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Factors Affecting Spatial Differences in Health Outcomes

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FACTORS AFFECTING SPATIAL DIFFERENCES IN HEALTH OUTCOMES

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Science

in

The Department of Agricultural Economics

by

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B.Sc., Kwame Nkrumah University of Science and technology, 2013

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This thesis is dedicated to my parents, Yaw Poku-Gyamfi and Theresa Addai Gyamfi. I would not have made it this far but for their love, patience, dedication, guidance and prayers. My love and thanks for them cannot be expressed in words.

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ABSTRACT

This study sought to establish the impact of the disparities between Metropolitan, Micropolitan and Non-Core communities on life expectancy. The study also assesses the impact of individual behavioral choices and certain social variables and county level policies on the life expectancy in a county.

A simple mean comparison analysis is employed to establish the differences in life expectancy across the various levels of the urban hierarchy in 1,553 counties in the United States. An ordinary least squares model is used to tease out the relationship between specific individual choice factors; smoking habits, obesity and exercise habits and socio-economic factors; medicare dollar per enrollee, income segregation in the county, social capital index of the county, percentage of the population foreign born in the county and the unemployment rate in 2000 and life expectancy. This study also estimates the effects of each correlate at various levels of the urban hierarchy.

The study concluded that the effects of both individual choice factors and socio-economic variables differ greatly across the various levels of rurality. This study adds to the existing body of knowledge on the subject of longevity and also assists policy makers in formulating health and economic policies that target these geographic areas.

CHAPTER 1: INTRODUCTION

Health and geography have been intertwined to assessing the economics of welfare and living standards in general. These dimensions triggered studies on health access, health outcomes, place and space effects, among others. Geographical differentials in health also have a long history, and over the years, there has been a variation in the importance given to the role area differences play in understanding health outcomes. While some work has deeply involved geographical characteristics in assessing individual-level risk factors, others have not deemed these characteristics as potential determinants of health outcomes.

The above observation is equally real and applicable to geographic characteristics and life expectancy. The past few years have witnessed an explosion of interest in neighborhood or area effects on health (Diez Roux, 2001). A compendium of empirical studies have been undertaken to better understand these possible area/neighborhood effects. These include studies that draw the relationship between neighborhood characteristics and morbidity and mortality rates, contextual and multilevel analyses that relate area socioeconomic context to health outcomes, and studies that have compared a number of well-defined neighborhoods (Moon, Subramanian, Jones, Duncan, & Twigg, 2005).

Strengthening conclusions regarding the presence and magnitude of neighborhood effects have necessitated addressing a series of conceptual and methodological issues. Many of these problems have bordered on the need to come up with a theory and specific hypotheses on the ways neighborhood and individual factors act together to give specific health outcomes. More importantly, problems like defining neighborhoods or relevant geographic areas, choosing relevant neighborhood characteristics, outlining the parts played by individual-level variables,

adding life-course and longitudinal dimensions, and also combining a variety of research designs have increased (Diez Roux, 2001).

The idea that “place” could be of importance to health gained prominence from the 1980s and early 1990s (Haan, Kaplan, & Camacho, 1987); (Carstairs & Morris, 1989); (Humphreys & Carr-Hill, 1991); (Krieger, 1992); (Diehr et al., 1993); and interest has increased steadily over time as a lot of reports on geographic differences in health outcomes have recently emerged in epidemiology and public health journals among others (Matteson, Burr, & Marshall, 1998); (Robert, 1998); (Bennett et al., 2015); (Chetty et al., 2016).

Pickett and Pearl (2001) embarked on a review of multilevel analyses of neighborhood socioeconomic context and health outcomes. The study sought to establish multilevel or contextual analyses of social factors and health as a bridge between two divergent epidemiological paradigms. These are the individual risk factor epidemiology and an ecological approach (Pickett & Pearl, 2001).

Chetty et al. (2016) set out to estimate the level, time trend, and geographic variability that relate income to life expectancy and to identify factors related to small area variation in the United States. Bennet et al. (2015) explored the future of life expectancy and life expectancy inequalities in England and Wales. Matthew (2017) analyzed the Behavioral Risk Factor Surveillance System (BRFSS) data for 398,208 adults to estimate the prevalence of some self-reported health-related behaviors by urban-rural status. These included sufficient sleep, current non-smoking, non-drinking or moderate drinking, maintaining healthy body weight, and meeting aerobic leisure-time physical activity recommendations (Matthews, 2017).

With the use of birth and sibling histories from demographic health surveys carried out in sub-Saharan Africa, Turan (2009) constructed age-specific birth rates and age-specific mortality rates at the country-region level. The data set was used to test the implications of a general equilibrium model linking life expectancy to fertility, education, and labor supply (Turan, 2009).

Gurven et al. (2008) built an evolutionary theory of human life span from the perspective of embodied capital and human adaptive complex. The study explored the future of human longevity as a vigorously debated subject among population scientists (Gurven, Kaplan, Winking, Finch, & Crimmins, 2008). The two dominant positions were from scientists who propose that human life expectancy is not likely to exceed 85 years (Hayflick, 2007) and others who suggest that life expectancy may reach 100 years in the 21st century (Vaupel, 1997).

A major fruit of efforts to provide a link between space and place effects on health outcomes is the Critical Access Hospital (CAH) program. The CAH program has represented one of the biggest changes in rural health policy. Introduced by the Balance Budget Act of 1997, the CAH program was created to preserve access to primary and emergency care services in isolated rural areas by improving the financial conditions of CAH hospitals and preventing some closures (Fannin & Nedelea, 2013). The CAH program has grown rapidly from 41 hospitals in 1999 to 1,055 hospitals in 2005 and to 1,327 CAHs in 2011. With many rural hospitals shutting their doors prior to the creation of the CAH program, Medicare cost-based reimbursement saved many small rural hospitals from closure and maintained adequate access to care in isolated areas ((Fannin & Nedelea, 2013).

RESEARCH PROBLEM AND OBJECTIVES

The foregoing points to a growing body of knowledge and inquiry related to geographical characteristics and its nexus with health, morbidity and life expectancy. Chetty et al (2016) and

Matthews (2017) identified the role of place-based effects on life expectancy. Partridge et al (2008) also made an argument of the space-based effects and most policies are formulated based on either the place- or space-based dimensions. While the link between place-based and space-based effects have been less pronounced in literature, the link has not been adequately established. This paper seeks to address two main problems which have not been carefully evaluated in previous literature. These problem statements are presented below.

1. The disparity in health outcomes (life expectancy at 40) across the various levels of rurality or Core Based Statistical Area (CBSA) county categories has not been well-established along alternative rural-urban hierarchy definitions.
2. The factors that account for these disparities have not been accounted for in earlier research.

These problems and their numerous underlining factors are going to be probed with a set of research questions and research objectives to help further understand the relationship between health outcomes and the various categories of counties in the United States.

Objective 1

Establish the impact of disparities between alternative urban and rural communities on life expectancy.

Question 1

Do disparities between urban and rural communities translate into a shorter life span for people living in rural areas?

Analytical Procedure

A simple comparison means analysis will be used to establish the differences in life expectancy at age 40 across the American rural-urban hierarchy. This approach would be similar to the

methodology used by Weber et al. (2017) to establish the differences in upward mobility among three CBSA categories. A pairwise difference in means of life expectancy across the levels of rurality shall be obtained and adjusted p-values and confidence intervals for multiple comparisons to establish the difference in means across four income levels in the various county categories.

Objective 2

- Evaluate the impact of individual behavioral choices on the life expectancy of a county.
- Understand how certain social variables and state and county level policies are associated with the life expectancy in a county.

Question 2

- Are individual behavioral choice variables associated with a disparity in life expectancy across the various CBSA categories?
- Do state level and county level policies, as well as other social variables, have an effect on the differences in life expectancy across the various CBSA categorizations?

Analytical Procedures

Life expectancy by county will be estimated as a function of county level health choice factors and the socioeconomic factors in the county. Five Ordinary least squares (OLS) models would be used to describe the association of these factors with county level life expectancy at age 40.

This study largely employs data from the health inequality project website (www.healthinequality.org) where all of the commuting zone (CZ), county, state, and national level statistics used are highlighted in Chetty et al. (2016). These data mainly consist of death records from the Social Security Administration's (SSA) Death Master File and deidentified

database of federal income tax that includes all individuals with a valid social security number between 1999 and 2014. There were a total of 1,553 counties across the United States included in the models for this research.

The remainder of the study is presented as follows. Chapter 2 presents a literature review which draws on the existing body of knowledge on the research subject. Chapter 3 discusses the methodology for the research which highlights the various research principles, tools, models, sampling techniques and assumptions employed in the research. Chapter 4 presents the findings that emerge out of the research. Chapter 5 presents the summary, recommendations and conclusion to the research.

CHAPTER 2: LITERATURE REVIEW

In more recent periods of time, the focus of studies around life expectancy has shifted slightly from the development of theory to empirical modeling. The first section of this literature review looks at some earlier theories developed around life expectancy and then dives into the more recent empirical studies on the subject.

THEORIES ON LIFE EXPECTANCY

A theory of how natural selection has acted on our biology throughout the course of human evolution is needed to understand how age-specific mortality, the aging process, and behavior respond to novel environmental variation (Pervin & John, 1999). Pervin and John (1999) argue that “in the environments in which humans spent the majority of their evolutionary history, natural selection has resulted in a species-typical human life span of about seven decades, as part of a larger adaptive complex.”

An evolutionary theory of human life span was built by Gurven et al (2008) from the perspective of embodied capital and human adaptive complex. They explored the future of human longevity as a vigorously debated subject among population scientists. The two dominant positions were from scientists who propose that human life expectancy is not likely to exceed 85 years (Fries, 1989 ; Hayflick, 2007), and others who suggest that life expectancy may reach 100 years in the 21st century (Vaupel, 1997).

Gurven et al. (2008) argue that the human response to the novel environments of today grows out of the human evolutionary history, and to a large extent, is predictable. The study develops a general framework for understanding gene-environment interactions that affect age-specific mortality and life expectancy and the role natural selection plays in determining the evolution of population gene distributions over time. The study presents the embodied capital theory of life history evolution, an extension of standard life history theory.

Gurven et al. (2008) applied these ideas to an understanding of the human case, and argue that our species occupy an adaptive niche selected for a coevolved suite of characteristics, or the human adaptive complex. Further, they present the theory about the important role the ability to live at least to age 65 has played in human adaptation. Many human characteristics could not have evolved without the ability to live to at least 65. Together with a longer life span, these features form an adaptive peak that is peculiar to humans, with other species occupying various other peaks in the adaptive landscape.

Pickett and Pearl (2001) embarked on a review of multilevel analyses of neighborhood socioeconomic context and health outcomes. The study sought to establish multilevel or contextual analyses of social factors and health as a possible reconciliation between two different epidemiological paradigms—individual risk factor epidemiology and an ecological approach. Using retrieved articles as their primary data source, the eclectic study pooled all original studies, published in English before 1 June 1998, of the effect of local area social characteristics on individual health outcomes. They adjusted for individual socioeconomic status and focused on populations in developed countries.

Out of the 25 reviewed studies, 23 reported a statistically significant association between at least one measure of the social environment and a health outcome (contextual effect), after adjusting for individual level socioeconomic status (compositional effect). Contextual effects were modest and much smaller than compositional effects.

