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Challenges to Economic Resiliency and Performance: Measuring the Regional Impacts of Rurality and Space

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CHALLENGES TO ECONOMIC RESILIENCY AND PERFORMANCE: MEASURING THE REGIONAL IMPACTS OF RURALITY AND SPACE

By

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An Abstract of the Thesis Presented
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It is commonly observed that there are inequalities found in economic growth, development, and performance between different regions. Because of this, it is vital for regional planners to have knowledge to which economic problems are present and to what extent (Armstrong and Taylor, 2000; Martin, 2005). With such knowledge, planners are able to tailor and implement regional policies in an informed manner that is better suited to address economic problems. Found in this work are two studies that contextualize separate economic problems which have been extensively discussed within regional sciences and rural studies.

The first study seeks to assess how a county's degree of rurality affects its capacity to resist and rebound from economic shocks. Rurality is a variable that challenging to define, but is nonetheless important to understand because identifying how regions can be rural provides necessary context for the justification of policy intervention (Cloke and Edwards, 1986; Beynon et al., 2016). We use county-level data from a series of federal agencies over the period of 2011 through 2015 to statistically estimate and visualize an urban-rural landscape of New England. Using this measure, we further test to see if a county's degree of rurality had an impact on its relative recovery speed in employment growth. Over the same period of 2011 to 2015, we test how these counties recovered from two years and beyond after the Great Recession. The findings suggest overall a county's

degree of rurality corresponded with slower levels of recovery in terms of employment in comparison to overall U.S. levels.

The second study seeks to explain how spatial factors such as market access and geographical remoteness influences a region's differential economic performance. While the discussion of factors contributing to economic performance is expansive for large areal units like nations, there is a need for more understanding on how factors that dampen economic performance at a granular level can influence the greater region's performance (Porter, 2003; Agarwal et al., 2009). We use data from the Census Bureau, National Park Service, and Google Geocoding Service in the one-year period of 2016 to: (1) estimate economic output as a proxy for performance in a system of equations, and (2) to see how such performance differentiates across geographic space. To approach this problem, we use a novel method of extracting and translating geographic data into distance measures at the census tract level to investigate how spatial factors influence economic performance. Overall, the findings from our jointly estimated system of equations highlight that larger distances to market access and remoteness negatively influences economic performance at the census tract level. Similarly, higher levels in variables such as workplace disability and the old-age dependency ratio had other dampening impacts.

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INTRODUCTION

1.1 Introduction

Regional inequalities in economic growth, wealth, and performance are well-documented observations. While these disparities typically act as a motivating factor for regional planners to create effective local and regional policy, they can also be a contentious point of discussion for how regional policy should be tailored (Armstrong and Taylor, 2000; Martin, 2005). While imbalances in economic conditions can persist across regions, the overarching goal of tailoring regional policy to places is to encourage development. Similarly, the view of what development should be is context and spatial dependent. Perspectives of what economic development may look like are broad and responsive to fundamental questions such as: *What kind of economic development? Who should economic development serve?* (Pike et al., 2006). Responses to these questions questions are vital to strategies aimed at addressing the persistence of economic inequalities. For example, the notion that economic development is region-specific, (Local Government Commission, 2004) distinguishes development and growth:

> *"One of the biggest myths is that in order to foster economic development, a community must accept growth. The truth is that growth must be distinguished from development: growth means to get bigger, development means to get better – an increase in quality and diversity."* ((Pike et. al., 2006); quoting (Local Government Commission, 2004).)

Regional and territorial competition has grown as a consequence to differential economic development between areas, where regional planners utilize their area's resources and support policies to mobilize capital and labor as a means attract more economic activity (Krugman, 1995). For the regions that are comparatively lesser off economically, planners may consider development strategies that seek to identify current economic conditions and advantages with the assistance of local stakeholders and to create local policy that avoids the pitfalls from a top-down approach (Pike et al., 2006; Goetz et al., 2011; Artz et al., 2015). While such an approach does not guarantee the success of policies, the fundamental principle behind such an approach is the empowerment for those within the region to identify their economic conditions and address such disparities through policy.

The crux of this thesis is the acknowledgment that regional inequalities exist. Specifically, this research seeks to assess the extent at which these economic imbalances are apparent and explain how other economic and geographic factors influence these imbalances. The common thread that ties this thesis together is underlying principle that any selection of regional policy necessitates the knowledge at which an economic problem is present. It is with this commonality between these two papers where this thesis approaches some of the more overarching problems observed within the literature.

1.2 Purpose of the Research

An attractive characteristic of this thesis is that it presents two different pieces of research that highlight disparities in the time of recovery from economic shocks and evaluating the potential drivers of disparities in economic performance between different localities. The next two thesis chapters here explain the importance of economic space at different levels and considers how regional policy may be tailored to confront the pitfalls from a lack of resiliency, and inform strategies for overcoming the hurdle of geography to better serve rural and remote areas.

The first paper contextualizes economic and sociodemographic differences between urban and rural counties and underpin the notion on how rurality is along a continuity, and where it starts and ends can be region-specific. Understanding how rural and urban areas differ, this chapter tackles the issue of economic resiliency, and specifically explores the speed at which regions recover from economic shocks. Given this, we seek to answer the research question: "how do rural counties differ from their urban counterparts with respect to recovery from economic shocks?"

The second paper is grounded in the notion that economic differences in output and performance are largely spatial in nature. Specifically, this chapter seeks to measure the extent to which disparities between the productivity of workers, employment, and labor market dynamics are explained by fixed spatial factors. Two unique components of this research are: (1) that we use a novel method to collect spatial data that would otherwise be a challenge to find and (2) that we numerically calculate spatial variables at a considerably granular scope. Given these nuances found within this chapter, we address two research questions: First, what are the significant economic factors that motivate the differences observed in relative economic performance between census tracts? Second, what are the spatial determinants of regional economic performance?

1.3 Thesis Organization

The remainder of this thesis is composed of three chapters. First, chapter 2 draws upon previous work in rural studies and calculates a measure of rurality between the period of 2011 to 2015 for New England counties. Using this index, we assess how the counties within our study area recovered from the Great Recession in comparison to the nation, giving special attention to rural-urban lines. Chapter 3 utilizes a novel method for extracting and calculating spatial variables and then using these variables to measure the spatial determinants of regional economic performance. Lastly, chapter 4 concludes this thesis by drawing upon the insights of the previous chapters and discusses what future research may look like for work related to economic resilience and performance respectively.

CHAPTER 2
MEASURING THE IMPACTS OF RURALITY ON ECONOMIC RESILIENCY

2.1 Introduction

Regional variation in responses to economic shocks has long provided valuable insight about the difference in capacity and vulnerability of economies. A growing literature surrounding economic resilience has established empirical frameworks to assess regional sensitivity and variation in the speed of recovery from economic shocks (Simmie and Martin, 2010; Martin, 2012; Martin and Sunley, 2015). Beyond this scholarship, little discussion has focused on the role of rurality in regards to economic resiliency.

Rural is defined as something relating to, or a characteristic of, the countryside rather than the town (Merriam-Webster, 2009). From an analytic perspective however, rurality plays a larger role than a mere characteristic. Early literature initially established the foundation of rural studies, what it means for a community to be rural, and how to quantify "rurality" (Cloke, 1977; Cloke and Edwards, 1986; Hoggart, 1988; Isserman, 2005; Cloke et al., 2006; Waldorf, 2006). Such work has helped policymakers and researchers understand the significance of rurality and how it affects economic policy (Halfacree, 1993; Beynon et al., 2016; Li et al., 2015). Beyond this, there has been an extensive discussion surrounding policy implementation in urban and rural regions. In turn, rural studies has opened an avenue for non-academic analysis on the design and expected performance of alternative development strategies at the national and state-wide level (Williams et al., 2013; Tudor, 2015; Office of Economic Development & International Trade, 2016; OECD, 2017; Bay Area Council Economic Institute, 2017). Some questions about policy implementation and efficacy nonetheless remain; for example, how can policymakers promote economic policies that are tailored in a manner to reach rural areas and established hubs of economic activity? How, if at all, is the impact of economic shocks different between an area with small (yet constant) economic activity and areas that suffer from perpetual economic declines? How does geographical isolation impact economic activity and the recovery from economic shocks? And lastly, do the effects of geographic isolation on economic activity and recovery to shocks vary systematically between time and space? To respond to such question, we analyze the linkages between rurality and economic resiliency.

To do this, we synthesize two fields of literature that focus on regional sciences and rural studies and empirically evaluate the impacts of a multivariate index of rurality on a measurement of economic resiliency. Drawing upon past work, we use factor analysis to develop a measure of rurality associated with differences between several geographic, socio-demographic, and economic variables. Then we evaluate differences in economic resilience with respect to rurality. In sum, our approach contributes to both the study of rural areas and regional sciences by analyzing the association of economic resiliency and rurality and providing insight to policymakers interested in the impacts of policy for rural areas.

2.2 Measuring Rurality

How one measures rurality can vary by academic discipline and specialty. For example, rural measures can shape the framework used by experts in health-care, education, and community development. Rural definitions similarly affect eligibility for federal grants and programs, and levels of federal assistance provided to rural communities (Arnold et al., 2005; Hart et al., 2005; Coburn et al., 2007; Pateman, 2011).

Among the abundance of rurality measures and the significance they carry, there exist two well-established definitions of rural produced by two different federal agencies (ie., the U.S. Census Bureau and the Office of Management of Budget) that are used by researchers and policymakers across the United States. While these established definitions are used quite frequently, they are not adequate for understanding different rural systems nor supporting all designs of research. As a whole, research design for rural-specific questions hold at stake the possibility of misrepresenting rural conditions as well as categorically mis-aligning areas as rural or urban which may not reflect reality (Isserman, 2005; Coburn et al., 2007).

In the coming subsections, there is an extensive discussion of the background and uses of common definitions of rural established by the Census Bureau and the Office of Management and Budget. This transitions to how agencies have improved their definitions and how they both have impacted the work of researchers and policymakers. Through understanding the methodology behind federal definitions of rurality and why a researcher might construct their own measurement, we in turn enrich our own empirical framework used to define rural. By carefully producing an end product that accurately reflects the rural-urban landscape, we substantiate the "rural" in our analysis of rural-urban differences in economic resilience.

2.2.1 Census Bureau Delineation of Rural

The Census Bureau defines rural as delineation of an area "that which is not urban." This delineation comes from an established set of socio-demographic and geographical characteristics for areas across the United States. Although stemming from a pre-defined set of variables, their definition of rural is by no means static. The Census Bureau has continued to iteratively build upon their definition to delineate areas "that-are-not rural" because of the complexity that naturally occurs in such a typological approach (Isserman, 2005; Waldorf, 2006; Ratcliffe et al., 2016). For example, Census Bureau designations of urban clusters (UC) and urbanized areas (UA) within the united States changed between 2000 and 2010 among changes in delineations (Table 2.1).

Table 2.1: Urban Area and Urban Clusters composition of the United States (2000 - 2010)

Area	Number of Areas	2010 Population	2000 Population	% of 2010 Population	% of 2000 Population
United States	3,573	308,745,538	281,421,906		
Urban		249,253,271	222,360,539	80.7%	79.0%
Urban Area	486	219,922,123	192,323,824	71.2%	68.3%
Urban Cluster	3,087	29,331,148	30,036,715	9.5%	10.7%
Rural		59,492,267	59,061,367	19.3%	21.0%

Source: 2010 Census Urban and Rural Classification and Urban Area Criteria, Department of Commerce

Researchers might employ this definition due to the geographical variation that it describes and that census data are a resource that is low cost and easily accessed (free and readily available through federal agencies). In addition, these definitions are used extensively in program funding decisions relating to rural health and economic development (Isserman, 2005; Ratcliffe et al., 2016).

2.2.2 Office of Management and Budget's Delineation

The Office of Management and Budget (OMB) defines rural at the county-scale (Figure 2.1) and provides standard geographical delineations for statistical purposes. Specifically, the definition of rural for the OMB falls under a subcategory for their standards that define metropolitan and metropolitan areas (Office of Management and Budget, 2010). This greater category is denoted as Core Based Statistical Areas (CBSA). To differentiate between micro- and metropolitan areas, they define a Metropolitan Statistical Area (MSA) as a CBSA with at least one urbanized area that has a population of at least 50,000 and comprises the central county and adjacent outlying counties. The Micropolitan Statistical Area (MiSA) is a CBSA with one urban cluster between 10,000 to 50,000 persons and comprises a central county or outlying counties containing the area. Lastly, nonmetropolitan CBSAs are "noncore" counties that do not contain an urban area and have populations less than 10,000.

