Salary Employment – 2000 to 2014

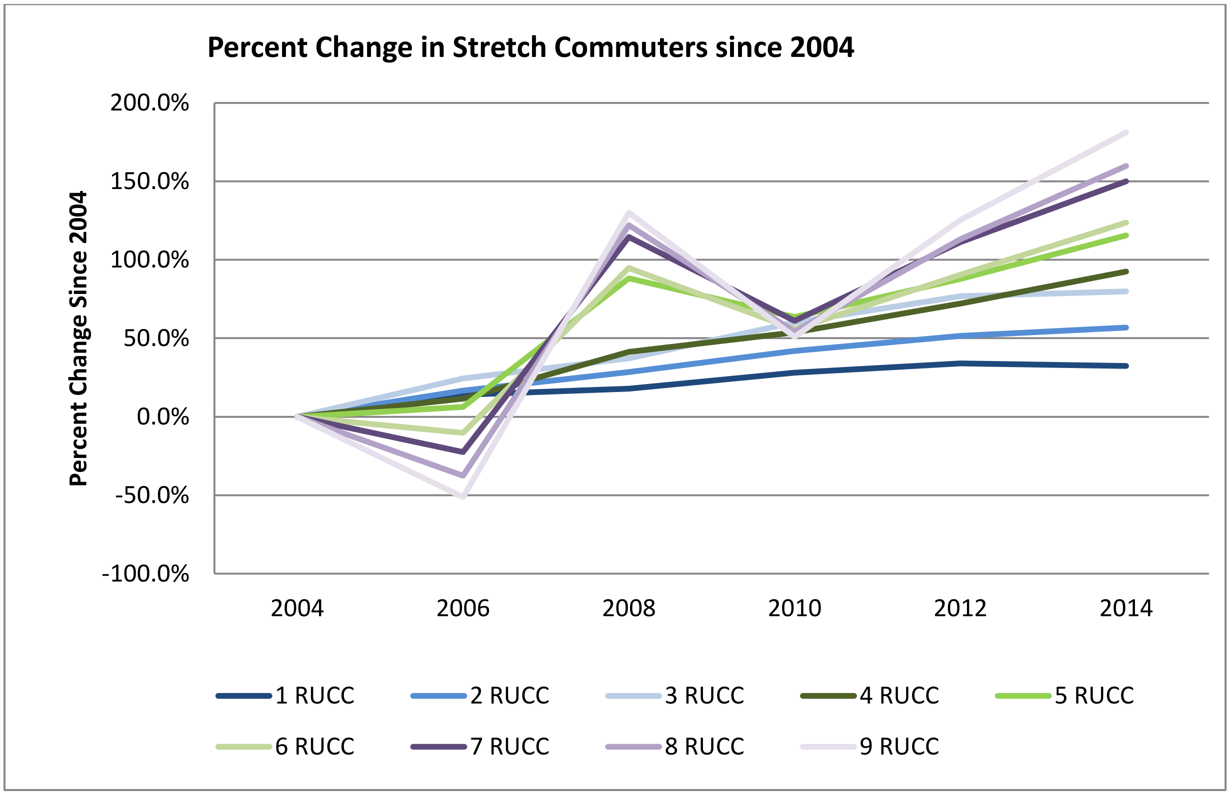


As suggested by the spatial depiction of stretch commuters, many rural areas tend to have a greater share of stretch commuters and have experienced a greater growth in stretch commuters. We further compare changes in stretch commuting using *Rural-Urban Continuum Codes (RUCC).* Rural-Urban Continuum Codes are designated by the USDA's Economic Research Service (ERS) and classify counties into one of nine categories based on their urban composition and proximity to a metropolitan statistical area (MSA). More simply, counties are classified by those that are either the most metropolitan or most rural in character. Counties located in metropolitan areas are classified with an RUCC of 1, 2 or 3 according to the metro area's population size. Non-metropolitan counties have codes of 4 to 9 and are based on population size and adjacency to metropolitan areas (see Appendix A).