Pickett and Pearl (2001) concluded that evidence for modest neighborhood effects on health is fairly consistent despite the heterogeneity of study designs, substitution of local area measures for neighborhood measures, and probable measurement error.

EMPIRICAL WORK IN HEALTH OUTCOMES

In addition to the conceptual work on life expectancy, there has been increasing empirical analysis evaluating factors impacting life expectancy. Bennett et al. (2015) explored the future of life expectancy and life expectancy inequalities in England and Wales. The study forecasted, for small area levels, the age-specific mortality and life expectancy with Bayesian spatiotemporal models. Variables that accounted for age, birth cohort, time, and space were all included in the model. In particular, geocoded mortality and population data between 1981 and 2012 from the Office for National Statistics were used in the model with the smallest error to forecast age-specific death rates and life expectancy to 2030 for 375 and 376 districts of England and Wales respectively.

Bennett et al (2015) found that life expectancy at birth in England and Wales was 79.5 and 83.3 years for men and women respectively in 2012. District life expectancies ranged between 75.2 years and 83.4 years for men and between 80.2 years and 87.3 years for women. Between 1981 and 2012, life expectancy increased by 8.2 years for men and 6.0 years for women, closing the female - male gap from 6.0 to 3.8 years. National life expectancy, as forecasted, is expected to reach 85.7 years for men and 87.6 years for women by 2030. This increase would further reduce the female advantage to 1.9 years. The forecast also indicated that life expectancy could reach or even go beyond 81.4 years for men and 84.5 years for women respectively in every district by 2030.

Interestingly, Bennett et al. (2015) observed that there were differences in the life expectancies across districts as measured between the 1st and 99th percentiles. (Districts are geographic subunits of a county in the administrative geography of the United Kingdom.) Life expectancies, at the district level, had been on the rise since 1981 and is predicted to keep increasing to 8.3 years (6.8–9.7) for men and 8.3 years (7.1–9.4) for women by 2030.

Chetty et al. (2016) set out to estimate the level, time trend, and geographic variability in life expectancy as it relates to income and to determine the factors related to small area variation. The study employed income data for the US population obtained from 1.4 billion deidentified tax records between 1999 and 2014. Social Security Administration death records were the source of the mortality data used to estimate race- and ethnicity-adjusted period life expectancy at age 40 years¹. This estimate was done by household income percentile, sex, and geographic area. In addition, factors hypothesized to lead to differences in life expectancy outcomes were also evaluated.

Chetty et al. (2016) found that between 2001 and 2014, higher income was correlated with greater longevity in the United States. Over time, the disparity in life expectancy across income groups increased. However, there were significant differences in the association between life expectancy and income across areas. Disparities in life expectancy across income groups reduced in certain areas and increased in others. The differences in life expectancy were correlated with health behaviors and social determinants of health.

Chetty et al. (2016) arrived at four broad conclusions. First, higher income was associated with greater longevity throughout the income distribution. The disparity in life expectancy between the richest 1% and poorest 1% of individuals was 14.6 years for men and 10.1 years for women. Second, differences in life expectancy grew over time. Between 2001 and 2014, life expectancy among the top 5% of the income distribution increased by 2.34 years and 2.91 years for men and women respectively, but by only 0.32 years for men and 0.04 years for women in the bottom 5%.

¹ Period life expectancy is defined as the expected length of life for a hypothetical individual who experiences mortality rates at each subsequent age that match those in the cross-section during a given year.

Third, there was substantial variation, across local areas, in life expectancy for low-income individuals. Life expectancy differed by approximately 4.5 years between areas with the highest and lowest longevity, in the lowest quartile. Differences in life expectancy ranged from gains of more than four years to losses of more than two years across areas between 2001 and 2014. Finally, geographic differences in life expectancy for individuals in the lowest income quartile had significant correlations to health behaviors such as smoking but did not have significant correlations to access to medical care, physical environmental factors, income segregation, or unemployment rates. Life expectancy for low-income individuals was positively correlated with the local area fraction of immigrants, the fraction of college graduates, and government expenditures.

Matthews (2017) premised his study on the observation that rural populations are recognized as health disparity populations mainly because of the prevalence of disease and high rate of premature death as compared to the overall population of the United States. The study notes that surveillance data about health-related behaviors are not often reported by urban-rural status. This makes comparing persons living in Metropolitan and those in non-Metropolitan counties difficult.

Matthews (2017) employed the Behavioral Risk Factor Surveillance System (BRFSS) which is an ongoing, state-based, random-digit-dialed landline- and cellular-telephone survey of non-institutionalized adults aged 18 years or higher, who were residents of the United States. The BRFSS gathers data on health-risk behaviors, chronic diseases and conditions, access to health care, and use of preventive health services related to the leading causes of death and disability (Matthews, 2017). The study analyzed BRFSS data for 398,208 adults (aged 18 or more) to estimate the prevalence of five self-reported health-related behaviors (sleep patterns, smoking

habits, nondrinking or moderate drinking, maintaining healthy body weight, physical activity recommendations) by urban-rural status.

Matthews (2017) found that approximately a third of U.S. adults practice at least four of these five behaviors. Compared with adults living in the four types of Metropolitan counties (large central Metropolitan, large fringe Metropolitan, medium Metropolitan, and small Metropolitan), adults living in the two types of Non-Metropolitan counties (Micropolitan and noncore) did not differ in the prevalence of sufficient sleep; had higher prevalence of nondrinking or moderate drinking; and had lower prevalence of current nonsmoking, maintaining normal body weight, and meeting aerobic leisure time physical activity recommendations.

The study also found that the total age-adjusted prevalence of 30.4% reporting at least four of the five health-related behaviors. Among the 13.3 million adults estimated to be living in noncore counties, the prevalence was lower than among those in Micropolitan counties, small Metropolitan counties, medium Metropolitan counties, large fringe Metropolitan counties, and large Metropolitan centers. The study by Matthews (2017) is arguably the first report of the prevalence of these five health-related behaviors that looks at the six urban-rural categories. Lower prevalence of three and clustering of at least four health-related behaviors that are associated with the leading chronic disease causes of death was recorded for Non-Metropolitan counties. Prevalence of sufficient sleep was consistently low and did not differ by urban-rural status.

Moy (2017) established the leading causes of death in Non-Metropolitan and Metropolitan Areas in the United States from 1999 to 2014. Heart Disease, Stroke, Chronic Lower Respiratory Disease, Cancer, and Unintentional Injury emerged as the five leading causes of death in the United States (Moy, 2017).

Moy (2017) found that non-Metropolitan areas, with regards to the five leading causes of death, have higher age-adjusted death rates and greater percentages of potentially excess deaths². Routine tracking of potentially excess deaths from the five leading causes of death in Non-Metropolitan and Metropolitan areas could be helpful to public health officials monitoring important rural health disparities and selecting effective programs and policies to improve the health of residents of rural areas. Moy (2017) recommend additional information on potentially excess deaths which could be useful in evaluating the success of public health interventions and to help identify the area of greatest importance when it comes to the allocation of resources. Advice could be sorted by State and local public health officials from officials in rural areas with fewer potentially excess deaths on ways to reduce mortality in their jurisdictions. There can also be increased coordination between these officials to ensure rural residents have timely access to specialized services.

In a related study, Garcia et al. (2017) sought to find how potentially excess deaths from the five leading causes of death can be reduced in the rural United States (Garcia, 2017). The study was set against the background that in 2014, approximately 62% of all 1,622,304 deaths in the United States were related to the five leading causes of death. During 2014, the number of potentially excess deaths from the five leading causes in rural areas was higher than those in urban areas (Moy, 2017).

Garcia (2017) concluded that there is a rural-urban disparity in age-adjusted death rates and potentially excess deaths in the United States from the five leading death causes. Rural

² Potentially excess death was defined as “deaths among persons aged below 80 years in excess of the number that would be expected if the death rates for each cause were equivalent across all states to those that occurred among the three states with the lowest rates.”

communities, compared with urban areas, record higher age-adjusted death rates and a higher number of potentially excess deaths from the five leading causes.

Other conclusions emanating from the study are that geographic, behavioral, structural and other interconnected social factors are often associated with higher death rates and potentially excess deaths. Historical trends indicate that adequately addressing the complex health outcomes, including mortality among the rural population, cannot be achieved solely by focusing on access to health care in rural areas of the United States.

Garcia (2017) recommended that improving and increasing the integration of primary, specialty, and substance abuse services must be the focus of rural policy makers if they seek to address the non-uniform achievements in the health care delivery system. Challenges of identifying modifiable factors, both societal and structural, which contribute to the disparity between rural and urban mortality outcomes from the five leading causes of death were also noted in the study. Further recommendations include additional analysis that can yield results that inform the strategic alignment of resources with condition-specific needs.

For the widening gap in age-adjusted death rates from unintentional injuries between rural and urban areas to be closed, the focus should be shifted towards designing, implementing, and monitoring locally informed initiatives in rural communities that aim at effective prevention and treatment of opioid misuse, including treatment of opioid overdose (Garcia, 2017).

Needs-based allocation of resources could also significantly impact rural health. Funding for programs that address risk factors associated with the five leading causes of death is allocated on a population basis which often leads to underfunded rural programs. To bridge the gap between rural and urban areas, an increased emphasis must be put on the need, and

epidemiologic burden of disease as major factors in targeting future allocation of public health and prevention funding (Garcia, 2017).

THE UNITED STATES URBAN HIERARCHY

The interrelationships among urban centers and between them and their rural fringes are among the most visible features of the expanding American urban landscape. Responding to technological, economic, and quality-of-life stimuli, households relocate to areas that offer greater net utility. Firms' cost-minimizing location decisions simultaneously influence household decisions and also respond to them. The resulting population flows drive the evolution of the hierarchical urban system. Interest in the spatial dimension of population dynamics burgeoned with the advent of the New Economic Geography (NEG) (Krugman 1991), which built on the urban-hierarchy lattice from traditional Central Place Theory (CPT) (Christaller 1933). In CPT, lower-tiered places depend on higher-tiered places for access to progressively higher-ordered goods and services offered at each tier. In extending CPT, the NEG formalizes the role of agglomeration in the dynamic formation of an urban system. Both theories prominently feature an urban hierarchy based on regional market potential, creating symbiotic interrelationships among tiers, including the rural fringe (Fujita et al. 1999).

Huff (1976) proposed a simple hierarchical migration model as a mechanism for the redistribution of population within a Christaller central place hierarchy. This is against the backdrop that given a predefined functional hierarchy, the migration process causes any initial population distribution to converge to an equilibrium distribution. Under certain special conditions however, the equilibrium is identical to a central place population distribution derived from economic base concepts.

Huff's (1976) migration model was based on five assumptions. One of these assumptions was that the migration process is defined within the context of a Christaller central place hierarchy. A second interrelated assumption is that the destination set for migrants leaving a central place or rural area is comprised only of those places which directly dominate or are directly dominated by their place of origin.

Addressing the question as to whether new economic geography agglomeration shadows underlie current population dynamics across the urban hierarchy, Patridge et al (2008) explores whether proximity to same-sized and higher-tiered urban centers affected the patterns of 1990-2006 U.S. county population growth. Generally, the study concluded that rather than casting New Economic Geography (NEG) agglomeration shadows on nearby growth, larger urban centers generally appear to have positive growth effects for more proximate places with populations less than 250,000. However, they found some evidence that the largest urban areas cast growth shadows on proximate medium-sized Metropolitan areas and of spatial competition among small Metropolitan areas.