Figure 2.1: U.S. County Core Based statistical Area delineations

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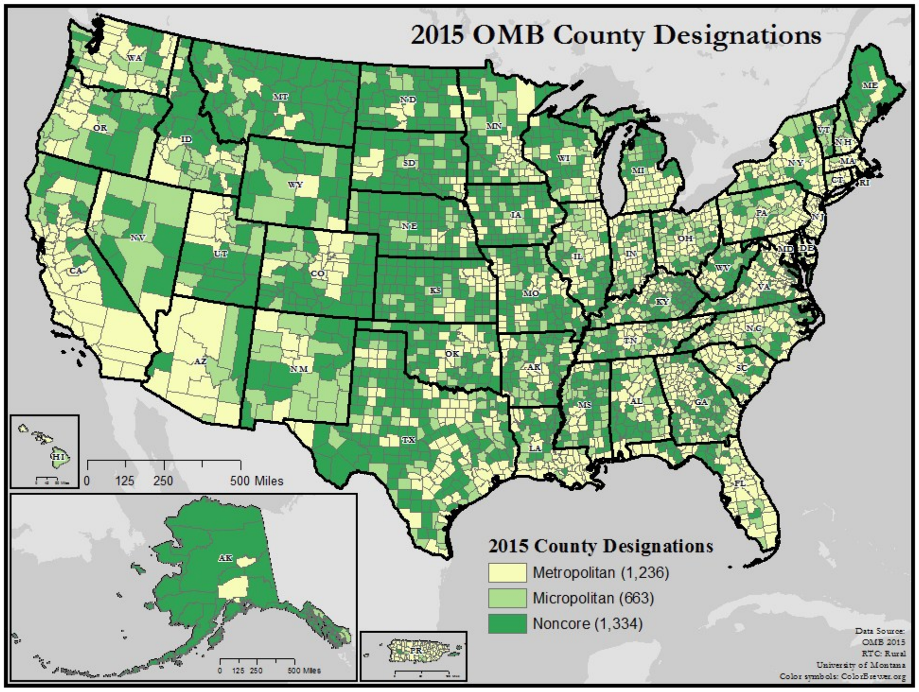


Federal agencies such as the Economic Research Service of the United States Department of Agriculture (USDA) and the National Center for Health Statistics of the Center for Disease Control and Prevention (CDC) use the OMB's measures for their agency-specific responsibilities. The Economic Research Service's popular system for defining rurality stems from the Rural-Urban Continuum Codes (RUCC), whereas the CDC's Urban-Rural Schema uses OMB measures and refine them to capture more variation by adding additional sub-categories. (United States Department of Agriculture, 1986; Ingram and Franco, 2006).

2.2.3 Statistically Applied Measurements of Rurality

Asking "what is rural" has always been a multifaceted question. When researchers use statistical estimators to measure rurality, they do so as a means to preserve the important aspects of rurality through such multivariate analysis. Early work applying such an approach used statistical estimation techniques to quantify rurality and to tease out the essential underpinnings of what makes a region more rural or urban while also allowing for quick replicability to assess how different rural regions fare over time (Cloke, 1977; Cloke and Edwards, 1986; Harrington and O'Donoghue, 1998). The older measures of rural contributed to the greater academic discussion during a time where the greater understanding of rurality was fuzzy (Hoggart, 1988, 1990; Halfacree, 1993). Over time, the appeal of these statistical approaches has grown for particular applications; for example, researchers are able to examine dynamic spatio-temporal aspects of rurality which are made possible with modern day statistical and computational power (Ocaña-Riola and Sánchez-Cantalejo, 2005; Waldorf, 2006; Prieto-Lara and Ocaña-Riola, 2010; Li et al., 2015; Beynon et al., 2016).

Similarly, current measures of rurality give policymakers and researchers a broader perspective beyond a discontinuous view of rural. Through capturing the nuance of rurality along a continuity, researchers have seized many opportunities to examine economic questions relating to the impact of rurality that would otherwise be improbable without the use of such calculations (Duenckmann, 2010; Li et al., 2015; Beynon et al., 2016; Dinh et al., 2017). Nonetheless, this form of measurement has introduced its own trade-offs. For example, we make a trade off from the limitations contained within a statistically quantified estimate of rurality and how it may or may not reflect reality alongside contributing to misspecification or violations of statistical assumptions in econometric analysis (Agarwal et al., 2009; Angrist and Pischke, 2009; Dinh et al., 2017).

2.3 Rural Linkages to Economic Resilience and Short-term Recovery

Economic resiliency has recently become a subject of investigation to understand how regions respond to shocks (Pendall et al., 2010; Pike et al., 2010; Martin and Sunley, 2015; Faggian et al., 2018). As a means to understand how regions may resist or be vulnerable to shocks, the evolution of its analysis has established aspects researchers ought to consider such as: *"Resilience of what? resilience to what? Resilience for whom?"* (Briguglio et al., 2006, 2009; Simmie and Martin, 2010; Dinh et al., 2017; Di Caro and Fratesi, 2018). To evaluate the ways regions have shown resiliency, researchers have used a wide range of models such as input-output estimation of region-level industries (Diodato and Weterings, 2015; Martin et al., 2016; Giannakis and Bruggeman, 2017), time-series analyses that investigates long-run trends (Fingleton et al., 2012; Cellini and Torrisi, 2014; Di Caro, 2015), multivariate indices and indicators (Masik and Rzyski, 2014; Dinh et al., 2017), and broad econometric models to estimate levels of impact pre- and post-economic shock (Angulo et al., 2018; Mazzola et al., 2018; Fratesi and Perucca, 2018; Rizzi et al., 2018).

The bedrock of empirical work acknowledges that resiliency is the capacity of a region to adapt to various forms of exogenous shocks (Martin, 2012; Martin and Sunley, 2015; Modica and Reggiani, 2015). Such discussion has also encouraged further empirical work for localized areal units and how the response to such shocks may differ between rural and urban localities (Fieldsend, 2013); the stock of human and financial capital, economic diversity and accessibility (Dinh et al., 2017); the examination pre-shock conditions, geographical place, and age structure (Kitsos and Bishop, 2018); and the role that entrepreneurs play that mitigate and help recover from economic shocks (Williams et al., 2013).

The contributions of entrepreneurs to the resilience of regions are of greater interest to researchers and federal agencies. Past discussion of entrepreneurial impacts has investigated features such as behavioral traits and abilities that help firms adjust to new economic circumstances, which can enhance the survival of firms and mitigating of industry-specific shock (Davis et al., 2007; Biggs et al., 2010; Zenka et al., 2017; Moore et al., 2018). Similarly, shocks to a region can also be offset by entrepreneurs where their prospects become more lucrative in relation to the decline in wages or employment opportunities (Glaeser et al., 2014); and offering alternative paths of local and rural development through business tax streams and migratory opportunities (Bosworth and Atterton, 2012; Baumgartner et al., 2013). Thus, the presence of entrepreneurs and entrepreneurial opportunities can both be important to rural regions. Entrepreneurial networks in these localized areas act as vital elements to the establishment of business and learning networks

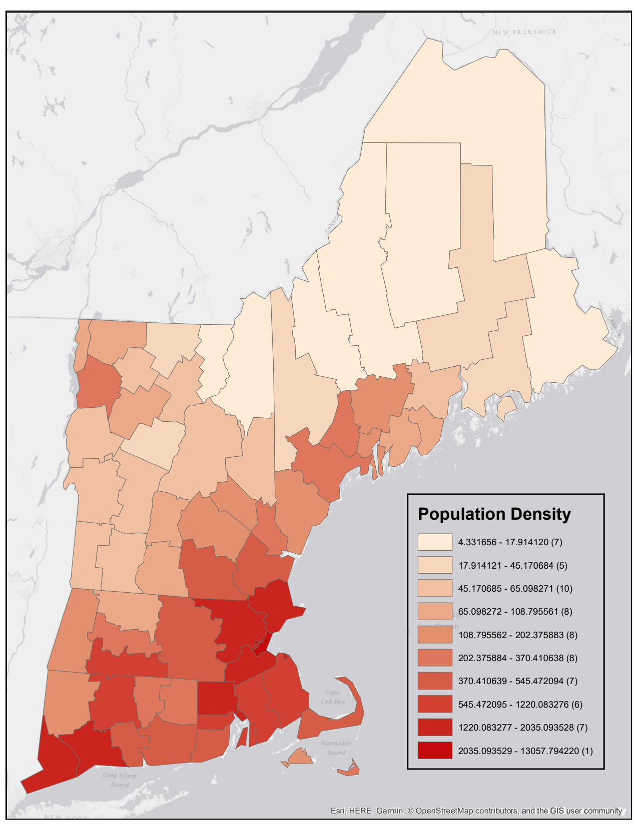
(Glover, 2012; Lang and Fink, 2018), drivers of improvement for the development of skills (Richter, 2017), and as transformative drivers in path creation for economic opportunities (Tonts et al., 2014; Cedric and Spigel, 2017).

2.4 Methodology

2.4.1 Study Area

To evaluate the impacts of rurality on a region's ability to rebound from economic shocks, we use county-level data in New England between the period 2011 to 2015. The start of this period takes place two years after the end of the Great Recession and provides short-run observations as how counties have fared. The region has a diverse mixture of rural and urban counties and thus provides an excellent study area to study differences in economic resilience (Figure 2.2).

Figure 2.2: Spatial distribution of population density in New England, 2015 American Community Survey 5-year averages



To further contextualize a rural-urban profile of New England, the region is home to two of the most rural states within the U.S. Under the Census delineation for Urbanized Areas. In 2010, the percentages of Maine and Vermont's population that lived outside of an urban area were 61.3 percent and 61.1 percent respectively. This is in stark contrast to more urban states such as Massachusetts and Connecticut which had 8 and 9.3 percent of their total respective population residing in a rural area in 2010 (United States Census Bureau, 2012b). The differences between New England counties do not end only with population density– both economic and demographic characteristics similarly vary (Table 2.2). While not proxies for rural individually, data such as income levels, the working age for people, and migration rates can similarly illustrate a richer depiction of rurality (Beynon et al., 2016).

Table 2.2: Selected characteristics of New England's least and most densely populated counties (2015 American Community Survey 5-year averages)

County	Pop. Density	Med. Income	Med. Male Age	Net Migration (%)
Least densely populated areas				
Piscataquis County, Maine	4.33	37495	46.6	0.2
Essex County, Vermont	9.35	36599	45.7	5.5
Coos County, New Hampshire	17.76	42312	44.8	-8.5
Hancock County, Maine	34.44	47030	43.6	-2
Orleans County, Vermont	39.16	42831	42.8	2.5
Most densely populated areas				
Suffolk County, Massachusetts	13057.79	55044	33.5	5.5
Bristol County, Rhode Island	2035.09	72458	42.6	4.8
Essex County, Massachusetts	1546.99	69068	42.1	4.7
Providence County, Rhode Island	1539.56	49743	39.1	-0.9
Fairfield County, Connecticut	1504.34	84233	42.5	-1.7

2.4.2 Calculating an Index of Rurality

To estimate our index of rurality we use data from several primary sources over the period of 2011 through 2015. For each year, we use county-level data from the American Community Survey's 5-year averages dataset hosted by the Census Bureau, which are best used to precisely analyze small geographical units and where there exist small populations (United States Census

Bureau, 2018), to develop annual estimates of key variables. Rurality is measured through a selection of key variables data for every year in our period: (1) the median income, (2) population density, (3) the male and female median working age, (4) percentage of a county's population with a bachelor's degree or higher, (5) percentage of a countys population with a high school degree, (6) the percentage of a county's population with no higher than a high school degree, (7) net migratory patterns, (8) housing availability, (9) the percentage of the population older than sixty-five, (10) unemployment levels, (11) the change in population in a one-year period, (12) the location quotient of a county's industrial composition in agriculture, (13) and access to broadband internet per 1,000 households (Table 2.3).