While metro areas (i.e. RUCC 1, 2 and 3) experienced steady growth in the number of stretch commuters, non-metro areas largely faced consistent variations in growth and decline between 2004 and 2006; 2006 and 2008 and again between 2008 and 2010 (Figure 6). In contrast, increases in stretch commuters within in these clusters of counties are more consistently positive since 2010. Note that these areas are more sparsely populated. As a result, it does not take a large numeric change to significantly affect the percent change in stretch commuters from period to period. Furthermore, the numbers of counties in the study area classified as RUCC 7, RUCC 8, and RUCC 9 are somewhat limited.

Accordingly, this small sample of counties may not reflect overall patterns in these rural areas relative to national distributions. Nonetheless, these patterns across non-metro areas suggest an opportunity for further inquiry.

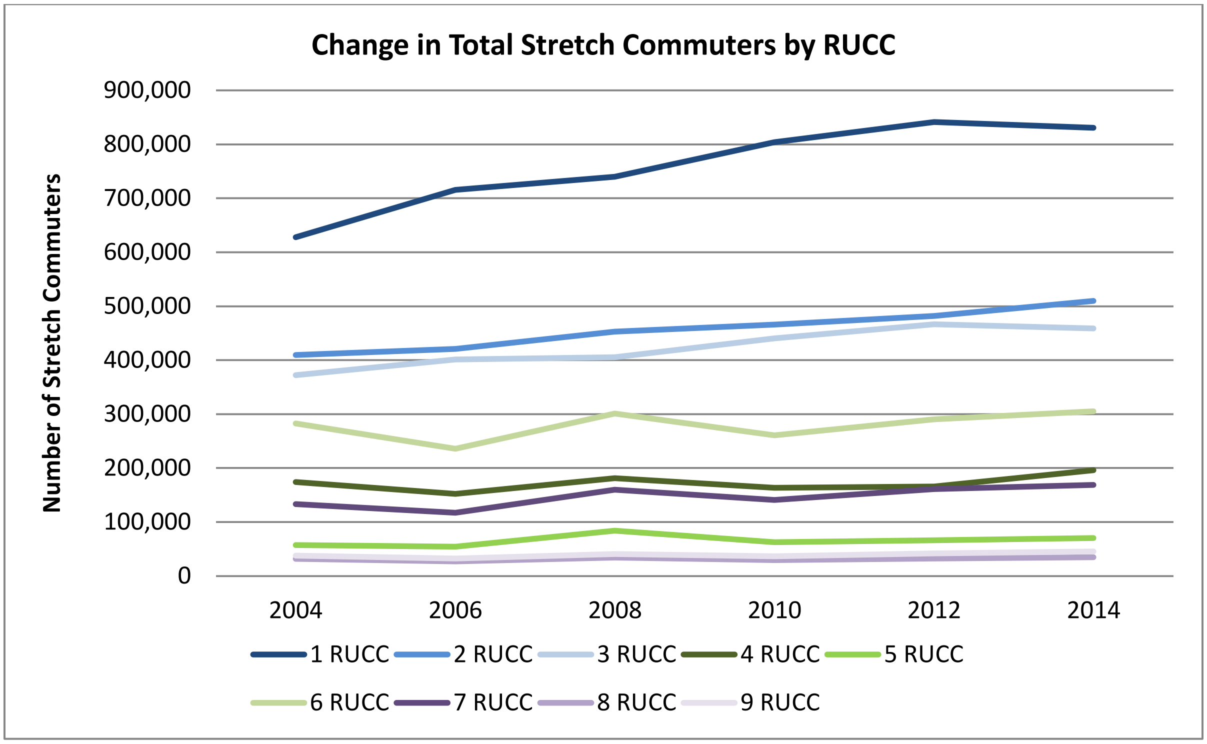
Figure 6 – Percent Change in Stretch Commuting by Rural-Urban Continuum Code



Source: LODES and Authors' Calculations

While rural areas have a larger share of workers who are classified as stretch commuters, long distance commuting is not limited to rural-urban continuum codes at the bottom of the rural-urban hierarchy. In fact, most stretch commuters are found in large, mid-sized and small metro areas (Figure 7). Those stretch commuters within large metropolitan areas are of particular interest as they could provide an opportunity for further exploring changes in intra-metropolitan travel patterns among low, medium and high income workers.