Further, they found that rural counties and smaller urban centers have significant positive interactions with their nearest higher-tiered urban areas, and the further removed a rural or smaller urban county was from each higher tier of urban center, the lower the growth of the rural or smaller urban county in question. Little evidence was found consistent with NEG growth shadows, the exception being spatial competition among small Metropolitan Areas (MAs). For counties located in larger MAs, spatial interactions with higher-tiered urban areas were much less evident. The general lack of growth shadows suggest that some predictions of NEG and Central Place Theory (CPT) are not particularly germane for describing the continued evolution

of the American urban system. Deconcentrating and sprawl also remain key features of intra urban area settlement patterns for large MAs.

In the spirit of developing regional science, Plane (2003) examines some literature in the field and argues that regional science has entered a product-specialization stage and that there may now be a need for some broad synthesizing research. Plane (2003) contends that studies of regional growth and development constitute the highest form of the regional scientist's art. The paper further argues for greater consideration to be given to disaggregating variables by demographics and paying greater attention to geographic units and scales.

In this light, Plane (2003) shed light on the system of Core-Based Statistical Areas (CBSAs) at its nascent stage of development at the time. He presented an experimental version of the new system of Metropolitan and Micropolitan Statistical Areas to illustrate some urban-scale effects evident in county-level growth trends. The study was inspired by the aftermath of the 2000 US census which saw the birth of a nationwide system of CBSAs under the then new Office of Management and Budget (OMB) approved standards (Federal Register 2000). CBSAs were to be inclusive of both Metropolitan Statistical Areas and Micropolitan Statistical Areas (Plane, 2003).

Like the MSAs before 2003, Metropolitan Statistical Areas defined according to the new standards were to be composed of groups of counties centered on Urbanized Areas of 50,000 or more population. The new Micropolitan Statistical Areas were to be built up from "Urban Clusters" having populations of 10,000 to 49,999. Urban Clusters are units analogous to Urbanized Areas in that they both delineate contiguous territory having high density of population. Collectively, Urbanized Areas and Urban Clusters are now in official OMB/Census Bureau parlance referred to as "Urban Areas" (Plane, 2003).

Subsequently and with the benefit of hindsight, Plane and Jurjevich (2009) explored the patterns and repercussions of age-articulated migration. They noted rates of geographical mobility vary greatly, and fairly predictably, across the life course. Analyzing special county-to-county migration tabulations of Census 2000 data, they discovered that when flows are disaggregated by age, radically different patterns of net population redistribution are taking place upward and downward within the national urban hierarchy. The movements at the late-career, empty-nester, and retirement stage are the most “demographically effective” or unidirectional. The elderly fleeing large Metropolitan areas have been congregating in Micropolitan and rural counties with special climatic and other natural amenities. The opposite net flow is found for younger adults, who have been flocking into mega-Metropolitan conurbations. At the midcareer stage, the net movement is from larger to medium Metropolitan areas (Plane and Jurjevich, 2009).

Plane and Jurjevich (2009) detail the age articulation of county-to-county migration flows with novel graphical portrayals and statistical measures; presenting thoughts on the relationship between intergenerational dependency and migration trends. They speculate about whether the current patterns of age-articulated movement up and down the urban hierarchy will continue as the baby boom retires and the echo cohorts come of age. Specifically, their analyses suggest many adult children may themselves have moved after leaving the childhood home and moved perhaps onward several times up and down the urban hierarchy. The life courses and residential histories of parents and their adult children thus entwine in ever more complex ways (Plane and Jurjevich, 2009).

Set in the 1980s when population growth was topical in regional studies, McGranahan and Salsgiver (1992) posited that population growth in non-metro counties adjacent to metro

counties was influenced by three factors in the 1980s: urban spillover, size of metro county and region. A non-metro county is an "adjacent county" if it is adjacent geographically to one or more Metropolitan Statistical Areas (MSA's) and at least 2 percent of its employed labor force commutes to the metro area(s) (McGranahan & Salsgiver, 1992).

On the score of urban spillover, where the metro county fared well, the adjacent county also generally did well. In terms of the size of Metropolitan County as a factor, the population of non-metro counties adjacent to large metro counties (more than 1 million population) grew faster than the population of other non-metro counties. Region as the third factor revealed that non-metro adjacent counties in the West experienced high population growth (McGranahan and Salsgiver, 1992).

Morrill et al (1999) assessed the definition of Metropolitan areas based on the 1990 US census. Discontent with the definition of Metropolitan areas at the time and the lack of differentiation within the Non-Metropolitan territory provided the incentive for their research. Census tracts rather than counties were used as the building blocks for assignment of tracts, not just to Metropolitan areas, but also to larger towns (10,000 to 49,999) and to smaller urban places (2,500 to 9,999). The analysis used 1990 census-defined urbanized areas and tract-to-tract commuter flows. They found a modest shift of population from Metropolitan to non-Metropolitan, as well as a significant reduction in the real size of Metropolitan areas, disaggregation of many areas, and frequent reconfiguration to a more realistic settlement form (Morrill et al, 1999).

POLICY LINK BETWEEN SPACE AND PLACE EFFECTS IN RURAL HEALTHCARE

A major fruit of efforts to provide a link between space and place effects that has been implemented in federal policy has been in the health sector, specifically focused on health

outcomes through the Critical Access Hospital (CAH) program. The CAH program represented one of the biggest changes in rural health policy. Introduced by the Balance Budget Act of 1997, the CAH program was created to preserve access to primary and emergency care services in isolated rural areas by improving the financial conditions of CAH hospitals and preventing some closures (Fannin & Nedelea, 2013).

The CAH program was created to help maintain availability of emergency and primary health care services in rural areas. This was accomplished by improving the financial conditions of CAH hospitals through Medicare cost-based reimbursement aimed at saving many small rural hospitals from closure while maintaining adequate access to care in isolated areas. To be eligible for the CAH program, hospitals had to be at least 35 miles by primary road or 15 miles by secondary road from another hospital. They must have less than 25 acute care beds with an average length of stay less than four days annually. These hospitals were also required to provide 24-hour emergency services (Fannin & Nedelea, 2013).

Results from Nedelea & Fannin (2013) suggested that the CAH Program may have decreased the allocation and cost efficiencies of those rural hospitals that converted to CAH status relative to prospectively paid rural hospitals, without significantly increasing their technical efficiency. The lessons of the CAH Program for future health policy from this study were that the CAH program has been able to improve the financial condition of rural hospitals and likely resulted in many rural and remote regions of the United States maintaining lifesaving in-patient health care options where they would not otherwise exist. Further, the increased inefficiency of CAHs has been driven by strategic investments in depreciated facilities and equipment.

Kaufman et al (2016) undertook a preliminary study to look at recent hospital closures and to understand the causes and the impact on rural communities. The 2009 financial performance and market characteristics of rural hospitals that closed from 2010 through 2014 were compared to rural hospitals that remained open during the same period, stratified by critical access hospitals (CAHs) and other rural hospitals (ORHs). Differences were tested while the relationships between negative operating margin and the explanatory variables, market factors, and utilization or staffing factors were explored using logistic regression.

Kaufman et al (2016) identified profitability, liquidity, capital structure, revenue, utilization (patient volume), and staffing as impacting hospital closures. The study essentially found that CAHs that subsequently closed from 2010 through 2014 had, in general, lower levels of profitability, liquidity, equity, patient volume, and staffing. In addition, ORHs that closed had smaller market shares and operated in markets with smaller populations compared to ORHs that remained open. Odds of unprofitability were associated with both market and utilization factors. Although half of the closed hospitals ceased providing health services altogether, the remainder have since converted to an alternative health care delivery model. Kaufman et al argued that it was possible to identify hospitals at risk of closure because financial and market characteristics appear to be associated with closure of rural hospitals from 2010 through 2014.

Wishner & Solleveld (2016) conducted case studies of three hospital closures that took place in 2015: Mercy Hospital in Independence, Kansas; Parkway Regional Hospital in Fulton, Kentucky; and Marlboro Park Hospital in Bennettsville, South Carolina. Two of these hospitals were in states that did not adopt the Medicaid coverage expansion under the Affordable Care Act (ACA) (Kansas and South Carolina), while one of the hospitals was located in a Medicaid expansion state (Kentucky). The choice of hospitals was influenced by criteria such as hospitals

that had closed recently, had not converted to another type of facility (e.g., an urgent care facility) following the closure; and had been reimbursed by Medicare under the prospective payment system (PPS) through predetermined fixed reimbursement rates, not on a cost basis.

The study found the following factors to have accounted for the closures: aging, poor, and shrinking populations; high uninsured rates and a payer mix dominated by Medicare and Medicaid; economic challenges in the community; aging facilities; outdated payment and delivery system models, and business decisions by corporate owners/operators. Consequently, the hospital closures reduced local residents' access to care, especially emergency care; raising calls for new care models which may better address the health care needs of rural communities. Interestingly, Kaufman et al (2016) and Wishner & Solleveld (2016) agree on the future outlook that more rural hospitals are set to close and this casts a gloomy expectation on rural communities' access to health care.

Though the CAH program was created incorporating both place and space dimensions in its development to maintain health care access aimed at improving health outcomes in rural areas of the United States, an increase in rural hospital closures in the US resulting in reduced access is still occurring. While some of this reduced access is occurring in non-CAH hospitals, other rural hospitals closures have occurred in hospitals with CAH status. This means the benefit that CAH gave by making rural hospitals more financially stable to improve health access thus improving health outcomes is becoming less effective. This has created the need to find alternative strategies for achieving health outcomes that go beyond simply providing health access. The relationships between health outcomes and other potential factors that policy could influence must be better understood. The research questions addressed by the models presented in the next chapter will help to provide a potential understanding of which behavioral and socioeconomic

factors may be targets of future policy to supplement or supplant access-based policies of recent decades such as CAH.

CHAPTER 3: THEORETICAL AND EMPIRICAL MODELS.

OBJECTIVE ONE

Many papers have tried to establish the differences in the response of Metropolitan and rural America to some socio-economic and individual choice factors. Research that has sought to establish these differences include works by Chetty et al. (2016) and Weber et al. (2017). Weber et al. (2017) employed a simple comparison means analysis to establish the differences in upward mobility among three CBSA categories. The same methodology is used in this paper to establish the differences in life expectancy at age 40 across the American urban hierarchy. This life expectancy is a period life expectancy. Chetty et al (2016) defined period life expectancy as “the expected length of life for a hypothetical individual who experiences mortality rates at each subsequent age that match those in the cross-section during a given year”. These period life expectancies aggregated at the county level are used in this study.

Simple descriptive statistics are used in this analysis. The mean values of the variables and their standard deviations are compared for three categories. These three categories are created on the Core Based Statistical Area (CBSA) system of classifying counties in the United States. A pairwise difference in means of life expectancy across the levels of rurality is obtained and adjusted p-values and confidence intervals are performed for multiple comparisons to establish the difference in means across four income levels in the various county categories.

OBJECTIVE TWO

From the literature, variations in life expectancy are explained by an individual’s choice factors (Matthews, 2017; Moy, 2017; Pickett and Pearl, 2001) and socioeconomic factors (Bennett et al, 2015; Chetty et al, 2016; Gurven et al, 2008; Hayflick, 2007) in the location the individual lives.