Table 2.3: Descriptive and summary statistics for rurality in New England counties (2011 - 2015)

Variable	Mean	Standard Deviation	Description
Income	57476.96	12696.44	Median household income. Small Area and poverty Estimates (SAIPE), 2011-2015.
Internet	786.58	114.9	Residential fixed internet access connections per 1,000 households. Form 477 FCC Data, 2011-2015.
Unemployment Rate	7.49	1.74	Rate of unemployment. Bureau of Labor Statistics, 2011-2015.
Male Median Working Age	42.71	2.16	Median working age of males. ACS 5-year averages, 2011-2015.
Female Median Working Age	43.03	2.5	Median working age of females. ACS 5-year averages, 2011-2015.
% of Population with no High School Degree	6.13	1.58	Percentage of adults with less than a high school degree. ACS 5-year averages, 2011-2015.
% of Population with High School Degree	31.64	5.87	Percentage of adults with a high school degree. ACS 5-year averages, 2011-2015.
% of Population with Bachelor's or Higher	31.86	8.49	Percentage of adults with a bachelor's degree or higher. ACS 5-year averages, 2011-2015.
Net Migration	0.13	4.6	Total number of persons entering or leaving county. Population Estimates Program (PEP) 2011-2015.
Housing Stock	95862.01	118426.3	Number of dwelling areas. ACS 5-year averages, 2011-2015.
Population Density	569.21	1576.367	Number of people living per square mile. 2009 ACS Geographic Indicators and ACS 5-year averages, 2011-2015.
% of Population Age 65 or Higher	16.21	2.92	Percentage of people age 65 or older. ACS 5-year averages, 2011-2015.
Population Change	0.01	0.55	Percentage change of total population. Economic Research Service (USDA), 2011-2015.
Location Quotient of Agriculture	1.6	1.7	Location quotient for agriculture. Bureau of Labor Statistics, 2011-2015.
Total observations: 335			

Using this set of variables, we use factor analysis to measure our index of rurality. Factor analysis is a statistical tool that describes the covariation between these variables in the form of a factor variable. As opposed to principal component analysis (PCA), a closely related estimator, factor analysis assumes a statistical model which uses the covariation from a set of variables to estimate a *latent* variable which has the unique feature of explaining the covariation in the original variables in terms of itself. This distinction is a valuable component to our framework because of the inherent fuzzy nature of rurality, which is something influenced by other observable variables (Waldorf, 2006). Drawing upon this, we assume a model that estimates rurality as a latent factor influenced by a set of observable characteristics as:

$$R = \mu + L\mathbf{X} + \varepsilon \tag{2.1}$$

where R is a single latent factor that estimates a "degree of rural" a county is,[1] μ as a vector of means for a given variable x, $\mathbf{X}$ as the vector of variables $x_1 \ldots x_n$ used to estimate the index, L denotes the set of factor loadings for each variable, and ε as the vector for the latent error term. Using factor analysis satisfies several key threads to our narrative. We have discussed that the extent to which a region is rural is fuzzy and that non-statistical metrics may lack precision. Factor analysis offers a solution to this concern by estimating rurality as an output from other relevant variables available to us. Second, our output contextualizes a temporal aspect where we can see how counties may persist or develop beyond its rural roots. This is widely attractive for our time period where across the nation rural employment has yet to return to pre-recession levels and federal agencies are supporting rural infrastructure for amenities such as broadband internet (Department of Agriculture, 2017).

To enhance our analysis, we utilize Cronbach's alpha, the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO), and Bartlett's test of spherecity to assess the consistency and validity of our data for factor analysis. The alpha is a lower-bound coefficient for a researcher's accepted

[1] In the context of this analysis we constrain rurality as a single factor from factor analysis. Such constraints have been relaxed in previous work to see how rural dynamics differentially vary due to other socio-demographic and economic variables (Beynon et al., 2016).

level of precision, the KMO for internal data adequacy for factor analysis (Table 2.4), and Bartlett's test for how related our variables are and their suitability for factor analysis.[2]

Table 2.4: Data validation statistics for the use of factor analysis

Cronbach's Alpha	
Cronbach's Alpha	$\alpha \geq .7$
Range of interitem correlations	$.15 \geq \alpha \leq 1$
Average interitem correlations	$.15 \geq \alpha \leq .5$
Kaiser-Meyer Olkin Measure	
.91 through 1	Marvelous
.81 through .9	Meritorous
.71 through .8	Middling
.61 through .7	Mediocre
.51 through .6	Miserable
Less than .51	Unacceptable

Beyond the tests for valid output from factor analysis, we use a fixed-effects model to evaluate changes in our measure across the initial and end-period of our sample. Because our index is examining a measurement across samples over a five year period, we must ensure that there is a check against homogeneity within our sample. We follow similar robustness checks from (Dinh et al., 2017) to check if our index of rurality shows systematic change between our initial period (2011) and end period (2015) by using a fixed-effects estimation. The use of a fixed-effect model in this context is adjusted for state-specific and time invariant effects in order to test for regional changes in rurality:

$$\underset{\{S_1 \ldots S_6\}}{R_{it}} = \alpha_i + \beta D_R + \varepsilon_{it} \tag{2.2}$$

Rurality is specified as our outcome variable R for county i in year t for state S. α denotes the

[2] Interitem correlations examine the extent to which the loading score on one variable is related to scores on all other variables in a scale. The output of factor analysis denotes a degree of redundancy to the extent which variables on a scale are assessing the same content (Cohen and Swerdlik, 2005). We supplement our full results of factor analysis with this in Appendix A.1.

time-invariant effect within the fixed effects model, D is a dummy variable equal to zero in 2011 and equal to one in 2015, and ε as our error term. We run this model six times to measure the change of rurality for every county in each specific state. In these estimations, the change in the constant term denotes the shift in rurality between these years. If $\alpha > 0$, this implies that the change in rurality has increased since 2011 while $\alpha < 0$ implies a decrease in the degree of rurality between the initial and end period. We also measure a shift of rurality for all county observations for our our index alongside a cross-comparison of OMB delineations of micro- and metropolitan statistical areas.

2.4.3 Measuring the Association of Rurality to Resilience

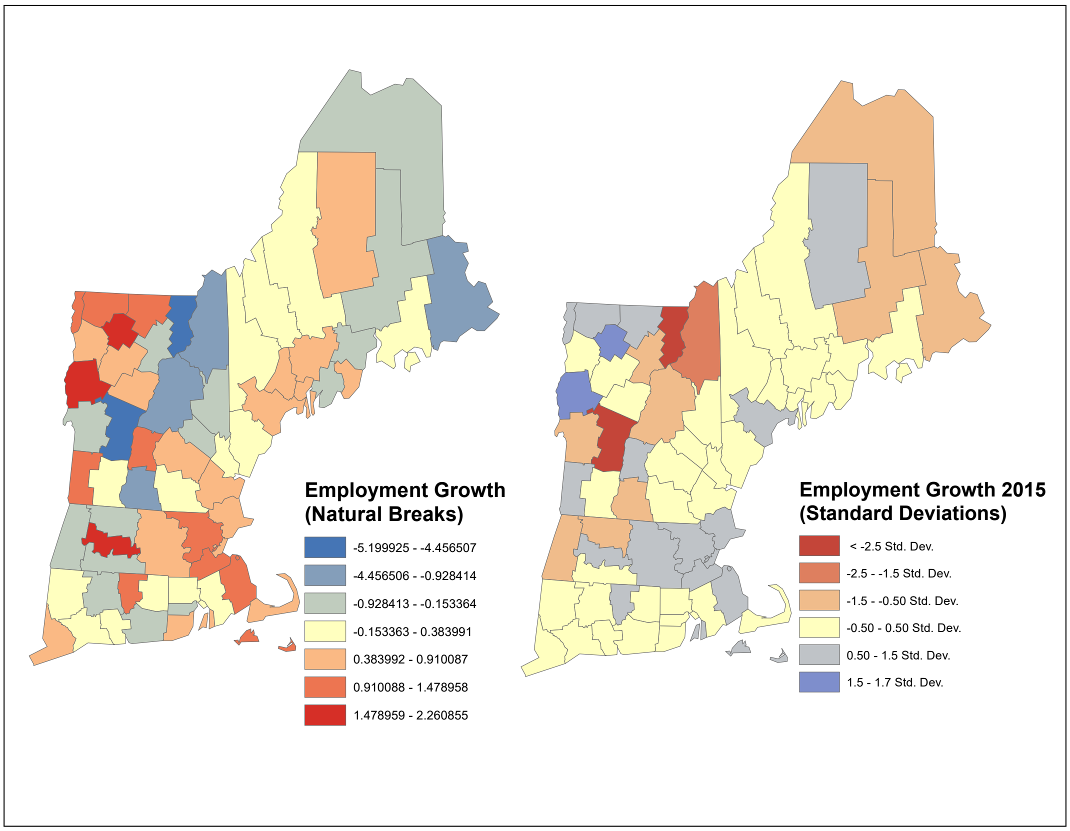
To investigate the linkage between the potential for regions to recover from economic shocks and their degree of rurality, we employ data from County Business Patterns that measures the relative growth of employment since 2009 for the years within in our sample (2011-2015). Our dependent variable is calculated as the ratio of growth in employment for a county to the growth of employment nationwide:

$$EGR = \frac{\Delta e_{i_{2009-t}}}{e_{i_{2009}}} \Bigg/ \frac{\Delta E_{r_{2009-t}}}{E_{r_{2009}}}, \tag{2.3}$$

where e is the level of employment in county i for each year of t within our sample and E is the greater level of employment within the United States (denoted as r). While a comparative statistic, this nonetheless reveals what counties rebounded from a recessionary shock in relation to a greater whole. Similar ratios have been utilized in regional economic studies that sought to explain economic resilience in part by a region's degree of resistance to economic shocks (Martin, 2012; Faggian et al., 2018).

This ratio represents short-run responses to recessionary shocks. Within the context of this work, we are interested in the changes in employment after the Great Recession. The year 2009 was considered to be the end of the Great Recession, which we justify as the initial period in which we calculate our dependent variable. While some areas across the nation saw growth in employment since 2009, there exist counties that have seen little or negative growth. For New England in particular, employment growth reveals an intuitive pattern where there is high growth in counties near metropolitan areas such as Boston, Massachusetts; Burlington, Vermont; Providence, Rhode Island; and Portland, Maine; and areas of high losses in more northern counties or otherwise peripheral and remote parts of the greater region (Figure 2.3).

Figure 2.3: Cross-sample decomposition of employment growth between 2009-2015 by levels and standard deviation



Alongside our dependent variable, we have identified several key variables to help predict the relative growth of employment in counties (Table 2.5). First, we control for the annual growth rate of nonemployer establishments. Nonemployers have been increasingly analyzed with regards to contribution of lagged establishment growth (Acs et al., 2009). A nonemployer is a business with no employees, reports at least $1,000 in annual sales receipts, and is subject to federal income taxes.

Similar to entrepeneurs, the existence of nonemployers creates learning opportunities for future businesses, flexible work options, and an economic cushion and empowerment for these type of employers (Acs et al., 2009; Kacher and Weiler, 2017; Moore, 2018). Furthermore, previous literature highlights nonemployers as a channel to mitigate economic shocks through a flexible output structure, diversification of a region's economy, and knowledge spillovers; and influences to the growth of future employers across rural and metropolitan areas (Fritsch and Noseleit, 2013a,b; Liang and Goetz, 2016; Moore et al., 2018).

Table 2.5: Summary statistics for the impacts of rurality on economic resilience

	All			Metro			Micro			Noncore		
Variable	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Employment Growth Ratio	-1.03	-70.41	11.21	-0.45	-13.10	11.21	-2.87	-70.41	6.33	-0.50	-21.12	6.95
Rurality	0.00	-2.39	2.71	-0.54	-2.39	0.85	0.44	-1.79	2.71	0.66	-2.37	2.13
Regional Specialization Index	0.26	0.10	0.65	0.19	0.10	0.39	0.28	0.18	0.53	0.35	0.23	0.65
Annual Growth rate of Nonemployer Firms	0.44	-6.31	7.70	1.00	-3.94	7.70	-0.15	-6.31	4.98	-0.10	-5.98	6.39
Log Median Income	10.91	0.96	11.39	11.05	10.68	11.39	10.89	10.48	11.19	10.63	0.96	11.37
Log Unemployment Rate	1.98	1.03	2.43	2.05	1.59	2.42	1.90	1.34	2.43	1.94	1.03	2.42
Log Number of Establishments	7.95	4.72	10.68	8.69	5.18	10.68	7.34	4.72	8.50	7.05	6.08	7.71
Log Employment Rate	4.10	3.82	4.30	4.12	4.00	4.22	4.11	3.94	4.19	4.05	3.82	4.30
Log Labor Force Participation	4.18	3.93	4.34	4.21	4.09	4.29	4.18	4.04	4.25	4.13	3.93	4.34
Population Density	569.21	4.33	13057.8	1051.7	45.16	13057.8	93.77	9.35	206.09	52.14	4.33	235.67
Log Median Age	3.76	3.49	3.85	3.73	3.49	3.85	3.78	3.72	3.83	3.78	3.70	3.85
Net Migratory Patterns	0.13	-15.60	30.50	0.86	-12.30	10.60	-0.92	-15.60	30.50	-0.33	-9.60	16.60
Observations:		335			170			79			86	

Beyond nonemployers, our analysis include several other key factors: (1) Net migratory patterns, defined as the difference between the number people moving in and out of the county in a given year; (2) the median age of the population in a given county; (3) the labor force participation rate in a county; (4) employment rate; (5) unemployment rate; and (6) the median per-capita income. We also control for the heterogeneity of industrial composition for different regions by adopting a measure of regional specialization in (Moore et al., 2018). This measure is the overall summation of the differences in county-level industry employment shares to the national average across all two-digit NAICS industries. With these variables, we estimate the following model to evaluate the relationship between economic resiliency and rurality:

$$\begin{aligned} EGR_{it} = \alpha_{it} + \gamma_0 Rurality_{it} + \gamma_1 RS_{it} + \gamma_2 NG_{it} + \gamma_3 EF_{it} + \gamma_4 INC_{it} + \gamma_5 UR_{it} \\ + \gamma_6 ER_{it} + \gamma_7 LFPR_{it} + \gamma_8 PD_{it} + \gamma_9 AGE_{it} + \gamma_9 MIG_{it} + \varepsilon_{it} \end{aligned} \quad (2.4)$$

where our dependent variable EGR is the ratio of a county's growth of employment since 2009 to United States's growth, α_{it} as our time and space invariant term, $Rurality$ is the value of rurality (measured through factor analysis) for county i in year t; RS, is a measure of regional specialization, where the extent in which county i's economy is more concentrated in specific industries; NG, is the annual growth rate of nonemployer establishments; and EF is the number of establishments across all industries in a given county; INC is the median income for a county, UR is the unemployment rate, ER is the employment rate; $LFPR$ is the rate of participation in the labor force; AGE is the median age; MIG is the net migratory pattern in a county during year t; and lastly, ε as our error term.