Figure 7 – Percent Change in Stretch Commuting by Rural-Urban Continuum Code



Source: LODES and Authors' Calculations

Exploratory Modeling

In addition to our descriptive analysis, we also conduct some preliminary exploratory modeling of stretch commuters. The intent of this exploratory analysis is three fold: (1) test the feasibility of computing changes in stretch commuting over time, (2) conduct simple descriptive analysis to better understand how stretch commuting has changed over time and across space, and (3) derive an empirical framework to model stretch commuting with an eye toward changes over time. The working hypothesis in this exploratory analysis is that stretch commuting has been expanding over time; specifically, people are willing to commute greater distances in order to live in one place and work in another. We do this by specifying a simple panel model: $\Delta SC_{t\rightarrow t+1} = f(SE_t, D_t)$. Here $SC_{t\rightarrow t+1}$ is the change in the number of workers that are stretch commuters, again defined as commuting more than 50 miles, from time *t* to time *t+1*, SE_t is a set of simple socioeconomic variables, and D_t is a set of time dummies. If we assume a simple linear function, we would expect the coefficients on the time dummies to be increasing over time: $\beta_{Dt} > \beta_{Dt-1} > \beta_{Dt-2} > \cdots$. Here we have the change in stretch commuters from 2004 to 2006, 2006 to 2008, 2008 to 2010, 2010 to 2012 and 2010 to 2014.

We have two measures of stretch commuting: (1) the change in the absolute number of stretch commuters, and (2) the change in the percent of workers that are stretch commuters. We use both measures as more of a simple robustness check offering different hypotheses requiring different measures of stretch commuting. We also use an aspatial fixed effects estimator along with a crude spatial error model with fixed effects. We explored two way fixed effects along with time fixed effects and the F tests for fixed effects rejected the two way fixed effects in favor of the time fixed effects model. This latter result lends some credence to the basic hypothesis that stretch commuting is shifting over time, or at least the study period explored here.

Our exploratory modeling results are provided in Table 2. The simple model explains only between 15 and 18 percent of the variation in the change in stretch commuting, suggesting that there are a range of other factors at play that we are not capturing. We also find that the spatial error parameter (ρ) is statistically significant reaffirming the spatial clustering suggested above. Note that the spatial parameter is negative suggesting that competition between regions (counties) outweigh cooperative factors. Within our commuting framework this makes intuitive sense: counties are competing with their neighbors for workers. We also find that the general results are stable across the two measures of stretch commuting and the aspatial and spatial estimators. This lends some credit to the robustness of our simple analysis.

We expect that an older population should place downward pressure on stretch commuting, and while the estimated negative coefficient confirms this hypothesis, the result is statistically insignificant. We also expect that a higher population/employment ratio, a simple measure of whether a county is more of a bedroom community or an employment hub, to be associated with growing levels of stretch commuting, and the data tend to support the hypothesis. Higher share of employment in manufacturing tends to place downward pressure on changes in stretch commuting, but the result tends to be statistically insignificant. A higher share of employment in farming is strongly linked to growth in rates of stretch commuting and is consistent with the descriptive results discussed above. Neither the unemployment rate nor per capita income have any statistically significant influence on change in stretch commuting. The lack of a result for the unemployment rate is somewhat surprising as one would expect that counties that have higher unemployment rates would see workers willing to commute greater distances for employment. It may be the case that an alternative measure of unemployment rates are required, or notions of persistent unemployment are more appropriate.

The focal point of our analysis is less the performance or insights gained from the control variables, but on the time fixed effects. We do find that the individual time fixed effects are statistically significant, but not in a way that is consistent with our working hypothesis: that over time the share of workers that are stretch commuting is increasing. Rather, the model is being driven by the spike change between 2006 and 2008. As discussed in the descriptive analysis above it is not clear to us why there would be a spike in the years at the beginning of the Great Recession. One possibility might hinge on relative housing prices. Because of the spike in housing prices leading up to the Great Recession is may be the case that workers were forced to commute greater distances due to relative housing prices. Prior research on commuting patterns has suggested that relative housing prices can be a major factor in people's decisions on residential location relative to employment location (e.g., Shields 1998). Regardless of the difficulty introduced by the 2006-2008 spike, there is sufficient evidence of general upward trends in stretch commuting to warrant further analysis.