Life expectancy is therefore estimated as a function of the above factors.

$$LE = f(\text{individual choice factors}, \text{socioeconomic factors}) \quad (1)$$

$$\frac{\partial \text{Life Expectancy}}{\partial \text{individual choice factors}} < \text{or} > 0 \quad (2)$$

$$\frac{\partial \text{Life Expectancy}}{\partial \text{Socioeconomic factors}} < \text{or} > 0 \quad (3)$$

This equation is estimated using the simple ordinary least squares (OLS) model. This model is used to tease out the relationship between these factors and life expectancy at age 40. The life expectancy for each of the counties is the dependent variable, and it is obtained from the health inequality project website (www.healthinequality.org). The specific choice factors and the socio-economic factors are the independent variables in the OLS model. The data for these variables were also obtained from the health inequality project website. The specific individual choice factors selected include smoking habits (measured by the percentage smokers in the county), obesity (percentage obese) and exercise habits (percentage of population who have had any exercise in the last 30 days). The socio-economic factors include medicare dollar per enrollee, income segregation in the county, social capital index of the county, percentage of the population foreign born in the county and the unemployment rate in 2000. The theoretical model in Equation 1 is transformed into the econometric model below and shown in Equation 4.

$$LE_{county} = \beta_0 + \beta_1 PS + \beta_2 PO + \beta_3 PE + \beta_4 MDPE + \beta_5 InS + \beta_6 SSc + \beta_7 PbF + \beta_8 UnP + \beta_9 HHI + \beta_{10} PcP + \beta_{11} PCLF + \beta_{12} LFP + \mu; \quad (4)$$

Where PS is the percentage of current smokers in the county, PO represents the percentage of population obese in a county, PE is the percentage of county population that exercised in the last 30 days, MDPE represents Medicare dollar Per Enrollee in the county, InS

represents income segregation within the county, SSc is the social capital index of the county, PbF is the percentage of immigrants or foreign born population in the county, UnP represents unemployment rate in 2000, HHI is the mean household income in the county, PCP is the percentage change in population (1980-2000), PcLF is the percentage change in labor force (1980-2000) and LFP is the labor force participation rate in the county.

Table 1 gives a detailed definition of all the variables and also gives the source of all the data used in the analysis. A second variation of the model is run in which slope dummies, d1 (Non-Core) and d3 (Metropolitan), are incorporated to capture place-based association of all the variables and life expectancy. The slope dummies are interacted with all the variables with and without intercept dummies to see how the response of each of the associate factors to life expectancy change given the place-based structure of the counties in the analysis.

A fourth model iteration is also estimated in which a distance variable (distance in miles to nearest Metropolitan County) was added. This is used to capture the space effects of the variables on life expectancy at age 40.

$$LE_{county} = \beta_0 + \beta_1 PS + \beta_2 PO + \beta_3 PE + \beta_4 MDPE + \beta_5 InS + \beta_6 SSc + \beta_7 PbF + \beta_8 UnP + \beta_9 HHI + \beta_{10} PCP + \beta_{11} PCLF + \beta_{12} LFP + \beta_{13} PNM_{et} + \mu \quad (5)$$

Table 1: Definition of Variables

Representation	Variable Name	Definition	Source
PS	Percentage smokers	BRFSS: percentage of current smoker in the county.	CDC Behavioral Risk Factor Surveillance System (BRFSS) 1996-2008 ²
PO	Percentage Obese	BRFSS: percentage of population obese in the county.	CDC Behavioral Risk Factor Surveillance System (BRFSS) 1996-2008 ²
PE	Percentage Exercise	BRFSS: percentage of population that exercised in the last 30 days	CDC Behavioral Risk Factor Surveillance System (BRFSS) 1996-2008 ²
SSc	Social Capital	Standardized index combining measures of voter turnout rates, the fraction of people who return their census forms, and measures of participation in community organizations	Rupasingha and Goetz (2008) ²
PbF	Percent Foreign born	Percentage of county residents born outside the United States	2000 Census SF3 Sample Data Table P021 ²
InS	Income Segregation	Rank-order index estimated at the census-tract level computed for each of the income brackets given in the 2000 census	2000 Census SF3 Sample Data Table P052 ²
MDPE	Medicare Dollar per enrollee	Age, sex, race, and price-adjusted Medicare reimbursements per enrollee in 2010 (\$)	Dartmouth Atlas 2010 ²

Table continues on page 28.

UnP	Unemployment rates	Unemployed civilian population 16 years and over divided by civilian labor force population 16 years and older	2000 Census SF3 Sample Data Table DP-3 ²
HHI	Mean Household Income	Aggregate household income in the 2000 Census divided by the number of people aged 16-64 (\$)	2000 Census SF3 Sample Data Table P054 ²
PcP	Percentage change in population	percentage change in county non-institutional civilian population from 1980 to 2000	1980, 2000 Census ²
PCLF	Percentage change in labor force	Fraction change in CZ civilian labor force population from 1980 to 2000	1980, 2000 Census ³
LFP	Labor force participation	Fraction of people at least 16 years old that are in the labor force	2000 Census SF3 Sample Data Table P043 ²
PNMet	Distance to nearest metro area	This shows the distance (in miles) to the nearest Metropolitan area.	2010 Census, the US Census Bureau
PNC_Met	Distance to nearest central metro	This shows the distance (in miles) to the nearest central Metropolitan area.	2010 Census, the US Census Bureau

³ Definitions and sources as used in Chetty et al (2016) and available for download from the project website (www.healthinequality.org)

The last model that was run was very similar to the fourth. It only had a different measure of distance which was the distance to the nearest central Metropolitan county. Modeling the distance to the nearest central Metropolitan county helps to identify if there is a differential return to proximity to higher ordered urban places.

$$LE_{county} = \beta_0 + \beta_1 PS + \beta_2 PO + \beta_3 PE + \beta_4 MDPE + \beta_5 InS + \beta_6 SSc + \beta_7 PbF + \beta_8 UnP + \beta_9 HHI + \beta_{10} PcP + \beta_{11} PCLF + \beta_{12} LFP + \beta_{13} PNCMet + \mu \quad (4)$$

The expected association between all the variables and life expectancy are presented in Table 2.

Table 2: Expected relationships of variables with life expectancy.

Representation	Variable Name	Parameter	Expected sign
PS	Percentage smokers	β_1	Negative
PO	Percentage Obese	β_2	Negative
PE	Percentage Exercise	β_3	Positive
SSc	Social Capital	β_4	Positive
PbF	Percent Foreign born	β_5	Positive
InS	Income Segregation	β_6	Negative
MDPE	Medicare Dollar per enrollee	β_7	Negative
UnP	Unemployment rates	β_8	Negative
HHI	Mean Household Income	β_9	Positive
PcP	Percentage change in population	β_{10}	Positive
PCLF	Percentage change in labor force	β_{11}	Positive
LFP	Labor force participation	β_{12}	Positive
PNMet	Distance to nearest metro area	β_{13}	Positive
PNC_Met	Distance to nearest central metro	β_{13}	Positive

DATA

Data for this research was obtained from the health inequality project website (www.healthinequality.org) where all of the commuting zone (CZ), county, state, and national level statistics that were used for the project were provided by Chetty et al. (2016). For this project, death records from the Social Security Administration's (SSA) Death Master File were used. Together with a deidentified database of federal income tax that includes all individuals with a valid social security number between 1999 and 2014 (Chetty et al, 2016). These two sets of data were used to estimate life expectancy at state, county and commuting zone levels using the maximum likelihood estimation (MLE) and the ordinary least squares (OLS) methods.

Data on rates of smoking, obesity and exercise were also obtained from the BRFSS database. The Behavioral Risk Factor Surveillance System (BRFSS) is an ongoing, state-based, random-digit-dialed landline- and cellular-telephone survey of noninstitutionalized adults above the age of 18, residing in the United States (Matthews, 2017). BRFSS data are weighted to represent state populations. The 2013 BRFSS is the most recent year for which the survey questionnaire had questions for both sleep and aerobic physical activity in addition to cigarette.

For this study, county classifications from the CBSA system, Metropolitan, Micropolitan and Non-Core county categories are used. The data considered for this study consists of 1553 counties observations from 1999 to 2014 including 182 Non-Core counties, 476 Micropolitan counties and 895 Metropolitan counties. There are a total of 3,142 counties in the United States. Since 1,589 counties were not considered for this study for lack of data on these counties, only counties with a population greater than 25,000 were considered for the study and these counties are shown in figure 1.

Two alternative categorizations of counties were also created which were solely based the county populations in 2000. For the first of our alternative categorizations, we approximate large

Micropolitan as having between 25,000 and 49,999 inhabitants, small Metropolitan having between 50,000 – 99,999 inhabitants and large Metropolitan having over 100,000 inhabitants. This categorization included 646 large Micropolitan counties, 390 small Metropolitan counties and 523 large Metropolitan counties. The map for this classification and all the results obtained for this run are shown in appendix B.

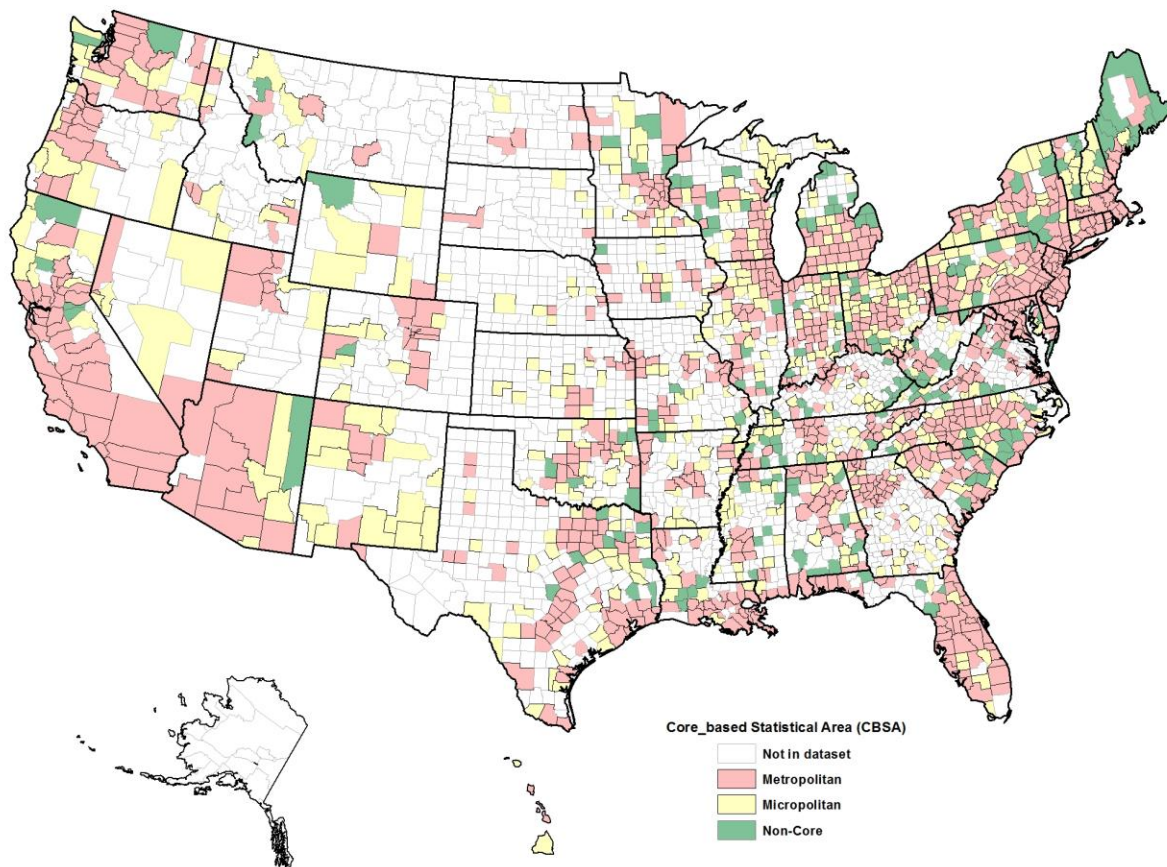


Figure 1: Map showing counties in sample as classified by population.