2.5 Discussion

2.5.1 Estimation Results from Factor Analysis

Table 2.6 shows the factor loadings on our variables for rurality from 2011 to 2015. We employed a varimax rotation, changing the orthogonal basis to find the rotation which maximizes the variance between our test variables. Complimenting these results are the results from our diagnostics. The KMO falls under an acceptable range greater than .7 and Bartlett's χ^2 highlights our data was acceptable for factor analysis. Due to the high amount of output from our estimation and diagnostics, Appendix A.1 show in detail the results of factor analysis for individual years.

Table 2.6: Estimation of rurality for New England counties (2011 - 2015)

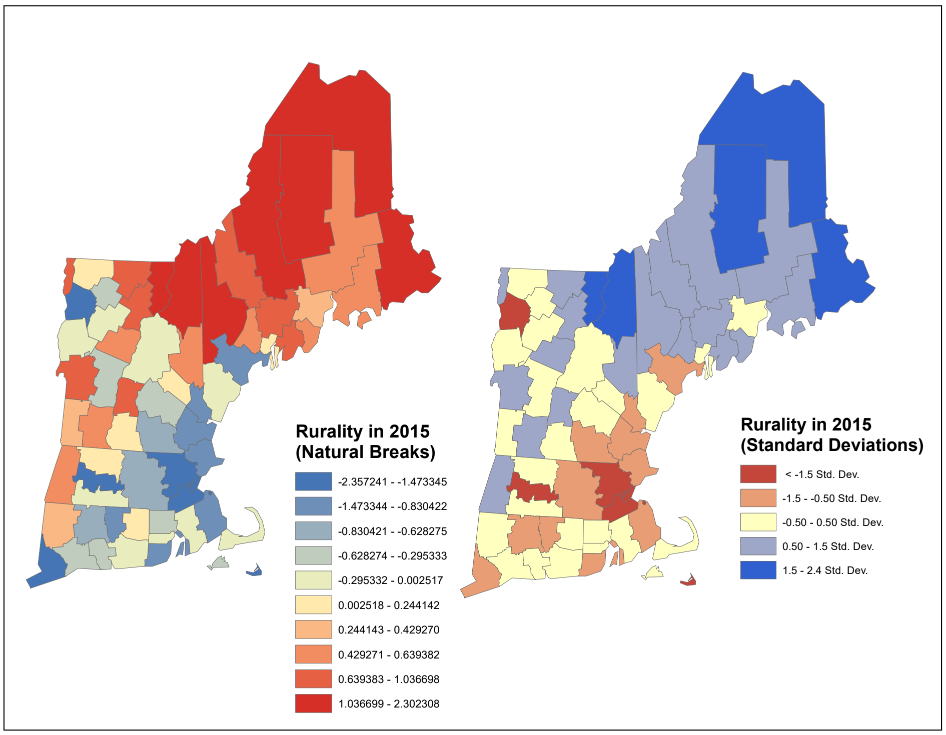
Factor Analysis					
Method: Principal Factors					n = 67
Rotation: Orthogonal Varimax					Retained Factors: 1
	Factor Loadings				
Variable	2011	2012	2013	2014	2015
Median Income	0.783	0.755	0.800	0.795	0.771
Internet	0.702	0.561	0.514	0.404	0.575
Unemployment	-0.196	-0.293	-0.292	-0.279	-0.229
Male Median Age	-0.638	-0.610	-0.604	-0.628	-0.667
Female Median Age	-0.647	-0.595	-0.543	-0.601	-0.654
Less Than High School	-0.499	-0.585	-0.594	-0.570	-0.535
High School Degree	0.843	-0.863	-0.899	-0.847	-0.870
Bachelor's or Higher	0.870	0.858	0.895	0.869	0.860
Total Net Migration	0.469	0.749	0.642	0.331	0.416
Housing	0.583	0.522	0.505	0.521	0.560
% of Pop. 65 or Older	-0.656	-0.633	-0.604	-0.668	-0.679
Population Density	0.485	0.438	0.428	0.425	0.470
Population Change	0.724	0.833	0.776	0.759	0.697
LQ of Agriculture	-0.446	-0.577	-0.448	-0.497	-0.484
Diagnostics					
Eigenvalue	5.634	5.973	5.630	5.256	5.520
% of Variance	0.519	0.544	0.527	0.508	0.526
Overall KMO	0.713	0.765	0.736	0.730	0.725
Bartlett's χ^2	895.88	934.78	871.39	782.81	834.79
$p > \chi^2$	0.000	0.000	0.000	0.000	0.000

We expect to see the signs of the factor loadings resemble the expected signs as shown in Table 2.6 because the loadings determine the impact the measure of rurality for a given county.[3] We expect, for example, population density to be positive as a higher concentration of people in a square-mile area can be associated with a higher degree of economic development. We see that across most variables in the period of 2011 to 2015 that our variables follow our expected signs. Median income, internet per 1000 households, net migration, the housing stock in a county, population density, and population change all have a positive factor loading on the score of rurality for a county. We also see that variables which should have negative signs such as unemployment, male and female median working age, the percentage of a county's population with less than a high

[3]A positive coefficient indicates that a county is *less rural* (or more urban) and a negative coefficient indicates a county is *more rural.*

school degree and high school degree, the percentage of the population aged sixty-five or older, and the location quotient of agriculture have corresponding negative values across years. The sole exception to this observation is with our high school degree variable which has a positive sign in 2011.

Figure 2.4: Sample-wide composition of rurality in New England counties during 2015



Mapping the results from factor analysis unveils the spatial disparity of rural and urban areas across New England for 2011 and 2015 (Figure 2.4). A more positive value denotes that an area is more rural and a negative value will denote the converse. There was little difference in the magnitude of rurality in New England as a whole, and on a state-by-state basis, there exist a wide range of change between our initial and end periods. We see that the state of Maine, New Hampshire, and Vermont become marginally more rural, and the state of Connecticut, Massachusetts, and Rhode Island become marginally more urban in this short window of time.

Table 2.7: Fixed effects estimation on the change of rurality between 2011 and 2015

Fixed Effects Estimation Group: County				n = 134 t = 2011, 2015
Region	D_R	Noncore (n=34)	Micropolitan (n=32)	Metropolitan (n=68)
Connecticut	-0.478*** (0.052)	-	-	-0.574*** (0.059)
Maine	0.702*** (0.045)	1.084*** (0.062)	-	-0.014 (0.066)
Massachusetts	-0.853*** (0.058)	-	-	-0.870*** (0.033)
New Hampshire	0.158*** (0.022)	-	0.54*** (0.035)	-
Rhode Island	-0.342*** (0.026)	-	-	-0.342*** (0.026)
Vermont	0.332*** (0.039)	0.377*** (0.063)	0.664*** (0.068)	-
New England	$-4.67e^{-9}$ (0.011)	0.724*** (0.044)	0.417*** (0.052)	-0.559*** (0.025)

Cluster robust standard errors shown in parentheses
*** - p > 0.001; ** - p > 0.05; p * - p > 0.1

Alongside the spatial distribution of our rural index in 2015, Table 2.7 highlights the average change and significance between our initial and periods through a fixed effects estimator. The region was segmented in two levels: We assess for changes of rurality first for individual states; second, by examining New England alone. We supplement the change of our rurality index with the change of rurality for each county and New England as denoted by OMB delineations. The listed observations for each column denotes the number of counties in New England that fall under each OMB classification and any unlisted coefficient is due to an insufficient sample size to measure the average change. Comparatively, the estimates for our rurality index highlight smaller changes between the two periods for more rural states.

2.5.2 Fixed Effects Estimates for the Impacts of Rurality on Economic Resilience

Our hypothesis is that after the end of the Great Recession (June 2009), counties that are more rural will see relatively less employment growth than what was gained across on the nation on average. To test this, Table 2.8 presents the results of our primary regression. While we cannot translate our coefficients to direct numbers in employment, the interpretation of coefficients indicate a relationship between the degree of rurality and how better or worse the growth of employment since 2009 was for counties. We also segment our results into two separate columns to compare between the estimate from ordinary least squares (OLS) with cluster robust standard errors and with fixed effects to provide insight on how the changes between state and yearly effects change our rurality variable.

Table 2.8: Regression output for the impacts of rurality on economic resiliency

Dependent variable: Employment Growth Ratio (EGR)

Variable	Model 1	Model 2
Rurality	**-1.847***** (0.645)	**-6.473**** (1.97)
Regional Specialization Index	-8.469 (10.049)	-8.584 (67.279)
Growth Rate of Nonemployer Firms	0.089 (0.094)	0.430 (0.282)
Log Median Income	**0.295*** **(0.138)**	-0.115 (0.061)
Log Unemployment Rate	-2.262 (3.402)	-9.052 (10.745)
Log Number of Establishments	-0.364 (0.462)	$2.87\text{x}10^{-4}$ (0.001)
Log Employment Rate	-17.803 (22.158)	-3.486 (1.981)
Log Labor Force Participation	2.916 (27.365)	2.340 (1.9)
Population Density	$9.58\text{x}10^{-5}$ $1.78\text{x}10^{-4}$	0.001 (0.003)
Log Median Age	13.350 (8.077)	**3.782*** **(1.658)**
Net Migratory Patterns	0.006 (0.078)	**-0.187**** **(0.071)**
Constant	15.896 (44.515)	-86.193 (71.036)
ρ	-	**0.769**
Fixed Effects	-	State
Observations	335	335

Cluster robust standard errors shown in parentheses
*** - p > 0.001; ** - p > 0.05; p * - p > 0.1

Rurality was coded to be positive for rural areas and negative for urban areas, lending to the reader a more intuitive reading of our results. Between our two regressions for this analysis we find that the degree of rurality has a nontrivial relationship to relative growth of employment across counties. For both models with and without fixed effects, the coefficient gained a higher magnitude and, while controlling for state and yearly effects, the relationship still holds. Interpreting our coefficients show that between relative employment growth and rurality that a one-point increase in our index yields a -1.847 and -6.473 decrease in growth on average for both model estimates. While a cursory glance would show that such a response is high, the range of values our observations take on for this variable is between a tight interval (Table 2.5). Thus, a one-unit increase rurality is an extreme shift to a variable that is relatively homogeneous within our sample.

For both models, few control variables are statistically significant, with some having weak relationships or losing their significance entirely once controlling for state and yearly effects. We see that within that model without fixed effects that the log of median income positively corresponded with the employment growth ratio, where a one-percent increase of the median income in counties indicated a .295 increase in the relative employment growth on average. Within our fixed effects regression, both the median age and net migratory patterns become significant with surprising signs. We find that the higher the median age was in a county, the higher a county saw relative employment growth on average; and, for net migration patterns, the converse was true. Some reasons why both net migration and the median age may have these signs is that our fixed effects is estimating both within-state and yearly effects of our predictors on the ratio of relative employment growth. As such, these signs may be indicative of a region-specific effect for our sample, as opposed to something that is representative of the United States.

2.6 Conclusions

Evaluating the relative speed of economic recovery with respect to a county's degree of rurality is no easy task because rurality is a variable that rarely changes in short periods of time.

Nonetheless, there are certain defining characteristics of what makes an area more or less rural that plays into a county's level of resilience. As such, stakeholders ought to construct policies that acknowledge, and ultimately overcome, such differences to help non-urban areas recover. Similarly, stakeholders must also be made aware of the fuzzy boundaries of rurality and that the methods in which policy can be reached to rural areas may differ individually. Consistent with (Beynon et al., 2016) and (Dinh et al., 2017), there is much to be drawn upon in the discussion of rurality's impact to a region's resilience and how an understanding of it can translate into policy-making decisions that can reach these areas to alleviate economic and social woes.

A goal of this research was to first synthesize regional science research with rural-specific literature to establish a framework in order to measure the impacts rurality has on economic resiliency. For researchers interested in rural studies, the first hurdle to pass is to ultimately define and identify what rural is due to its fuzzy characteristics and how it can differ between regions and academic disciplines. In light of this, we utilized a reproducible framework of measuring rurality through the use of factor analysis. With our measure of rurality, we then implemented the measure in a model to analyze its relationship with a region's degree of economic resilience. The driving hypothesis behind evaluating this relationship is that rural counties will have a lower degree of resiliency to economic shocks on average and we uncovered estimates which suggest just that.

Utilizing past work such as (Martin, 2012) and (Faggian et al., 2018) to measure economic resiliency, we employed the ratio of employment growth in counties to nation-level employment growth since 2009. Consistent with past work, we found differing degrees of recovery in relative employment growth between rural and urban counties. Rather than interpreting this ratio's margins, the direction of coefficients informs us the relative speed at which rural and urban counties recovered on average. It is important to highlight that a key aspect to this paper is that its framework is context-specific to the Great Recession. Our results reflect the relative speed at which rural and urban regions rebounded from economic shocks as it relates specifically to this shock.