Table 1: Exploratory Analysis of Stretch Commuting

	Number of Commuters				Share Commuters			
	Aspatial		SEM		Aspatial		SEM	
% Pop Over Age 65	-0.2367		-0.1124		-0.2323		-0.1072	
	(0.5555)		(0.7327)		(0.5507)		(0.7353)	
Population/Employment Ratio	0.0631	*	0.0791	**	0.0512		0.0686	**
	(0.0529)		(0.0020)		(0.1052)		(0.0056)	
Share of Employment in Manufacturing	-0.2982	*	-0.2046		-0.2483		-0.1491	
	(0.0795)		(0.1512)		(0.1320)		(0.2783)	
Share of Employment in Farming	0.9876	**	1.0715	***	0.8699	**	0.9410	**
	(0.0012)		(0.0001)		(0.0033)		(0.0003)	
Unemployment Rate	-0.7118		-0.4627		-0.4851		-0.2634	
	(0.3934)		(0.5047)		(0.5486)		(0.6936)	
Per Capita Income	-0.0199		0.0033		-0.0204		0.0021	
	(0.4590)		(0.7787)		(0.4331)		(0.8494)	
Time Fixed Effect 2004	-0.3176	***	-0.2897	***	-0.3280	***	-0.3011	***
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Time Fixed Effect 2006	0.3928	***	0.4191	***	0.3844	***	0.4097	***
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Time Fixed Effect 2008	-0.1656	***	-0.1505	***	-0.1377	**	-0.1229	***
	(0.0001)		(0.0001)		(0.0006)		(0.0001)	
Time Fixed Effect 2010	-0.0322		-0.0260		-0.0762	*	-0.0694	*
	(0.4262)		(0.4972)		(0.0520)		(0.0615)	
Spatial Parameter ρ	——		-0.2700	***	——		-0.2820	***
			(0.0001)				(0.0001)	
R^2	0.1453		0.1777		0.1476		0.1824	

Marginal significance (p-value) in parentheses.
***: Significant at 99.9% level.
**: Significant at 95.0% level.
*: Significant at 90.0% level.

Future Research Needs and Opportunities

As suggested, our work considering changes in stretch commuting patterns is largely exploratory and preliminary. We find that stretch commuting has increased over time and that these changes have varied across the rural-urban continuum. However, there is work yet to be done with the dataset. We intend to complete the analysis for all time periods rather than simply relying on the six time periods of data produced for this overview. Furthermore, we expect to extend the geographic areas beyond the six state study area used here. Expanding the calculations across additional states and eventually nationally would provide additional opportunities to consider spatial variations in the analysis. Most importantly, we need to examine the data set for potential inconsistencies and irregularities. We expect to identify census tracts that experience irregular or substantial changes in employment figures across subsequent time periods. We could consider using a spatial lag or smoothing approach to address these potential inconsistencies. As we have the individual travel distances between all census tracts in our study area, we could also change our distance threshold from 50 miles to some other value or range of values.

Once the dataset has been further refined, we also intend to expand the analysis of determinants of stretch commuting by evaluating a greater number of control variables. Of particular interest is whether these determinants have responded to period effects from the Great Recession or whether stretch commuter patterns are influenced by other longer term structural changes across the rural-urban continuum. The data also provide an opportunity to explore whether or not the growth in stretch commuting may be influenced by the long term decline in residential mobility (or vice versa).

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Appendix A – Description of Rural-Urban Continuum Codes

RUCC	Description
Metropolitan Counties	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Non-Metropolitan Counties	
4	Counties with an urban population of 20,000 or more and adjacent to a metro area
5	Counties with an urban population of 20,000 or more and not adjacent to a metro area
6	Counties with an urban population of 2,500 to 19,999 and adjacent to a metro area
7	Counties with an urban population of 2,500 to 19,999 and not adjacent to a metro area
8	Counties that are completely rural or have less than 2,500 urban population and are adjacent to a metro area
9	Counties that are completely rural or have less than 2,500 urban population and are not adjacent to a metro area

Source: USDA Economic Research Service