The third alternative was performed in which new thresholds for small and large Metropolitan areas were set to evaluate sensitivity to the definition of small and large Metropolitan counties. Large Micropolitan counties in the new classification still contained a

population between 25,000 and 49,999. Small Metropolitan counties were redefined to include counties with populations between 50,000 and 250,000 while large Metropolitan counties in this classification were counties with a population of not less than 250,000. The map and results for this classification are also shown in appendix C.

CHAPTER 4: RESULTS.

This chapter contains the results and discussion for all the analyses performed in this study.

Tables and figures are used to show key findings. I first establish the spatial differences in life expectancy among the three categories of counties analyzed and show how the correlates of life expectancy vary between the three county categories. Some place effects and spaces effects of variations in life expectancy are also shown. All these analyses are replicated for the alternate classifications of counties and attached in the Appendix.

ESTABLISHING SPATIAL DIFFERENCES IN LIFE EXPECTANCY.

Means differences across urban hierarchy

A simple means comparison, similar to the one used by Weber et al. (2017), is used in this part of the analysis to establish the difference in life expectancy averages across the county categories. These means are shown graphically in figure 2.

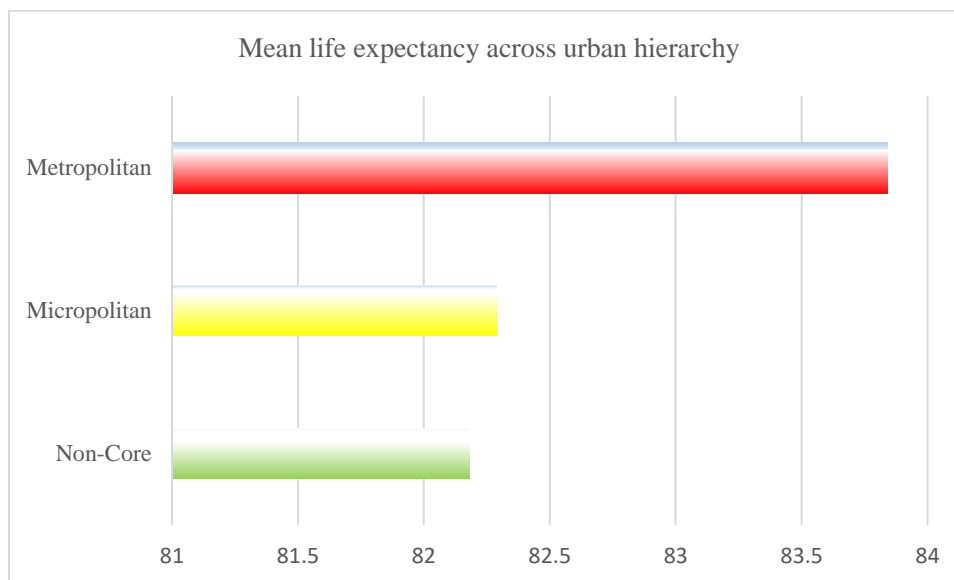


Figure 2: Mean life expectancy across the urban hierarchy.

The average life expectancy at age 40 for Non-Core counties in the United States is 82.18 years with a standard deviation of 1.29. For Micropolitan counties, the average life expectancy at age 40 is 82.29 years with 78.36 years and 86.64 years being the minimum and maximum county averages. Metropolitan counties also have a life expectancy of 83.84 years at age 40. The minimum average county life expectancy is 79.07 years and the maximum is 87.06 years as shown in Table 3.

Table 3: Summary statistics for urban hierarchy life expectancy.

	Mean	Std. Dev.	Min	Max
Non-Core	82.18	1.29	78.22	85.31
Micropolitan	82.29	1.29	78.36	86.64
Metropolitan	83.84	1.31	79.07	87.06

A means test for equality was conducted for the three group means, assuming homogeneity and the tests⁴ concluded that the means of life expectancy at age 40 for Non- core and Micropolitan counties are significantly different from those of the Metropolitan counties. However, there were no statistically significant differences between the means for Non-Core and Micropolitan counties. The results of the mean comparison tests are summarized in table 4. Although statistical differences in the means are shown, the difference between the means as well as the minimum and maximums were small ranging only between one and two years across all categories.

⁴ The test used in this analysis is the pairwise Tukey comparison of means with equal variances.

Table 4: Pairwise comparison of means for urban hierarchy.

	Non-Core	Micropolitan	Metropolitan
Non-Core	-		
Micropolitan	-.107 (.114)	-	
Metropolitan	-.655*** (.106)	-.547*** (.074)	-
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Mean differences within income quartiles across the urban hierarchy

When analyzed in terms of income quartiles⁵, life expectancy at 40 showed no significant variations across the urban hierarchy for all four income quartiles. The mean life expectancy at age 40 for the bottom quartile of the income distribution in Non-core counties was 78.88 years with a minimum of 75.46 years and a maximum of 84.35 years. These summary statistic are shown in table 5. For Micropolitan counties, the mean was 78.68 years with 75.50 and 84.05 being the minimum and maximum respectively. 78.70 years was the mean life expectancy at 40 for the bottom quartile in Metropolitan counties with a minimum of 75.46 and a maximum of 84.19 years. A pairwise means comparison test for the group means was run and showed that the means for all three categories were not significantly different from each other.

⁵ The income quartiles used in this study were created in the income inequality project. Household incomes were for all observations were ranked and grouped into four income quartiles based on percentage ranking.

Table 5: Summary statistics for urban hierarchy per income quartile.

	Mean	Std. dev.	Min	Max
1 st Quartile				
Non-Core	78.88	1.53	75.46	84.35
Micropolitan	78.68	1.47	75.50	84.05
Metropolitan	78.70	1.51	75.46	84.19
2nd Quartile				
Non-Core	82.15	1.14	79.60	85.87
Micropolitan	82.08	1.17	78.86	86.20
Metropolitan	82.08	1.17	77.50	87.40
3rd Quartile				
Non-Core	84.13	1.20	80.69	87.79
Micropolitan	84.17	1.14	80.07	87.66
Metropolitan	84.13	1.18	77.50	88.46
4th Quartile				
Non-Core	86.04	1.32	80.61	88.98
Micropolitan	85.87	1.31	78.44	89.37
Metropolitan	85.91	1.41	76.48	91.45

For the second quartile, life expectancy at 40 for Non-Core counties was 82.15 years with a minimum and maximum of 79.60 and 85.87 years respectively. For Micropolitan areas, the mean was 82.08 years with a minimum of 78.86 years and a maximum of 86.20 years. For this income quartile, the mean life expectancy at age 40 in Micropolitan counties was 82.08 years with 77.50 and 87.40 being the minimum and maximum ages respectively. A pairwise means comparison test showed that there was no significant differences in means for these three groups.

In the third income quartile, 84.13 years is the mean life expectancy at 40 for Non-Core counties. These counties also had a minimum life expectancy of 80.69 years and 87.79 years was their maximum. Micropolitan counties in this quartile have a mean of 84.17 years and 80.07 years and 87.66 years as their minimum and maximum life expectancies. Metropolitan counties had a mean life expectancy at 40 or 84.13 years, a minimum of 77.50 years and a maximum of 88.46 years. The pairwise means comparison test for differences between the 3 categories showed no significant differences in their means.

The mean life expectancy at age 40 for the fourth income quartile of Non-Core counties was 86.04 years with a minimum of 80.61 year and a maximum of 88.98 years. In Micropolitan counties, the mean was 85.87 years with 78.44 and 89.37 years being the minimum and maximum respectively. The Metropolitan counties had a mean of 85.91 years for this income quartile with minimum and maximum life expectancies of 76.48 and 91.48 respectively. There were no significant differences in these means when a pairwise means comparison test was conducted for this category. Table 6 summarizes all the mean comparison tests for all four quartiles across the urban hierarchy.

Table 6: Test of means for urban hierarchy across income quartiles.

	Non-Core 1 st Quartile	Micropolitan	Metropolitan
Non-Core	-		
Micropolitan	.208 (.131)	-	
Metropolitan	.178 (.128)	-.026 (.085)	-
2nd Quartile			
Non-Core	-		
Micropolitan	.071 (.102)	-	
Metropolitan	.069 (.095)	-.002 (.066)	-
3rd Quartile			
Non-Core	-		
Micropolitan	-.036 (.102)	-	
Metropolitan	.002 (.095)	.039 (.066)	-
4th Quartile			
Non-Core	-		
Micropolitan	.176 (.119)	-	
Metropolitan	.125 (.112)	-.050 (.078)	-

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

CORRELATES OF LOCAL AREA VARIATION IN LIFE EXPECTANCY

This section of our results looks at the base model analysis of life expectancy looking at its association with the two groups of variables. The descriptive statistics of all the variables used in our regressions are presented in table 7.

Table 7: Descriptive statistics of life expectancy correlates.

Variable	Obs	Mean	Std. Dev.	Min	Max
LE	1553	82.60	1.36	78.22	87.06
PS	1553	20.60	5.19	1.85	42.46
PO	1553	27.24	6.65	4.37	58.73
PE	1553	73.53	8.18	45.14	92.03
UnP	1553	4.98	1.62	2.00	17.69
InS	1553	4.31	3.25	0.16	17.88
SSc	1553	-0.28	1.12	-4.26	3.79
PbF	1553	4.54	5.71	0.16	50.94
HHI	1553	135,268.32	66,652.89	30,125.82	1,333,001.03
PcP	1553	28.48	41.28	-45.23	598.79
PCLF	1553	39.64	46.54	-48.64	691.13
MDPE	1553	9357.15	1421.75	6117.42	16323.47
LFP	1553	62.81	6.55	32.43	80.89
PNMet	1553	3.67	10.72	0	125.65
PNC_Met	1553	5.12	12.09	0	125.65

The average county level percentage of smokers was 20.6% and percentage of obese population at the county level across our sample was 27.2%. In the sample, there was approximately 73.5% of the population of each county on average that exercised.

The results for the base regression model and all the model iterations incorporating place-based slope dummies and space-based effects (miles to metro and central metro) are summarized in table 8.