Taken altogether, we believe this work can act as a stepping stone for future research and provide insight to policymakers on how economic policy can further target rural areas. Knowing why some regions may recover faster than others is vital for social and economic well-being, and learning how rurality may dampen recovery provides to policymakers a deeper understanding of other variables that impact the efficacy of policy.

CHAPTER 3
MEASURING AND UNDERSTANDING THE SPATIAL DETERMINANTS OF RELATIVE ECONOMIC PERFORMANCE IN MAINE

3.1 Introduction

Measuring regional economic performance is a multidimensional process. Regional disparities in wages, employment levels, and labor market conditions can impact the performance of regions (Hanson, 2001; Porter, 2003; Martin, 2003; Agarwal et al., 2009; Delgado et al., 2014). However, when one tries to estimate a region's level of performance they may overlook the issues of simultaneity within their model. To illustrate, changes in employment may cause wages to systematically respond and feed back into the variation of employment. Similarly, spatial aspects such as the measurable distance to market and the proximity to economic centers highlight a systematic pattern of regional inequality where peripheral areas feature slow growth and development, contrasting regions near or within economic centers (Roos, 2001; Niebuhr, 2003; Hering and Poncet, 2006; Rice et al., 2006; Agarwal et al., 2009).

This work seeks to evaluate the spatial determinants of economic performance and highlight how the degree of market access and remoteness can impact a region's level of output. To this end, we first discuss past research in economy geography, contextualize the role of market access and remoteness in regards to how regions perform, and highlight other driving factors that contribute to economic performance. Second, we specify a model with simultaneous equations using data available from the U.S. Census alongside geographic data from the National Park Service and Google's Geocoding Service to help explain potential spatial differences in performance. Overall, our findings suggest there exist spatial inequalities of economic performance at the census tract level. We also find other economic factors impacting overall performance such as an aging workforce, workplace disability, and the level of human capital.

3.2 Past Discussions and Research

3.2.1 Measuring Regional Economic Performance

A large vein of research within regional sciences emphasizes the characterization of economic development and performance to be largely unequal between regions. Seminal work theorized that observable regional economic inequalities may be a characteristic of the broader force of agglomeration and how the spillovers and externalities thereof dissipates across economic space (Marshall, 1920; Hoover, 1948; Harris, 1954). From this, the theory of New Economic Geography (NEG) was proposed and established a framework for the occurrence of regional divergence and spatial agglomeration. Generally, as more linkages between industries in a region are established, the costs between transportation and trade steadily decreases until an optimal threshold where costs become sufficiently low, thus triggering more development within a core area (Krugman, 1991; Fujita et al., 1999; Fujita and Thisse, 2002; Baldwin and Martin, 2003). Relating to regional economic performance, the framework of NEG highlights a period of initial growth and decline. As the degree of interconnectedness between industries in a region rise from agglomerating forces, economic growth rises until a point of urban congestion and slows economic growth thereafter (Rauch, 1993; Dumais and Ellison, 1997). Simultaneously, as this process occurs, regional divergence occurs and reinforces an economic "core" where industries are tightly linked with minimized costs, and a "periphery" where the spillovers of agglomeration diminish outwards (Krugman, 1991, 1996a; Martin, 2008).

While the framework NEG solidified itself within regional sciences, there was a large need for empirical validation when numerical methods struggled with computational solutions and being applicable to regional policy (Black and Henderson, 1999). To date, there have been numerous of NEG-specific analyses that measure the impacts of spatial agglomeration. Such work includes evaluating the impacts of agglomeration through many dimensions, such as showing that high degrees of industrial localization can spur an increase in the birth of firms and increases in foreign investment (Wheeler and Mody, 1992; Rosenthal and Strange, 2003); the distance at which spatial spillover from agglomeration economies decay varies between industry type (Dekle and Eaton, 1999; Lo Cascio et al., 2019); and lastly, variation in trade patterns have been extensively discussed as a measurable variable of regional divergence (Ottaviano et al., 2002; Behrens, 2005a,b; Brunow and Grunwald, 2014; Hanlon and Miscio, 2017). Original NEG papers established how the externalities of agglomeration contributes to economic growth (Krugman, 1996b); however, there has been mixed empirical results between different studies that test the relationship between higher national growth and the degree of agglomeration (Martin, 2005, 2008; Lees, 2007).

Understanding the linkage between agglomerating forces and economic performance was largely motivated by the observation that regions were largely unequal in terms of output. A similar vein of literature sought to explain this feature through the clustering of firms in regions. Clusters are a group of tightly linked industries and have become an attractive measure for policymakers to utilize when they seek to reinforce economic development and performance (Delgado et al., 2016; Slaper et al., 2018). Such studies that focus on clusters assert that the initial conditions, economic structure, and inter-firm networking within a region also contribute to regional differences in economic growth (Porter, 1990, 2003; Audretsch and Fritsch, 2002). Similarly, the work of (Delgado et al., 2014) suggests that the strength of regional clusters matter for the growth of employment, corroborating similar empirical studies further promoting policy approaches that encourages reinforcing pre-established comparative advantages within a region's economy (Overman and Puga, 1999; Fujita and Thisse, 2002; Porter and Ketels, 2003; Hausmann and Klinger, 2007; Nathan and Overman, 2013).

In pursuit of the gains in economic growth and development, policymakers must remain cognizant of their region's current economic conditions and industrial composition. More recent studies discuss a sense of favoritism among regional planners giving priority to seemingly lucrative industries without identifying the current industries that have a higher degree of relative concentration (Martin and Sunley, 2003; Crawley and Munday, 2017). Ultimately, while clusters have been identified positively with growth and higher levels of performance they also have the potential to fall short of their image as a wonder growth strategy due to a lack of proper knowledge and fail to yield any benefit to regional performance (Asheim et al., 2009; Spencer et al., 2010).

3.2.2 Market Access and Peripherality

Between many discussions within regional economic literature, the significance of market access has been a reoccurring variable for explaining regional inequalities of economic development, growth, and performance. Pertinent to both NEG and cluster theory, "market access" highlights the potential of localities to engage in markets and how the degree of engagement can vary across geographic space. In relation to spatial agglomeration, localities within a core economic area face smaller costs to trade and transportation comparatively to regions outside the core as the externalities to agglomeration decay spatially outward (Krugman, 1991; Niebuhr, 2004). Thus, areas that are closer with market potential may systematically yield higher levels of performance in comparison to areas that are not. In such a manner, the capacity for regions to actualize the gains from having access to markets is ultimately spatial in nature.

Related to empirical observation of market access and its impact on regional performance, how one measures market access is relative to the form of analysis undertaken. Market access has been measured in terms of impacts to, or levels of, trade flows between regions (de Sousa et al., 2012); average levels of transportation costs (Combes et al., 2012); geography and the distance between separate points (Redding and Venables, 2004; Dijkstra and Poelman, 2008; Agarwal et al., 2009; Barbero et al., 2018; Verstraten et al., 2019); in terms of commuting times and patterns (Rice et al., 2006; Agarwal et al., 2009; Kimbrough III, 2016); and as a function of the degree of trade integration between regions (Hanson, 2001).

Ultimately, agglomeration places an emphasis on the capacity in which areas can access markets because of regional variation in factor prices across economic space. This variation can similarly be observed in other regional hierarchies across different fields of literature. Akin to the core-periphery model, the framework for an urban hierarchy compliments similar theories of economic geography to see how regional inequality of economic development persist across rural-urban space (Tabuchi and Thisse, 2006; Fallah and Partridge, 2007; Partridge et al., 2008). While spatial agglomeration strengthens economic cores through the minimization of costs between industries, how this may apply across a spectrum of urban-rural space can in part be dampened by the degree of remoteness. Remoteness has been a variable researchers have used to explain why spatial inequalities may persist along a rural and urban spectrum. Previous studies have utilized degrees of remoteness in such a manner to assess how agglomeration effects impacted population dynamics in regions surrounding economic centers (Renkow and Hoover, 2000; Khan et al., 2001; Partridge et al., 2007); and as a contributing factor of wage disparities from systematic differences in levels of human capital accumulation between core and peripheral regions (Redding and Schott, 2003; Arnold et al., 2005; Breinlich, 2006; Fally et al., 2010).

In response to the disparities between peripheral and core regions across the urban hierarchy, researchers have sought to underline alternatives paths of growth for rural and remote areas. Drawing parallels to the use of industrial clusters by planners to promote growth, recent work highlights the usage of natural amenities as a growth strategy within rural areas (Courtney et al., 2006; Partridge et al., 2008; Irwin et al., 2009). Similarly, more recent empirical studies have found measurable spatial spillovers within region and its geographic and economic neighbors due to natural attraction related tourism and related industries (Yang and Fik, 2014; Ma et al., 2015; Naranpanawa et al., 2019). The importance of amenities for rural economic development is two-fold: Within the urban-rural space, the location of firms along a rural-urban axis may face geographically-dependent hurdles where, on average, those within a rural area may face unique barriers to growth (Fieldsend, 2010; Lee and Cowling, 2015; Ferreira et al., 2016). Second, among rural areas, the capacity in which those areas may utilize their amenities can attract growth in comparison to remote areas that may lack such opportunities (Gorton, 1999; Phillipson et al., 2018).

Thus, while separate from the previous discussion of NEG and cluster theory, market access and remoteness are similarly vital to understanding why some regions perform better than others as well as understanding the challenges to economic growth among remote areas in particular.

3.2.3 Identifying Variables Contributing to Economic Performance

There has been an extensive search in understanding the determinants of economic performance within regional science literature. A metric such as performance hinges on what indicators are chosen to measure to it. Such variables that try to reflect economic performance have varied across studies such as examining performance through productivity of workers, firms, and region-level data (Rice et al., 2006; Porter et al., 2004; Curry and Webber, 2012; Patacchini and Rice, 2007). Similarly, the variation within industry-specific employment trends and growth have been utilized (Porter, 2003; Delgado et al., 2014; Jones and Henley, 2008); as well as with labor force participation rates, highlighting supply-side dynamics within labor markets and its impacts on region-wide output (Porter et al., 2004).

While measuring performance is complex and has been largely investigated, the body of research surrounding economic performance specific towards rural areas is comparatively new (Agarwal et al., 2009; Wang et al., 2015). Between rural communities in particular, the determinants of economic performance may be uniquely impacted by population dynamics and the accumulation of economic and human capital (Sørensen, 2018). Similarly, other tangible forms of rural capital such as economic diversification, the access to services, stock of natural resources, and management of local development have been identified as other factors of stability and drivers of performance (Svendsen and Sørensen, 2007; Sánchez-Zamora et al., 2014).

As opposed to being a metric of regional economic performance, there have been a series of explanatory variables highlighting why regions perform better than others. Factors such as workplace disability and age of a region's workforce may dampen of performance in comparison to areas whose working population are much younger and healthier (Weil, 2006; Aiyar and Ebeke, 2007; Börsch-Supan, 2001; Kapteyn and Smith, 2007; Agarwal et al., 2009; Styczyska and Zaman, 2013; Pekarek, 2018). As opposed to strict age measures, the use of a dependency ratio between the number of workers to retirees has also been similarly to measure the effects of age (Jones and Henley, 2008; Vicens-Feliberty and Reyes, 2015). As previously discussed with regards to market access and remoteness, commuting patterns have consistently been used to explain for variation in region-wide productivity (Renkow and Hoover, 2000; Patacchini, 2008). Akin to industrial clusters, economic structure, firm-level linkages, and the concentration of industries have been examined (Courtney et al., 2006; Delgado et al., 2014; Rupasingha, 2017; Spencer et al., 2010); the number of entrepreneurs (Audretsch and Keilbach, 2004; Valliere and Peterson, 2009; Acs et al., 2012; Baumgartner et al., 2013); population density (Partridge et al., 2008; Agarwal et al., 2009); and lastly, the presence and efficacy of state and local governments (Agarwal et al., 2009; Pike et al., 2010; Lee and Cowling, 2015).