Table 8: Regression results for all OLS models

	Base model	Place intercept dummy model	Slope dummies Model	Slope and intercept dummy model	Place dummies and space variable A	Place dummies and space variable B
VARIABLES	(1) Life Expectancy	(2) Life Expectancy	(3) Life Expectancy	(4) Life Expectancy	(5) Life Expectancy	(6) Life Expectancy
PS	-0.0463*** (0.00437)	-0.0466*** (0.00437)	-0.0327*** (0.00695)	-0.0309*** (0.00728)	-0.0297*** (0.00728)	-0.0302*** (0.00728)
PSd1			0.0253** (0.0113)	0.0102 (0.0123)	0.0106 (0.0122)	0.00978 (0.0122)
PSd3			-0.0465*** (0.00909)	-0.0459*** (0.00966)	-0.0471*** (0.00966)	-0.0469*** (0.00967)
PO	-0.0166*** (0.00374)	-0.0156*** (0.00373)	-0.00286 (0.00533)	-0.00187 (0.00545)	-0.00159 (0.00545)	-0.00167 (0.00545)
POd1			0.000634 (0.0102)	-0.00949 (0.0107)	-0.00989 (0.0106)	-0.00975 (0.0106)
POd3			-0.0353*** (0.00760)	-0.0337*** (0.00796)	-0.0340*** (0.00795)	-0.0350*** (0.00798)
PE	0.0399*** (0.00394)	0.0407*** (0.00395)	0.0395*** (0.00527)	0.0423*** (0.00629)	0.0429*** (0.00628)	0.0428*** (0.00629)
PEd1			-0.0146 (0.00951)	-0.0375*** (0.0120)	-0.0389*** (0.0120)	-0.0389*** (0.0120)
PEd3			0.00270 (0.00613)	0.00468 (0.00839)	0.00401 (0.00838)	0.00473 (0.00838)
UnP	-0.0501*** (0.0151)	-0.0504*** (0.0151)	-0.0621*** (0.0223)	-0.0560** (0.0234)	-0.0569** (0.0234)	-0.0567** (0.0234)
UnPd1			0.00898 (0.0432)	-0.0235 (0.0447)	-0.0295 (0.0447)	-0.0256 (0.0447)
UnPd3			0.0277 (0.0303)	0.0291 (0.0321)	0.0289 (0.0320)	0.0309 (0.0321)

Table continues on page 41.

InS	-0.0130*	-0.0136*	-0.0336	-0.0327	-0.0311	-0.0315
	(0.00721)	(0.00783)	(0.0209)	(0.0208)	(0.0208)	(0.0208)
InSd1			0.162**	0.152*	0.140*	0.143*
			(0.0799)	(0.0797)	(0.0797)	(0.0798)
InSd3			0.00268	0.000941	-0.000404	0.00204
			(0.0226)	(0.0226)	(0.0225)	(0.0225)
SSc	0.293***	0.295***	0.327***	0.324***	0.327***	0.325***
	(0.0218)	(0.0219)	(0.0362)	(0.0363)	(0.0362)	(0.0363)
SScd1			-0.116	-0.0763	-0.0798	-0.0783
			(0.0773)	(0.0779)	(0.0778)	(0.0779)
SScd3			-0.0624	-0.0615	-0.0640	-0.0632
			(0.0465)	(0.0465)	(0.0465)	(0.0465)
PbF	0.0523***	0.0530***	0.0674***	0.0671***	0.0687***	0.0682***
	(0.00473)	(0.00471)	(0.00898)	(0.00896)	(0.00897)	(0.00897)
PbFd1			-0.0586**	-0.0664**	-0.0797***	-0.0739**
			(0.0287)	(0.0286)	(0.0291)	(0.0289)
PbFd3			-0.0168	-0.0157	-0.0172	-0.0171
			(0.0107)	(0.0107)	(0.0107)	(0.0107)
HHI	3.52e-06***	3.40e-06***	8.68e-06***	8.72e-06***	8.64e-06***	8.63e-06***
	(3.90e-07)	(3.91e-07)	(1.19e-06)	(1.19e-06)	(1.19e-06)	(1.19e-06)
HHId1			8.17e-07	-1.10e-06	-1.05e-06	-8.95e-07
			(3.26e-06)	(3.30e-06)	(3.29e-06)	(3.29e-06)
HHId3			-6.64e-06***	-6.66e-06***	-6.59e-06***	-6.59e-06***
			(1.27e-06)	(1.27e-06)	(1.26e-06)	(1.27e-06)
PcP	-0.0130***	-0.0124***	-0.0203***	-0.0201***	-0.0205***	-0.0201***
	(0.00254)	(0.00253)	(0.00419)	(0.00418)	(0.00418)	(0.00418)
PcPd1			0.00566	0.00534	0.00928	0.00697
			(0.0116)	(0.0115)	(0.0116)	(0.0116)
PcPd3			0.00842	0.00832	0.00888*	0.00880*
			(0.00531)	(0.00530)	(0.00529)	(0.00530)
PCLF	0.0162***	0.0156***	0.0195***	0.0192***	0.0196***	0.0192***
	(0.00222)	(0.00222)	(0.00362)	(0.00363)	(0.00362)	(0.00362)

Table continues on page 42.

PCLFd1			-0.00651 (0.00947)	-0.00553 (0.00945)	-0.00820 (0.00949)	-0.00653 (0.00945)
PCLFd3			-0.00537 (0.00461)	-0.00526 (0.00462)	-0.00569 (0.00461)	-0.00559 (0.00461)
MDPE	-0.000158*** (1.64e-05)	-0.000159*** (1.65e-05)	-0.000172*** (2.45e-05)	-0.000163*** (2.69e-05)	-0.000159*** (2.69e-05)	-0.000161*** (2.69e-05)
MDPEd1			-9.46e-05** (4.32e-05)	-0.000197*** (5.32e-05)	-0.000188*** (5.32e-05)	-0.000190*** (5.32e-05)
MDPEd3			8.34e-05*** (3.03e-05)	8.90e-05** (3.54e-05)	8.63e-05** (3.53e-05)	8.78e-05** (3.53e-05)
LFP	-0.000956 (0.00398)	0.000278 (0.00404)	-0.0186*** (0.00644)	-0.0159** (0.00726)	-0.0147** (0.00726)	-0.0149** (0.00727)
LFPd1			0.0234** (0.0111)	0.00263 (0.0130)	0.00614 (0.0130)	0.00427 (0.0130)
LFPd3			0.0289*** (0.00757)	0.0293*** (0.00897)	0.0283*** (0.00897)	0.0284*** (0.00897)
d1		0.248*** (0.0654)		4.818*** (1.539)	4.551*** (1.540)	4.678*** (1.540)
d3		0.104** (0.0492)		-0.291 (1.091)	-0.110 (1.092)	-0.202 (1.091)
P_Near_Metro					0.00694** (0.00277)	
P_Near_Cmetro						0.00441** (0.00225)
Constant	82.01*** (0.492)	81.79*** (0.501)	82.01*** (0.495)	81.45*** (0.848)	81.27*** (0.849)	81.32*** (0.850)
Observations	1,553	1,553	1,553	1,553	1,553	1,553
Adj. R-squared	0.700	0.703	0.726	0.731	0.726	0.725

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Individual behavioral choice variables.

Model results indicate the presence of smokers negatively affects life expectancy in a county. Specifically, a percentage increase in smokers is associated with a reduction in life expectancy by about 0.05 years or 19 days, *ceteris paribus*. The estimation of the parameter is also highly significant with a confidence of 99 percent. Moreover, percentage of smokers in a county is shown to be significant across different models with different control variables.

Obesity was also estimated to be negatively affect county level life expectancy. A percentage increase in the obese population of a county was associated with a reduction in life expectancy by about 0.02 years or a week, *ceteris paribus*. This parameter estimation is also highly significant with a confidence of 99 percent. The percentage obese in a county is also shown to be significant across different model specifications.

Exercise is the only variable in this category that has a positive effect on life expectancy at the county level. The percentage of the population that exercised was associated with an increase in life expectancy by about 0.04 years or 15 days with a percentage increase, *ceteris paribus*. This parameter estimation is shown to be significant across different models with different control variables.

Socioeconomic characteristics.

Unemployment was estimated to negatively affect life expectancy in a county. Specifically, a percentage point increase in the unemployment rates leads to a reduction of life expectancy by about 0.05 years or 18 days, *ceteris paribus*. The estimation of the parameter is also highly significant with a confidence of 99 percent. However, the unemployment rate in a county is not shown to be significant across different models with different control variables.

Social capital index is estimated to have a positive effect on life expectancy at the county level. A one point increase in the social capital index of a county is associated with an increase in

life expectancy of approximately 0.29 years or 106 days, *ceteris paribus*. This parameter estimation is shown to be significant across different models with different control variables.

We estimate that the presence of immigrants positively affects life expectancy in a county. Specifically, a percentage increase in the immigrant population in a county leads to an increase in life expectancy of about 0.05 years or 18 days, *ceteris paribus*. The estimation of the parameter is also highly significant. The percentage of immigrants in a county is shown to be significant across different models with different control variables.

INTRODUCTION OF PLACE DUMMIES.

In order to capture the place specific variations in life expectancy at age 40, I assigned two dummy variables, *d1* and *d3*, to represent Non-Core and Metropolitan counties respectively in the second specification of our model. In this equation, there were significant variations in life expectancy that were not captured by the health and socioeconomic variables, hence the dummies turn out significant. Life expectancy in Non-Core counties was about 0.25 years higher than that of the Micropolitan counties holding everything constant. Metropolitan counties also had a life expectancy about 0.10 years longer than Micropolitan counties, *ceteris paribus*. The signs and magnitudes of all the other variables remained approximately the same.

VARIATIONS IN LIFE EXPECTANCY ACROSS LEVELS OF RURALITY.

The third model interacted the place dummies from the second equation with the variables from the base model (Model 1) to create slope dummies that captured variation in each of the variables across the urban hierarchy. An F-test was also used to ascertain the significance of these place variations.

Individual choice variables

From the first two equations, the county level percentage of smokers was significantly and negatively associated with life expectancy. From this equation, that association also varies across county categories. The effects of percent smokers on Non-Core county life expectancy is less than in Micropolitan counties. The effects tend to be larger however in Metropolitan areas than in Micropolitan areas according to the results. A one percent increase in smokers in a Metropolitan county is associated with a reduction in county life expectancy by about 3.5 weeks (0.07 years) while it is associated with a 0.03 years or 11 day reduction in Micropolitan counties (baseline).

There are a number of reasons for this place variation in the effects of smoking on life expectancy. The quality of air in Metropolitan counties may be more polluted compared to Micropolitan counties. Studies performed in Metropolitan counties have shown high levels of atmospheric impurities owing to vehicular and aircraft emission in counties like Los Angeles county (Shirmohammadi et al., 2017). Also, the population densities of the Metropolitan areas means a one percent change in the number of smokers in a county represents a large increase in the effects of detriments associated with smoking including second hand smoking. These effects tend to get smaller on life expectancy as the population density reduces in Micropolitan and Non-Core counties.

When looking at obesity, there is no significant difference in the effects of obesity on the life expectancies of Non-Core counties and Micropolitan counties. However, there is a significant difference in the effects of a percentage change in the obese population of Metropolitan counties, a 0.03 year or 11 day reduction in life expectancy, compared to a 0.002 year reduction in county average life expectancy in Micropolitan counties.

One possible reason for this increased effect of obesity on life expectancy as one moves higher on the urban hierarchy is potentially an environmental issue (Poston & Foreyt, 1999). Its primary determinants are high levels of inactivity and excess caloric intake. Poston and Foreyt (1999) also included place of residence as a key contributor. These factors create an obesogenic environment which is quite common in Metropolitan areas. This tends to compound all obesity related health issues in Metropolitan areas.

From the results, I do not observe significant differences in the effects of exercising on life expectancy at the county level across the urban hierarchy. I cannot conclusively point to the cause of this lack of difference across the urban hierarchy primarily due to the manner in which the variable is measured. It is possible that the percentage of people who exercise in the cities work on intensive margin; that is, the variable might have an associated measurement error.

Table 9 shows the F test results for the third equation.

Table 9: F test results.

Test	Summation	F (1,1516)	Prob. > F
PSd1+ PS=0	-0.0074	0.65	0.4213
PS+ PSd3=0	-0.0792	161.48	0.0000
POd1+ PO=0	-0.00223	0.06	0.8011
PO + POd3 = 0	-0.03816	45.65	0.0000
PEd1 + PE = 0	0.0249	8.37	0.0039
PE + PEd3 = 0	0.0422	75.22	0.0000
UnPd1+ UnP=0	-0.05312	2.01	0.1569
UnP + UnPd3 = 0	-0.0344	2.53	0.1117
InSd1 + InS = 0	0.1284	2.78	0.0958
InS+ InSd3=0	-0.03092	12.59	0.0004
SScd1+ SSc=0	0.211	9.52	0.0021
SSc+ SScd3=0	0.2646	81.92	0.0000
PbFd1+ PbF=0	0.0088	0.11	0.7442
PbF+ PbFd3=0	0.0506	74.21	0.0000
HHId1+ HHI=0	9.50E-06	9.76	0.0018
HHI+ HHId3=0	2.04E-06	21.77	0.0000
PcPd1 + PcP = 0	-0.01464	1.84	0.1750
PcP + PcPd3 = 0	-0.01188	13.25	0.0003
PCLFd1+ PCLF=0	0.01299	2.21	0.1376
PCLF + PCLFd3 = 0	0.01413	24.38	0.0000
MDPEd1 + MDPE = 0	-2.67E-04	49.31	0.0000
MDPE + MDPEd3 = 0	-8.86E-05	17.12	0.0000
LFPd1 + LFP = 0	0.0048	0.25	0.6202
LFP+ LFPd3=0	0.0103	4.24	0.0397

Socioeconomic characteristics.

Looking at the results from the third equation, the effect of household income on life expectancy was greater in Micropolitan counties than in Metropolitan counties but there were no significant differences in life expectancy between Micropolitan counties and Non-Core counties due to household income, holding all else constant. This is likely owed to the fact that cost of living in Micropolitan areas is lower than in Metropolitan counties. An increase in household income makes it possible for individuals living Micropolitan areas to have more disposable income that can be spent on health investments like health insurance and healthier eating choices.

The social capital index effects on life expectancy were not significantly different between Metropolitan, Micropolitan and Non-Core counties. Immigrant population increase effects on Micropolitan county life expectancy (increase of about 25 days) was significantly different from Metropolitan county effects (increase by about 3 days). There were no significant differences of the effects of immigration on life expectancy at 40 between Micropolitan and Metropolitan counties.

Unemployment rates effects were not significantly different across the urban hierarchy along with variables like percentage change in labor force and percentage change in population. Medicare dollar per enrollee effects of life expectancy, though small, was significantly different between Metropolitan, Micropolitan and Non-Core counties. The percentage in the labor force also had significant differences in their effects between Metropolitan, Micropolitan and Non-Core counties.

In the fourth equation, the variations in life expectancy across the various county categories were shown using both the slope dummies for all the variables and the two intercept dummies, d1 and d3. A change in the signs and magnitudes for slope dummies were evaluated. For d1, the intercept dummy for the Non-Core counties, we observe saw a change in magnitude of about double compared to the second model. The sign for this dummy remains the same and this coefficient is statistically significant indicating about a four year higher average life expectancy for Non-Core counties compared to Micropolitan counties, holding all else constant. For the intercept dummy d3, the coefficient was not significant.

SPACE BASED VARIATIONS.

Two additional models were estimated in this study to capture the space-based variations in life expectancy across the place-based CBSA categories. In equation 5, a space variable,

distance to the nearest Metropolitan area was added. The magnitude and direction of the health and socioeconomic variables remained the same under this model specification. For the space variable, holding all else constant, a 1-mile increase in the county's distance to the nearest Metropolitan area increased life expectancy by about 0.007 years or 2.5 days, *ceteris paribus*.

The sixth model also incorporated another space variable, distance to nearest central Metropolitan County. Holding all else constant, a one mile increase in the county's distance to the nearest central Metropolitan area increased life expectancy by about 0.004 years or 1.5 days, all things being equal. The inclusion of these two distance variables did not have any measurable effect on the significance and signs of the other variables in previous iterations of the model. These results point to a higher life expectancies associated with living further away from Metropolitan counties. This may seem counterintuitive, but it likely means there are other latent unmeasured factors or factors that have been excluded from the model that are distance removed urban centers benefits of life expectancy. Some of these factor may include crime rates, drug activities, homicide and suicide rates and these factors when incorporated in the model may have an effect on the significance of the distance variable. These findings might suggest that Micropolitan counties have a slightly higher mix of services (such as healthcare services) as compared to Non-Core areas that can generate long-run health outcome benefits.

CHAPTER 5: CONCLUSION

One of the major policy goals at federal level has been to address the socioeconomic disparities in health ((Health & Services, 2010). This research used health outcomes, specifically life expectancy, to show these disparities across the urban hierarchy in the United States. There have been several debates in the literature as to how these disparities are created and how they have evolved over time. In this study, data available on the health inequality website was used to better understand the disparities in life expectancy across the US urban hierarchy. Differences in life expectancy were also established across four income quartiles across the US rural-urban hierarchy. The research also showed the place and space effects of health choice variable and socioeconomic variables on life expectancy at age 40 at the county level. These analyses yielded findings which are discussed in this chapter.

LIFE EXPECTANCY VARIATIONS ALONG THE URBAN HIERARCHY CONTINUUM

The first objective of this paper was to establish the differences in health outcomes, in this case, life expectancy at 40, across the US rural-urban hierarchy. This was accomplished with the use of simple comparison means analysis of period life expectancy at age 40 for Non-Core, Micropolitan and Metropolitan counties across the US. This approach is similar to the methodology used by Weber et al. (2017) to establish the differences in upward mobility among three CBSA categories

The first major finding of this study was that life expectancy at age 40 increased along the rural-urban hierarchy continuum moving from Non-Core to Metropolitan counties. The average life expectancy of Metropolitan counties was approximately 1.7 years greater than it was in Non-Core counties. The disparity was not sensitive to the introduction of income classifications.

From earlier works such as Chetty et al (2016) and Matthews (2017), life expectancy variations had been analyzed at the state level, county level and across income variations. This paper expanded that study to show variations across the place-based county categories and to better understand the place and space effects these categories have on life expectancy. Being able to show the variations in life expectancy at the county level between Non-Core counties, Micropolitan counties and Metropolitan counties, as this study did, gives policy makers better insights as to how to formulate targeted policies to help reduce these disparities.

CORRELATES OF LOCAL AREA VARIATION

The second objective of this research project was to establish the association of individual behavioral choices and socioeconomic variables on the life expectancy in a county. To accomplish this objective, five ordinary least squares (OLS) models were used to describe the association of these factors to county level life expectancy at age 40.

The second major finding of the study was that the effects of individual choice factors (smoking, obesity and exercise) on life expectancy at age 40 showed significant differences along the US rural-urban hierarchy continuum. As the percentage of a county's population that smokes increases by one percent, the average life expectancy at age 40 for the county goes down by about 0.05 years according to the data used in this study. There is also a reduction in life expectancy at age 40 of about 0.02 years when the obese percentage of a county is increased by one percent. A one percent increase in the county's population that exercised increased life expectancy by 0.04 years.

When these effects were further analyzed, results indicated that the effects of smoking on life expectancy at age 40 were greater in Metropolitan counties than in Micropolitan counties. The effects also tended to be greater in Micropolitan areas than in Non-Core areas. This shows

an increasing negative association of smoking on life expectancy moving up the rural-urban hierarchy. The effects of obesity on life expectancy at age 40 were very similar to the effects of smoking. It was weaker in Micropolitan areas as opposed to Metropolitan areas and weaker in Non-Core areas than it was in Micropolitan areas. The effects of exercise on the other hand did not show differences in effects of the life expectancy at 40 across the various CBSA categories. In summary, Non-Core areas were less negatively associated with behavioral choices hypothesized to reduce life expectancy compared to Micropolitan and Metropolitan.

The final major finding of the study was that the socioeconomic correlates used in the study had significant associations with life expectancy at age 40. The variation of these factors across the urban hierarchy however did not have a consistent pattern. A socioeconomic variable like medicare dollar per enrollee show differences between all three county categories. This was consistent with some of the earlier life expectancy theories related differences in life expectancy with lack of social cohesion or inequality (Cheadle et al., 1991).

POLICY IMPLICATIONS

The existing policies for increasing health access such as the Critical Access Hospital (CAH) have become less effective in improving health outcomes across rural areas in more recent periods of time. Policies focused at encouraging positive behavioral choices need greater investments to achieve improvements health outcomes. Specifically, these investments should incentivize healthy choices at the county level. These healthy choices would include reducing smoking and improving eating and exercise habits. However, a cookie cutter, one size fits all policy approach to improving behavioral choices would work less effectively in Micropolitan counties as compared to Metropolitan counties. The same holds true for socioeconomic policy interventions. Given that there are differential effects between Non-Core, Micropolitan and

Metropolitan counties in terms of the association of socioeconomic characteristics and health outcomes, there may be a need for heterogeneous policies to accomplish similar desired health outcomes.

LIMITATIONS

There were several limitations to this study. First, the period life expectancy used in this research is a much targeted definition for life expectancy. No inferences can be made outside the scope of this period for general life expectancy in the United States. Second, over 1589 counties are excluded from our sample mainly for a lack of data from these rural counties. It narrows the scope of the research and hinders an in-depth analysis of the spatial variations in life expectancy in more rural remote locations.

Also, the research only looked at associations between life expectancy and its correlates and thus makes it impossible to draw any causal inferences from the analyses done in this paper. Furthermore, the model did not capture all the possible correlates of life expectancy and there could be some possible multiplicative effects occurring among these variables.

FUTURE RESEARCH

This research could be expanded to cover smaller Micropolitan and Non-Core counties (those counties with less than 25,000 population). With the addition of these counties, the picture of life expectancy across the entire country can more clearly be understood and efforts could be made to further identify some of the place-based and space-based effects of some key variables.

Future research could also focus on access to health care and other health care variables that can better show the associations between life expectancy and the county categories. Research could also be performed to understand these associations which would possibly lead to coming up with

causal models and studies associated with the causal effects of some of these behavioral and place-based socioeconomic factors on life expectancy.

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APPENDIX A. : SUPPLEMENTAL DATA FOR CHAPTER 3

This appendix contains the results for the pairwise correlation analysis done for the variables used in our analysis discussed in the paper.

Table A.1: Pairwise correlation of variable

	LE	PS	PO	PE	UnP	InS	SSc	PbF	HHI	PcP	PCLF	MDPE	LFP
LE	1.00												
PS	-	1.00											
	.054												
PO	-	0.26	1.00										
	0.52												
PE	0.67	-	-	1.00									
		0.47	0.52										
UnP	-	0.17	0.37	-	1.00								
	0.36			0.35									
InS	0.28	-	-.39	0.33	-	1.00							
		0.23			0.25								
SSc	0.38	-	-	0.34	-	0.05	1.00						
		0.17	0.18		0.28								
PbF	0.34	-	-	0.17	0.11	0.41	-0.1	1.00					
		0.29	0.28										
HHI	0.59	-	-	0.46	-	0.37	0.07	0.51	1.00				
		0.36	0.48		0.26								
PcP	0.29	-	-	0.23	-	0.09	-	0.26	0.31	1.00			
		0.18	0.25		0.17		0.33						
PCLF	0.31	-	-	0.24	-	0.05	-	0.16	0.29	0.98	1.00		
		0.17	0.25		0.22		0.27						
MDPE	-	0.31	0.28	-	0.16	-	-	-	-	-	-0.02	1.00	
	0.51			0.46		0.01	0.38	0.03	0.26	0.01			
LFP	0.48	-	-	0.49	-	0.32	0.32	0.06	0.37	0.20	0.25	-0.34	1.00
		0.29	0.36		0.56								

APPENDIX B. : ALTERNATE ANALYSIS FOR CBSA CATEGORY 1.