3.3 Data

3.3.1 Study Area

To measure the spatial determinants of relative economic performance and how other economic variables affect it, we employ a series of data from the 2016 American Community Survey 5-year averages for every census tract within Maine. Census tracts are defined as a relatively permanent subdivision of counties or similar geographical entities whose primary purpose is to provide a stable set of geographical units for the presentation of statistical data. These areal units are delineated by the number of inhabitants where the average population lies close to 4,000 and may see a minimum and maximum value of 1,200 and 8,000 respectively (United States Census Bureau, 2012a). Similarly, the 5-year averages from the Census Bureau compliments the granularity of the data we analyze. As opposed to the 3- and 1-year averages, these estimates have a higher level of precision and are used for analyses surrounding small geographical units and smaller populations (United

Table 3.1: Descriptive and summary statistics of Maine census tracts

Variable Name	Parameter	Definition	Mean	Standard Deviation	Minimum	Maximum
Dependant Variables						
Productivity	*Yp*	Median Earnings per Worker	28721.99	6548.42	4602.00	51769.00
Employment Rate	*Ye*	Proportion of people aged 16-74 years that are employed	93.55	3.38	73.70	99.40
Labor Participation Rate	*Yr*	The proportion of the people aged 16-74 that are in the labor force.	62.11	7.88	40.40	82.40
Explanatory Variables						
Number of Financial Institutions	S_1	Number of financial sector related firms in census tract	5.34	3.07	1.00	16.80
Education	S_2	Percentage of adults 23-74 who have a bachelor's degree or higher	28.18	13.72	8.20	73.10
Enterprise	S_3	Percentage of working population that are self employed	9.14	4.98	1.00	36.50
Distance to Closest Market	D_1	Distance from closest market (miles)	30.10	34.40	0.38	173.62
Distance from State or National Park	D_2	Distance from closest state or national park (miles)	13.78	8.61	0.20	45.31
Economic Structure	*E*	Proportion of industries that are non-Agriculture	96.66	4.15	70.00	100.00
Government Structure	*G*	Percentage of employment as government workers	14.17	5.44	1.90	34.5
Population Density	*P*	Ratio of total population to square miles (land)	958.80	2541.57	0.16	23363.94
Household Size	*H*	Average household size between owner and renter occupied size	2.29	0.25	1.43	3.17
Time to Work	*M*	Time to travel to work (minutes)	23.56	6.23	8.50	44.40
Occupational Health	*O*	Percentage of those employed that have a disability	0.94	0.03	0.81	1.00
Old-Age Dependency Ratio	*A*	Ratio of working age population to retirees	31.10	12.01	2.20	85.70
Observations: 351						
Years: 1						

States Census Bureau, 2018). The list of variables used for this analysis is available in Table 3.1.

Maine offers several unique factors that gives weight to it as a proper area for analyzing the spatial impacts to economic performance. Maine is currently the subject of serious focus with regards to initiatives that alleviate poor economic conditions such as a lack of broadband, rising costs to health care, and the need for a state-wide economic strategy (Headwaters Economics, 2012; Maine Development Foundation, 2017; Investment Consulting Associates, 2018). Relevant to our work is the issue of geography which is commonly viewed as a mitigating factor to the efficacy of policy and overall economic performance. The state has a geographical area of 35,385 square miles, with a total width and length of 205 and 320 miles respectively. A prominent share of the state's population and economic activity taking place in southern and central counties, while also featuring 61.3 percent of the total population living in non-urban parts of the state (United States Census Bureau, 2012b). Thus, we can utilize Maine's sociodemographic and geographical features to evaluate the spatial and economic impacts to the region's level of performance.

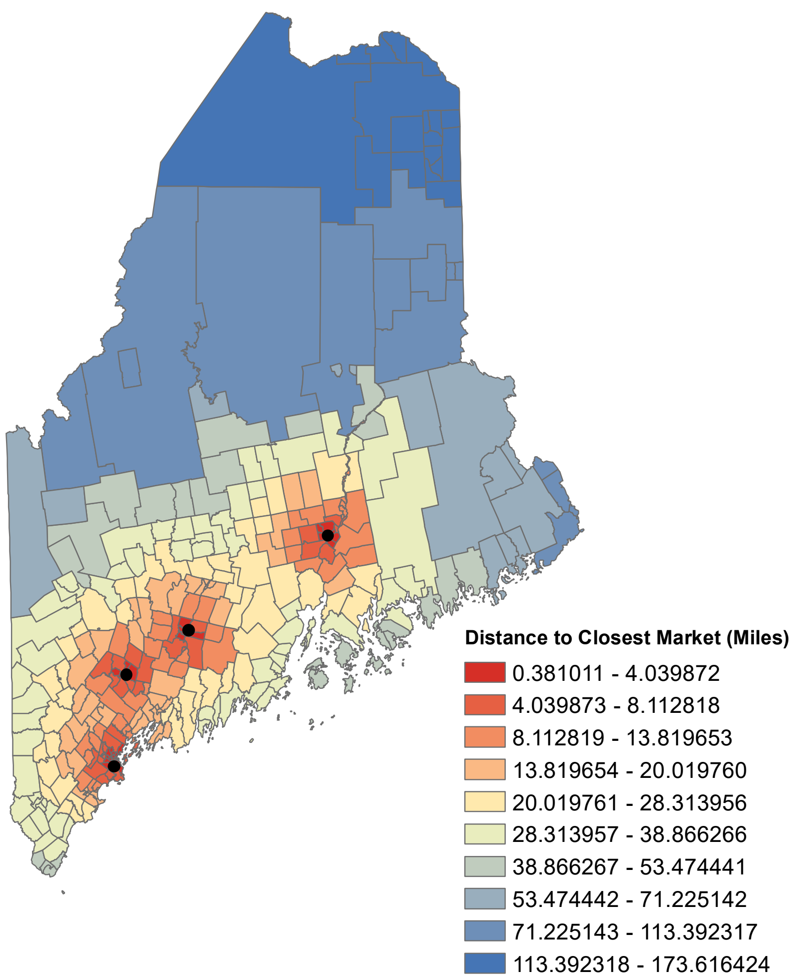
3.3.2 Defining Spatial Variables

To analyze the spatial determinants of economic performance, we include two specific variables that: (1) measures the distance between census tract i to major market m and (2) a remoteness variable that measures the distance between census tract i to the nearest State or National Park p. With Python, we take advantage of several application programming interfaces (API) from the Census Bureau to collect the coordinates for Maine's census tracts; Google's Geocoding Service's for the centroids of Portland, Lewiston, Augusta, and Bangor, Maine; and lastly, the National Park Service's for the coordinate data to all State and National Parks within a fifty-mile buffer zone surrounding the state. For market access, we use the Vincenty formula that translates the latitude and longitude for two locations and calculates the geodesic distance between the two points. For all census tracts we calculated the distance between these each census tract and market and retained the distance between a given census tract and the closest city in miles (Figure 3.1).

While market access measures the geodesic distance between a census tract to its closest major market, we also wish to control for remoteness in a similar fashion. While some census tracts may be further away from a major market, they may still have some form tangible capital such as natural amenities or rural tourism. While perhaps they perform slower on average compared to census tract within an economic core, having a high stock of natural attractions or being neighbors to census tracts that do may also gain spatial and economic spillovers thus able to perform relatively higher than those that do not (Yang and Fik, 2014; Ma et al., 2015; Naranpanawa et al., 2019). To control for this, we similarly calculate distance for each census tract between each state and national park within the area and return back the distance to closest park.[1] The State of Maine has a non-trivial share of recreation-based tourism within outlying areas and thus we may exploit the distances to state and national parks as means to control for a census tract's degree of remoteness (Roper et al., 2006; Outdoor Industry Association, 2017).

For both market access and remoteness, a benefit from using geodesic measurements come from closely accounting the heterogeneity of the road network within the State. Specifically, the

Figure 3.1: Distance between census tracts and nearest markets



[1]In the spirit of transparency, the python code written to collect the data, calculate the distances, and retain the pair that had the shortest distance can be found in Appendix B

central and southern parts are more dense in comparison to the north and far-west and eastern parts of Maine which may systematically change the impact of market access through geography. Generally with geodesic distances, calculations across smaller distances are comparatively smaller than euclidean and larger for greater distances. A similar approach was undertaken in the past to analyze the empirical relevance of NEG and the impacts of city location by controlling for the density of road across the United States in such a manner (Ioannides and Overman, 2004; Fujita and Mori, 2005).

3.3.3 Empirical Model

A system of equations were used to measure how economic and spatial variables impact economic performance. Following (Dunnell, 2009) and (Agarwal et al., 2009), economic output was decomposed into three separate equations to measure the spatial determinants on productivity, employment, and labor force participation rates simultaneously. Similarly, we control for endogenous co-variation between each dependent variable within our system. Endogeneity is a large concern for this analysis as each of our individual components of economic output (productivity, employment, and labor force participation) may systematically respond to the change of another one and would thus limit the causal inference of our estimates.

Following the steps in (Agarwal et al., 2009), we use three-stage least squares to jointly estimate the impacts of several spatial variables on economic performance as defined by our decomposition of economic output. Given our model specification, each decomposed variable will still be normally interpreted as any left-sided variable but because they are taken to be endogenous we similarly measure each dependent variable's impact on the other. Equations (3.1), (3.2), and (3.3) detail our system of equations:

$$\ln Y_p = \Phi_0 + \Phi_1 \ln Y_e + \delta_i \sum_{i=1}^{3} \ln S_{pi} + \gamma_j \sum_{j=1}^{2} D_{pj}$$
$$+ \Phi_2 \ln E_p + \Phi_3 \ln G_p + \Phi_3 \ln P_p + \varepsilon_p \tag{3.1}$$

$$\ln Y_e = \chi_0 + \chi_1 \ln Y_p + \delta_i \sum_{i=1}^{3} \ln S_{ei} + \gamma_j \sum_{j=1}^{2} D_{ej}$$
$$+ \chi_2 \ln E_e + \chi_3 \ln G_e + \chi_4 \ln O_e$$
$$+ \chi_5 \ln A_e + \varepsilon_e \tag{3.2}$$

$$\ln Y_r = \beta_0 + \beta_1 \ln Y_e + \delta_i \sum_{i=1}^{3} \ln S_{ri} + \gamma_r \sum_{j=1}^{2} D_{rj}$$
$$+ \beta_2 \ln H_r + \beta_3 \ln O_r + \beta_4 \ln P_r$$
$$+ \beta_5 \ln M_r + \beta_6 \ln A_r + \varepsilon_r \tag{3.3}$$

Where Y_p is defined as productivity of workers in a census tract, Y_e is the employment level, and Y_r is the given labor participation rate. Definitions to our explanatory variables and their designated parameters are given within Table 3.1. Similarly, we use the Hausman test of model specification to test if three-stage least squares is more efficient in estimating the coefficient for each model in comparison to two-stage least squares. Similarly, because we use a system of equation we test for the rank and order conditions necessary for proper model identification.

3.4 Discussion

The R^2 calculated during two-stage least squares indicates that our statistical model fit the data well. Similarly, results of the Hausman test for model selection reveal that the estimates from

Table 3.2: Primary regression output from jointly-estimated three stage least squares

Variables	Joint Estimation using Three Stage Least Squares Productivity Model	Employment Model	Labor Force Participation Rate Model
Constant	**10.537******	1.163	**2.644****
	(**1.305**)	(0.792)	(**0.444**)
Endogenous covariates			
Earnings	-	0.079	**0.169******
		(0.073)	**(0.054)**
Employment	-0.186	-	-
	(0.2919)		
Number of Financial Institutions	**0.164******	0.006	-
	(0.025)	(0.014)	
College Education	**0.153******	**0.016******	**0.064******
	(0.057)	**(0.006)**	**(0.002)**
Government Infrastructure	0.011	-0.01	-
	(0.044)	(0.008)	
Economic Structure	-0.211	0.052)	-
	(0.276)	(0.057)	
Share of Self-Employed Workers	0.037	-0.004	-
	(0.031)	(0.003)	
Housing Availability	-	-	**0.168******
			(0.027)
Occupational Health	-	**0.509******	0.188
		(0.187)	(0.156)
Population Density	**-0.036******	**-0.010******	-0.0006
	(0.010)	**(0.004)**	(0.004)
Commuting Patterns	-	-	-0.003
			(0.023)
Old-Age Dependency Ratio	-	**-0.125******	-0.147
		(0.016)	(0.014)
Distance to Major Market	**-0.0009****	-0.0002	**-0.0004****
	(0.0005)	(0.002)	**(0.0002)**
Distance to State/National Park	-0.001	**-0.002******	**-0.002******
	(0.002)	**(0.0006)**	**(0.0006)**
R^2 from 2SLS	0.21	0.57	0.65
Hausman Test for Model Selection	2.19		
Choice:	Accept 3SLS		
$(K-k_i)-m_i$	(4-1)	(3-1)	(4-1)
Observations:	351	351	351

Robust standard errors shown in parentheses
*** - p > 0.001; ** - p > 0.05; p * - p > 0.1

three-stage least square are more efficient (Table 3.2). Because our model uses simultaneous equations we must satisfy both rank and order condition. Our model selection shows that between our three models there are more omitted exogenous variables the the number of endogenous variables in each equation thus illustrating the model is not overidentified.

Beyond this, we discuss the marginal effects from our spatial variables on productivity, employment, and labor force participation; expand upon our results by discussing the impacts of other control variables within each individual equation, and lastly, discuss briefly the validation for identification of our system with regards to the necessary and sufficient condition of full rank.

3.4.1 Spatial Determinants of Economic Performance

Our research question sought to uncover what impacts, if any, spatial variables such as the access to local and majors markets had on a region's economic performance. We hypothesized that there was negative relationship between distance to a market and economic output. To this end, our variables were coded to return distance in miles to easily interpret the margins from our regression. Overall we find that our results corroborate such a hypothesis.

For productivity, the distance to major market variable was significant, yielding an average decrease of .0009 to median earnings across census tracts; and for our peripherality variable, we found no such relationship. Within the employment in particular, the proximity to local markets had prevailing impact over our other market access variable. Specifically, we found that a one-mile increase in the distance from a State or National Park yielded, on average, a -0.0002 percent decrease to the employment rate. Lastly, both the distance from a major market and to a state or national park had a significant relationship to the variation in labor force participation rates for census tracts. On average, a one-mile increase away a census tract was to a nearby major market and to a park corresponded with a percentage decrease of -0.0004 and -0.002 in labor force participation rates respectively.

At first glance, the coefficients for our spatial variables may seem peculiarly small. Although we must be cautious with conflating statistical significance with the magnitude of coefficients in empirical research (Kennedy, 2002), we should similarly expect the magnitude of these parameters to be small given the scale of our study area. Because Maine is three-hundred twenty miles long, the impacts from a lack of market access become more apparent across longer distances. Akin to

Tobler's first law of geography,[2] the impacts of these spatial variables *ought* to be more pronounced for census tracts that are much more further away from Maine's major markets.

3.4.2 The Impacts of Other Control Variables on Productivity, Employment, and Labor Force Participation

We find several prominent impacts within our productivity model. Consistent with previous work, variables such as: the number of financial institutions, the percentage of a census tract's population with a bachelor's degree or higher, and population density yielded a 0.164, 0.153, and -0.036 percent change in the median earnings on average. Alongside this, we found no effect from our endogenous variable employment.

Similar to our previous model, we find no impacts to employment from median earnings. Other controls such as college education, occupational health, and the old-age dependency ratio did have an effect on the level employment across census tracts. College education had a modest impact compared to the productivity model where a one-percent increase in the population with a bachelor's degree or higher increased the employment rate by 0.016 percent on average. Consistent with similar work that analyzed work force dynamics, a one-percent increase in the workforce without a disability yielded a 0.509 percent increase to employment; and lastly, a one-percent increase to dependency ratio corresponded with a -0.125 percent change to employment on average.

With our labor force participation model we find that earning, our endogenous variable, was significant and where a one-percent increase in median earnings corresponded with a 0.169 percent increase in participation rates. Like the past two models, college education had a similar, positive impact to the participation rates. Specifically, a one-percent increase in the number of persons with

[2]"Everything is related to everything else, but near things are more related than distant things." (Tobler, 1970)

a bachelor's degree had an increase of 0.064 percent on average. Last, we found a positive relationship with the number of dwelling stocks where a one-percent increase in the availability of housing for a census tract corresponded with a 0.168 percent increase in the labor force participation rates on average for a given census tract.

3.4.3 Identification of the Model

Identification is a problem related to system of equations where whether an equation within that system can be uniquely identified and estimated. Should our system contain similarly valued parameters from a same underlying distribution, two or more equations within the system will have observational equivalence and thus lack identification (Wooldridge, 2010; Greene, 2012). To show that our model is adequately identified we must surpass both rank and order conditions.[3] The rank condition for identification is satisfied when there is exactly one solution from our reduced-form equations (full rank), and order is satisfied if we show that the number of exogenous variables omitted from each equation is at least the same as the number of endogenous variables included.

While we show that each equation in our system had more omitted exogenous variables than endogenous ones (Table 3.2), we have yet to validate if our system has full rank.[4] At the time of this analysis, Stata's reg3 command does not have a built in function that checks if the system of equations satisfies the rank condition for identification, and to circumvent this hurdle we used we used the checkreg3 command to verify that our estimates for three-stage least squares are meaningful by satisfying this condition (Baum, 2007). Given this, Table 3.3 highlights this test and shows that we have satisfied both rank and order conditions for identification.

[3]Rank and order conditions follow the specific logical categories of necessity and sufficiency. The rank condition is the necessary and sufficient condition for a set of equations within a system to show identification and order is merely a necessary condition.

[4]While it is uncommon for a system of equations to fail the rank condition if the order condition is satisfied, it would be more alarming and indicative of misspecification should we fail the rank condition (Greene, 2012).

Table 3.3: Rank condition test for system identification

Endogenous coefficients matrix

Variable	Earnings	Employment	LPart
Earnings	-1		
Employment	0	-1	
Lpart	0	0	-1

Exogenous coefficients matrix

EQ	Earnings	Employment	Investment	Education	Gov't Spending	Economic Mix	Self-Employment	Pop. Density
Yp	-	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Ye	0.5	-	0.5	0.5	0.5	0.5	0.5	-
Yr	0.5	-	-	0.5	-	-	-	0.5

	Housing Stock	ΔMarket	ΔPark	Disability	Old-Age Dependency	Part-time	Time to Work
Yp	0.5	0.5	0.5	-	-	-	-
Ye	0.5	0.5	0.5	0.5	0.5	-	-
Yr	0.5	0.5	0.5	0.5	0.5	-	0.5

Eq 1 is identified
Eq 2 is identified
Eq 3 is identified

System is identified

3.5 Conclusions

Economic performance can be identified and measured through many methods. Specifically, this work sought to measure the impacts of space on economic performance by first identifying economic output as a system of individual components that can be estimated simultaneously. After identifying our model we calculated the spatial determinants of economic performance through geographic distance to markets and the degree of remoteness. The use of spatial variables within our system was a considerable feat due to the fact that calculating their impacts across economic space is not a simple task. Beyond such hurdles, there is much to draw upon. We believe that this work can uniquely contribute insight to to such stakeholders through offering a novel framework that measures the impacts that market access has on a region's economic performance.

Although much value is present in this research, there lie certain limitations to note. While we controlled for endogenous variation in our dependent variables by using three-stage least squares, there may be alternative methods to tease out causal impacts directly related to market access and remoteness. Novel use of natural experiments in the past have quantified the role of market access and how it contributes to economic activity (Redding and Sturm, 2008; Machikita and Okazaki, 2017). Thus, future opportunities may arise to expand the knowledge surrounding the spatial determinants of economic performance on a similar level as this work. Our second concern involves future work needing to consider temporal dynamics that are present across economies. This paper does not focus on such factors and thus we cannot make any inferences as how the impact from these variables change with respect to time. While there is value in time-series analyses that exploit time and geographic variables to measure the impacts on future output, they are beyond the scope of this work. Understanding these limitations, the main findings this research nonetheless provide several highlights for policymakers and future research.

First, we successfully illustrated a statistical relationship between primary and secondary markets with economic output through our spatial variables. For our productivity model in particular, there existed a negative association between a larger distance to the State's primary markets and the level of earnings. This did not hold for our peripherality variable where we expected a similar relationship with distance to parks. Surrounding these parks are smaller, localized economies centered closely towards recreation and accommodations to tourists (Roper et al., 2006; Yang and Fik, 2014; Ma et al., 2015). Thus, while some census tracts were not close to our primary markets, the census tracts that were closer to these secondaries markets would have still performed marginally better than those completely remote from any markets. Such an explanation can be validated through our the signs coefficients in employment and labor force participation models which showed that a one-mile increase away a census tract was from these parks yielded -0.0002 under both models.

Second this research reinforces past literature which underlined a multidimensional perspective to regional economic performance. Decomposing economic output into several defining parts (productivity, employment, labor market participation) illustrated how spatial and economic variables may impact individual components of regional output. Similarly, this work was conducted on a level that has only recently begun to see attention. In doing so, we reveal several relationships which may secondarily highlight a need for policy intervention for certain aspects for Maine's economy. Variables such as workplace health (defined through the percentage of a census tract's workforce *without* a disability) and the old-age dependency ratio revealed a negative association between the level of economic performance at the census tract level. Stakeholders within the State have investigated the impacts of an aging work force, and we reinforce these findings and a need policies that focus on addressing similar issues (Colgan, 2006; Breece et al., 2015; Maine Department of Labor, 2016).

And lastly, our work sought to underline that space does matter. To that end, we established a framework which was able to highlight several relationships between the dimensions of economic output and geographic space. While were successful in the pursuit, the relationship between economic output and space, as well as how the impacts of space transform between different scopes, have yet to be fully uncovered. Like past research, this piece is one of many that further expands the knowledge of economic geography and how it may better serve local and regional policy with regards to both rural and urban areas.

CHAPTER 4
CONCLUSIONS

This research focused on two different regional economic issues with respect to a rural-urban dimension. While there exists many classifications of region-type, it is nonetheless important to understand how economic differences within a region will influence the outcome of policies. Ultimately, the purpose of this thesis was to find evidence of such an observation. Between both of our papers we find evidence to suggest that economic space is a factor that is ever present and has an influence on a region's capacity to resist and rebound from economic shocks and its overall performance.

The first study in this thesis sought to answer (1) how can we robustly estimate an index of rurality that circumvents the limitations found in other discontinuous measures used in other studies and (2) how, if at all, does a region's degree of rurality impact its capacity to rebound from economic shocks. Through the use of factor analysis we estimated a measurement of rurality that satisfies a series of robustness checks and displays variation in rurality between time and space. With this measure, we had also found that rural counties tend to be slower in recovery on average as it relates to our case study's background. The ramifications of our results are also nuanced with how economic resilience was measured. While it is a topic that has gained serious attention within regional sciences, there exist many ways to estimate it. Our dependent variable was a ratio of employment growth for a given county to the nation-level growth. While it has been used by prominent regional economists, this alone cannot directly illustrate how much slower rural counties were. Given that rurality is relatively homogeneous in a short time period, future research may want to go beyond this study by looking at long-run patterns of recovery.

Given the nuances of our study, there are nonetheless still some implications of this analysis that will be of interest to policymakers and regional planners. Fundamentally, policymakers must understand the fuzzy boundaries of rurality and how a county's degree of rural will influence its capacity to respond to economic shocks. This chapter succeeded in illustrating just that. We uncovered a relationship highlighting differential levels of recovery between counties along an urban-rural continuum. Understanding how rurality may impact the speed of recovery from economic shock better informs policymakers and the tailoring of economic policy to address such issues.

Our second paper sought to analyze a problem separate from economic resiliency. Instead, this paper was focused on: (1) identifying a method in which we may assess the relative economic performance of Maine at the census tract level; (2) utilize the novel idea of using multiple APIs to collect coordinate data as a means to calculate spatial variables and see how they impact productivity, employment and labor force participation. With these research objectives and referring to past research, we estimated relative performance as a decomposition of economic output through the use of three-stage least squares. In the interest of inferring a causal relationship, we treated each model's dependent variable as endogenous and similarly provide robustness checks to highlight the validity of our work.

With such a model, we found a several interesting results: both distance to major markets and the degree of remoteness (which we defined as the distance to a state or national park) had statistical significance in explaining the spatial heterogeneity in productivity, employment, and labor force participation between regions. Beyond our spatial variables, other factors such as the percentage of the population with a college degree, the percentage of workers without a disability, and the old-age dependency ratio were also significant. As it relates to the spatial determinants of regional economic performance, we find a general trend where census tracts that are further away from major markets will be less productive and have lower labor participation rates on average. Similarly, census tracts that are further away from smaller markets that utilize natural amenities through recreation and tourism see a similar pattern of lower rates of employment and labor force participation on average. While different from market access, these impacts of remoteness similarly bolster the findings of previous regional economic literature that highlight the spatial disparity between regions with and without natural amenities and how they utilize their resources to promote economic development.

The results from our second chapter provide considerable policy insights. First, we corroborate the concerns of policymakers and analysts within the state surrounding the challenge of effective policy implementation across a wide geographic space. Through calculating our spatial variables in terms of measurable distance, the margins to our spatial variables suggest that remote areas which are further away from economic centers are characterized by relatively poorer performance compared to areas that are closer. Second, this study supports policymakers in their challenge of resolving economic troubles in Maine such as the aging workforce and workplace health by validating their statistical significance within an econometric model.

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APPENDIX A

FULL OUTPUT FROM FACTOR ANALYSIS

Table A.1: Mean averages of factor variables (2011 - 2015)

	Mean				
Variable	2011	2012	2013	2014	2015
Median Income	56847.930	57162.720	57325.000	57781.420	58267.730
Internet	726.866	765.672	780.597	810.448	849.254
Unemployment	7.266	7.649	7.955	7.634	6.946
Male Median Age	42.496	42.681	42.821	42.791	42.740
Female Median Age	42.760	42.988	43.088	43.149	43.160
Less Than High School	6.519	6.342	6.097	5.936	5.757
High School Degree	31.836	31.531	31.230	32.819	30.788
Bachelor's or Higher	31.118	31.312	31.831	32.290	32.760
Total Net Migration	0.163	-0.409	0.604	1.013	-0.709
Household Size	95471.870	95666.610	95793.280	96067.000	96311.300
% of Pop. 65 or Older	15.287	15.684	16.163	16.666	17.226
Population Density	561.369	565.210	568.938	573.375	577.155
Population Change	0.008	-0.016	0.100	0.007	-0.072
LQ of Agriculture	1.647	1.627	1.602	1.569	1.567

Table A.2: Standard deviations of factor variables (2011 - 2015)

	Standard Deviation				
Variable	2011	2012	2013	2014	2015
Median Income	12772.110	12636.670	12650.400	12869.460	12885.840
Internet	114.920	112.212	110.425	106.079	94.345
Unemployment	1.649	1.705	1.821	1.745	1.655
Male Median Age	2.086	2.131	2.149	2.209	2.250
Female Median Age	2.382	2.459	2.499	2.576	2.652
Less Than High School	1.630	1.567	1.569	1.549	1.484
High School Degree	5.845	5.792	5.714	6.302	5.660
Bachelor's or Higher	8.414	8.491	8.505	8.570	8.650
Total Net Migration	4.039	4.397	4.140	5.911	4.151
Household Size	118677.40	118865.50	119031.80	119370.60	119759.00
% of Pop. 65 or Older	2.651	2.716	2.831	2.962	3.080
Population Density	1539.060	1562.067	1584.732	1609.715	1632.110
Population Change	0.424	0.579	0.563	0.621	0.542
LQ of Agriculture	1.971	1.881	1.742	1.518	1.555

Table A.3: Minimum values of factor variables (2011 - 2015)

	Minimum Values				
Variable	2011	2012	2013	2014	2015
Median Income	35123	36486	35916	35567	36599
Internet	500	500	500	500	500
Unemployment	2.800	3.100	3.200	3.200	3.000
Male Median Age	33.200	33.100	33.300	33.300	33.500
Female Median Age	32.600	32.500	32.600	32.600	32.700
Less Than High School	3.200	3.500	2.800	3.100	3.400
High School Degree	22.100	21.900	21.500	21.700	20.600
Bachelor's or Higher	15.200	14.800	14.700	14.100	15.400
Total Net Migration	-10.000	-15.600	-7.400	-11.000	-12.300
Household Size	5015	5020	5020	5022	5025
% of Pop. 65 or Older	10.479	10.500	10.623	10.700	10.803
Population Density	4.423	4.401	4.379	4.361	4.332
Population Change	-0.840	-1.552	-1.030	-1.167	-1.625
LQ of Agriculture	0	0	0	0	0

Table A.4: Maximum values of factor variables (2011 - 2015)

	Maximum Values				
Variable	2011	2012	2013	2014	2015
Median Income	84979	84087	85478	86529	88262
Internet	900	900	900	900	900
Unemployment	10.9	10.9	11.4	11	10.5
Male Median Age	46	46.8	46.6	46.7	46.7
Female Median Age	46.5	46.8	47	46.8	46.9
Less Than High School	10.8	10.4	10.1	10	9.5
High School Degree	44.3	44.6	45	46.6	45.6
Bachelor's or Higher	49.8	50.2	50.7	51.3	52
Total Net Migration	8.8	10.6	19.4	30.5	7.7
Household Size	610063	611338	612535	614879	617089
% of Pop. 65 or Older	24.651	25.100	25.755	26.400	27.060
Population Density	12269.250	12465.620	12658.310	12868.690	13057.790
Population Change	1.162	1.648	2.521	2.766	1.095
LQ of Agriculture	12.506	12.001	10.403	8.809	8.397

Table A.5: Cronbach's Alpha (2011 - 2015)

		Cronbach's Alpha				
Variable	Sign	2011	2012	2013	2014	2015
Median Income	+	0.8632	0.8798	0.8629	0.845	0.8609
		(0.3268)	(0.3603)	(0.3262)	(0.2954)	(0.3226)
Internet	+	0.8673	0.8875	0.8764	0.8636	0.8683
		(0.3346)	(0.3777)	(0.3529)	(0.3276)	(0.3365)
Unemployment	-	0.8902	0.9002	0.8873	0.8711	0.8859
		(0.3841)	(0.4095)	(0.3772)	(0.3421)	(0.374)
Male Median Age	-	0.8715	0.8867	0.872	0.8551	(0.8671)
		(0.3429)	(0.3757)	(0.3438)	(0.3123)	(0.3343)
Female Median Age	-	0.8709	0.8874	0.8753	0.8571	0.8681
		(0.3417)	(0.3775)	(0.3507)	(0.3158)	(0.3361)
Less Than High School	-	0.876	0.8876	0.8732	0.8563	0.872
		(0.352)	(0.3778)	(0.3463)	(0.3144)	(0.3439)
High School Degree	-	0.8581	0.8746	0.8573	0.8417	0.8554
		(0.3175)	(0.3492)	(0.316)	(0.2902)	(0.3128)
Bachelor's or Higher	+	0.859	0.8747	0.8573	0.8396	0.8555
		(0.319)	(0.3494)	(0.3161)	(0.287)	(0.3129)
Total Net Migration	+	0.8781	0.88	0.8711	0.8674	0.8776
		(0.3565)	(0.3607)	(0.3419)	(0.3347)	(0.3555)
Housing Stock	+	0.8733	0.8904	0.8771	0.8606	0.872
		(0.3464)	(0.3846)	(0.3544)	(0.3221)	(0.3439)
% of Pop. 65 or Older	-	0.8689	0.8849	0.8715	0.8521	0.8661
		(0.3377)	(0.3717)	(0.3428)	(0.3072)	(0.3322)
Population Density	+	0.8775	0.8933	0.8797	0.8645	0.875
		(0.3552)	(0.3918)	(0.3601)	(0.3293)	(0.35)
Population Change	+	0.864	0.8754	0.8634	0.8429	0.8629
		(0.3282)	(0.3508)	(0.3271)	(0.2922)	(0.3262)
LQ of Agriculture	-	0.8773	0.8866	0.8774	0.8608	0.8734
		(0.3548)	(0.3756)	(0.355)	(0.3224)	(0.3467)
Total		0.8795	0.8925	0.8799	0.8649	0.8795
		(0.3427)	(0.3723)	(0.3436)	(0.3138)	(0.3377)

Average Interitem Correlation in Parathenses

Table A.6: Factor loadings of variables (2011 - 2015)

Factor Analysis/Correlation
Method: Principal Factors n = 67
Rotation: Orthogonal Varimax Retained Factors: 1

	Factor Loadings				
Variable	2011	2012	2013	2014	2015
Median Income	0.783	0.755	0.800	0.795	0.771
	(0.3869)	(0.4306)	(0.3595)	(0.3678)	(0.4051)
Internet	0.702	0.561	0.514	0.404	0.575
	(0.5071)	(0.6849)	(0.7356)	(0.8365)	(0.6693)
Unemployment	-0.196	-0.293	-0.292	-0.279	-0.229
	(0.9616)	(0.9144)	(0.9146)	(0.9224)	(0.9474)
Male Median Age	-0.638	-0.610	-0.604	-0.628	-0.667
	(0.5924)	(0.6279)	(0.635)	(0.6059)	(0.5555)
Female Median Age	-0.647	-0.595	-0.543	-0.601	-0.654
	(0.5813)	(0.6457)	(0.7056)	(0.639)	(0.5722)
Less Than High School	-0.499	-0.585	-0.594	-0.570	-0.535
	(0.7515)	(0.6579)	(0.6478)	(0.6749)	(0.7138)
High School Degree	0.843	-0.863	-0.899	-0.847	-0.870
	(0.2431)	(0.2551)	(0.1914)	(0.2828)	(0.2424)
Bachelor's or Higher	-0.870	0.858	0.895	0.869	0.860
	(0.2887)	(0.2635)	(0.1985)	(0.2449)	(0.2609)
Total Net Migration	0.469	0.749	0.642	0.331	0.416
	(0.7801)	(0.4389)	(0.5873)	(0.8906)	(0.8266)
Housing Stock	0.583	0.522	0.505	0.521	0.560
	(0.6604)	(0.7273)	(0.7452)	(0.7288)	(0.6868)
% of Pop. 65 or Older	-0.656	-0.633	-0.604	-0.668	-0.679
	(0.5703)	(0.5992)	(0.6348)	(0.5533)	(0.5393)
Population Density	0.485	0.438	0.428	0.425	0.470
	(0.7648)	(0.8084)	(0.8168)	(0.8198)	(0.7794)
Population Change	0.724	0.833	0.776	0.759	0.697
	(0.4761)	(0.3058)	(0.3982)	(0.4245)	(0.5149)
LQ of Agriculture	-0.446	-0.577	-0.448	-0.497	-0.484
	(0.8014)	(0.6674)	(0.7993)	(0.7527)	(0.7663)
Eigenvalue	5.634	5.973	5.630	5.256	5.520
% of Variance	0.519	0.544	0.527	0.508	0.526
Overall KMO	0.713	0.765	0.736	0.730	0.725
Bartlett's χ^2	895.883	934.788	871.397	782.817	834.796
p-value	0.000	0.000	0.000	0.000	0.000

Uniqueness of Variance in Parentheses

APPENDIX B

PYTHON CODE

Figure B.1: Python code: getAllParks, getZipCoords

```
import requests, json, pandas as pd, geopy, time, xmltodict
from geopy.geocoders import Nominatim
from geopy.distance import vincenty
def getAllParks():
    key =
    base = 'https://developer.nps.gov/api/v1'
    endpoint = '/parks?'
    name = '/parkCode'
    auth = '&limit=600&api_key=%s'%key
    resp = json.loads(requests.get(base+endpoint+name+auth).text)
    cols = list(resp['data'][0].keys())
    df = pd.DataFrame(index = [], columns = cols)
    for i in range(len(resp['data'])):
        for col in cols:
            df.loc[i, col] = resp['data'][i][col]
    df.to_csv('nps.csv')
def getZipCoords(ZIP):
    geolocator = Nominatim()
    location = geolocator.geocode(ZIP)
    return (location.latitude, location.longitude)
```

Figure B.2: Python code: getParkCoords

```
def getParkCoords(park):
    key =
    base = 'https://developer.nps.gov/api/v1'
    endpoint = '/parks?'
    name = 'parkCode=%s'%park
    auth = '&limit=600&api_key=%s'%key
    resp = json.loads(requests.get(base+endpoint+name+auth).text)
    latLong = resp['data'][0]['latLong']
    try:
        lat = float(latLong.split('lat:')[1].split(',')[0])
        long = float(latLong.split('long:')[1])
    except IndexError:
        print('API did not return coordinates for %s'%park)
        return 0
    return (lat, long)
```

Figure B.3: Python code: distanceToPark, distanceToNearestPark

```
def distanceToPark(ZIP, park, zipCoords = None):
    parkCoords = getParkCoords(park)
    if zipCoords == None:
        zipCoords = getZipCoords(ZIP)
    if parkCoords != 0:
        return vincenty(parkCoords, zipCoords).miles
    else:
        return 99999
def distanceToNearestPark(ZIP):
    zipCoords = getZipCoords(ZIP)
    parkCodes = list(pd.read_csv('nps.csv')['parkCode'])
    shortestDistance = 99999
    i = 0
    startTime = time.time()
    for park in parkCodes:
        distance = distanceToPark(ZIP,park, zipCoords = zipCoords)
        if distance < shortestDistance:
            shortestDistance = distance
            closestPark = park
        i += 1
        now = time.time()
        timePerIteration = (now-startTime)/i
        remainingIterations = len(parkCodes) - i
        timeRemaining = timePerIteration*remainingIterations/60
        percentDone = i/len(parkCodes)*100
        print('%f%% done; estimated time remaining:
        %f minutes'%(percentDone, timeRemaining))
    return closestPark, shortestDistance
```

BIOGRAPHY OF THE AUTHOR

Elena Smith was born in Augusta, Maine on September 17th, 1993. In June of 2012, she graduated from Erskine Academy. After graduating high school, she began attending the University of Maine in August 2012. During the progress of her undergraduate program, she experienced the loss of her grandfather, who was a highly prominent family figure in her life. Overcoming this, she graduated with a double major in Economics and Political Science in August 2016. In the summer of 2016, she worked for the Island Institute as a data analyst and made major contributions to the the Island Institute's publication on economic and community indicators for Maine's coastal and remote island communities *"Waypoints: Community Indicators for Maines Coast and Islands."*

She enrolled into the University of Maine's graduate program in the Fall of 2016 and conducted research under Dr. Andrew Crawley; was a teaching assistant for Dr. Keith Evans in his undergraduate econometrics course in both Spring 2017 and 2018; conducted research surrounding forest-based communities with Dr. Kathleen Bell and Dr. Mindy Crandall of the School of Forestry; and lastly, was a graduate assistant with the Office of Institutional Research and Assessment. She was nominated in April 2019 as "Graduate Student Employee of the Year" for her part in the institution-wide team for the University of Maine's 10-year accreditation renewal from the New England Council of Higher Education (NECHE). In June, she will begin her career working for DNV GL as a consultant in their Portland, Maine office doing energy evaluation and analysis.

Beyond her academic and professional career, Elena has several interests. She is an avid traveler, having spent several months abroad working in Germany with her partner; loves to hike, and enjoys playing card and board games with her closest friends. She hopes to one day hike all sixty-seven mountains in New England that have an elevation of 4,000 feet or higher and hike Nordkalottruta, the 800km Arctic Path through Sweden, Finland, and Norway. Elena Selene Smith is a candidate for the Master of Science and Master of Arts degree in Economics and Global Policy from the University of Maine in May 2019.