This contains the analyses for the alternate analysis performed for county categories. Large Micropolitan counties in this classification contained a population between 25,000 and 49,999. Small Metropolitan counties are defined to include counties with populations between 50,000 and 100,000 and large Metropolitan counties in this classification are counties with a population of not less than 1000.000. Figure 1 shows a map of the counties in this category. This category contained 646 large Micropolitan counties, 390 small Metropolitan counties and 523 large Metropolitan. The counties in this category are shown in Figure B.1 below.

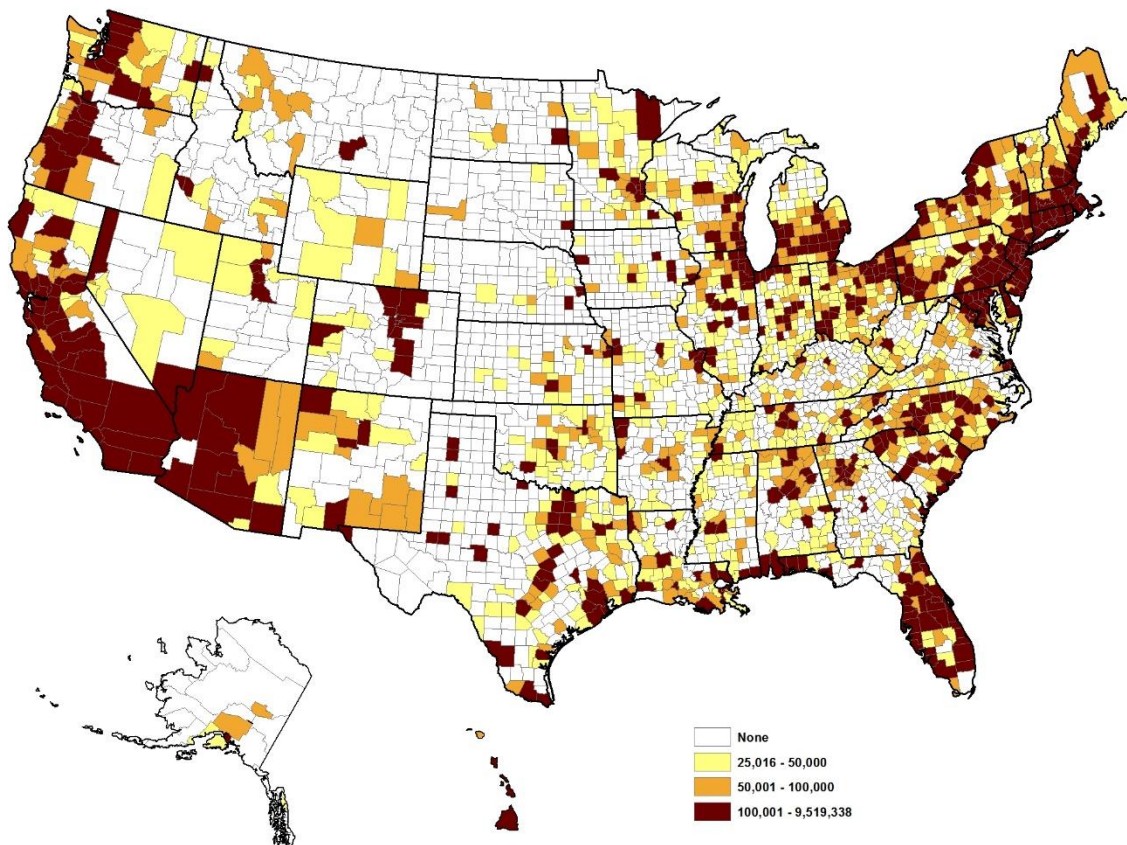


Figure B.1: Map showing counties in sample as classified by population.

ESTABLISHING SPATIAL DIFFERENCES IN LIFE EXPECTANCY.

The analyses shown in this section is the same as presented in Chapter 3 but along the alternative place-based categories. Spatial differences in life expectancy are first established among the three categories of counties. Tables B.1 shows the mean life expectancies in large Micropolitan, small Metropolitan and large Metropolitan counties.

Table B.1: Summary statistics for urban hierarchy life expectancy.

	Mean	Std. Dev.	Min	Max
Large Micropolitan	82.21909	1.319002	78.22048	86.63791
Small Metropolitan	82.56769	1.244203	79.15881	86.21507
Large Metropolitan	83.10722	1.25781	79.06905	87.06013

A means test for equality was conducted for the three group means, assuming homogeneity and these tests results are shown in Table B.2.

Table B.2: Pairwise comparison of means for urban hierarchy.

	Large Micropolitan	Small Metropolitan	Large Metropolitan
Large Micropolitan	-		
Small Metropolitan	-.3486001*** (.0821156)	-	
Large Metropolitan	-.8881322*** (.0752886)	-.539532*** (.0856136)	-

Table B.3 shows the income quartile level summary statistics for these three categories and a test of mean equality is performed and shown in Table B.4.

Table 10: Summary statistics for urban hierarchy per income quartile

	Mean	Std. dev.	Min	Max
		1 st Quartile		
Large Micropolitan		1 st Quartile		
Small Metropolitan	78.61334	1.400963	75.4583	84.34502
Large Metropolitan	78.57644	1.329691	75.4997	83.55318
	78.98637	1.709589	75.45859	84.19208
Large Micropolitan		2nd Quartile		
Small Metropolitan	82.0673	1.305686	77.50161	87.39986
Large Metropolitan	82.0892	1.089496	79.3178	85.79514
	82.1137	1.045596	78.85533	85.11933
Large Micropolitan		3rd Quartile		
Small Metropolitan	84.06365	1.356281	77.50368	88.24662
Large Metropolitan	84.18531	1.129825	80.23071	88.45938
	84.20135	.9224058	81.30137	87.37562
Large Micropolitan		4th Quartile		
Small Metropolitan	85.65013	1.678844	76.47741	91.45098
Large Metropolitan	85.87424	1.219851	82.18167	88.92638

Table 11: Test of means for urban hierarchy across income quartiles.

	Large Micropolitan	Small Metropolitan	Large Metropolitan
1 st Quartile			
Large Micropolitan	-		
Small Metropolitan	.0368973 (.095932)	-	
Large Metropolitan	-.3730321*** (.0879563)	-.4099293*** (.1000185)	-
2nd Quartile			
Large Micropolitan	-		
Small Metropolitan	-.0219326 (.0750738)	-	
Large Metropolitan	-.0463662 (.0688323)	-.0244335 (.0782718)	-
3rd Quartile			
Large Micropolitan	-		
Small Metropolitan	-.1216571 (.0749814)	-	
Large Metropolitan	-.1376963 (.0687476)	-.0160392 (.0781755)	-
4th Quartile			
Large Micropolitan	-		
Small Metropolitan	-.2241042** (.0861925)	-	
Large Metropolitan	-.6292052*** (.0790266)	-.4051009*** (.0898642)	-

CORRELATES OF LOCAL AREA VARIATION IN LIFE EXPECTANCY

This section of results presents the base model analysis of life expectancy looking at its association with the two groups of variables. Table B.5 shows the results for the base regression model and all the model iterations. Table B.6 shows results of the F-test used to ascertain the significance of the place variations.

Table 12: Regression results for all OLS models

VARIABLES	(1) LE	(2) LE	(3) LE	(4) LE	(5) LE	(6) LE
PS	-0.0527*** (0.00412)	-0.0533*** (0.00415)	-0.0584*** (0.00844)	-0.0586*** (0.00843)	-0.0583*** (0.00840)	-0.0587*** (0.00840)
PSd1			0.0294*** (0.00975)	0.0287*** (0.00982)	0.0305*** (0.00979)	0.0299*** (0.00979)
PSd5			-0.0751*** (0.0132)	-0.0705*** (0.0134)	-0.0708*** (0.0133)	-0.0705*** (0.0133)
PO	-0.0227*** (0.00350)	-0.0219*** (0.00352)	-0.0257*** (0.00731)	-0.0266*** (0.00735)	-0.0254*** (0.00733)	-0.0263*** (0.00733)
POd1			0.0189** (0.00833)	0.0194** (0.00841)	0.0194** (0.00837)	0.0198** (0.00838)
POd5			-0.0508*** (0.0121)	-0.0470*** (0.0122)	-0.0482*** (0.0122)	-0.0473*** (0.0122)
PE	0.0276*** (0.00279)	0.0268*** (0.00282)	0.0324*** (0.00462)	0.0301*** (0.00515)	0.0299*** (0.00512)	0.0303*** (0.00513)
PEd1			-0.0132** (0.00538)	-0.0121* (0.00627)	-0.0111* (0.00625)	-0.0116* (0.00625)
PEd5			0.0187*** (0.00680)	0.0283*** (0.00832)	0.0285*** (0.00828)	0.0281*** (0.00829)
UnP	-0.0436*** (0.0151)	-0.0450*** (0.0151)	-0.0492* (0.0269)	-0.0615** (0.0295)	-0.0607** (0.0293)	-0.0593** (0.0294)
UnPd1			0.000221 (0.0316)	0.00725 (0.0356)	-0.00255 (0.0355)	-0.000141 (0.0355)
UnPd5			0.0429 (0.0370)	0.0743* (0.0410)	0.0736* (0.0408)	0.0721* (0.0409)
InS	-0.0113 (0.00722)	-0.0196** (0.00867)	-0.00994 (0.0164)	-0.00985 (0.0164)	-0.00698 (0.0163)	-0.00679 (0.0163)

Table continues on page 67.

InSd1			-0.0322 (0.0249)	-0.0318 (0.0249)	-0.0183 (0.0250)	-0.0179 (0.0252)
InSd5			-0.0458** (0.0199)	-0.0448** (0.0199)	-0.0477** (0.0199)	-0.0479** (0.0199)
SSc	0.298*** (0.0218)	0.302*** (0.0219)	0.308*** (0.0425)	0.310*** (0.0426)	0.319*** (0.0424)	0.316*** (0.0425)
SScd1			0.0264 (0.0522)	0.0255 (0.0522)	0.0136 (0.0521)	0.0193 (0.0521)
SScd5			-0.112* (0.0575)	-0.118** (0.0575)	-0.126** (0.0573)	-0.124** (0.0574)
PbF	0.0493*** (0.00470)	0.0494*** (0.00474)	0.0488*** (0.0132)	0.0501*** (0.0132)	0.0493*** (0.0132)	0.0492*** (0.0132)
PbFd1			0.0130 (0.0158)	0.0117 (0.0158)	0.0143 (0.0158)	0.0146 (0.0158)
PbFd5			-0.00976 (0.0147)	-0.0100 (0.0148)	-0.00926 (0.0147)	-0.00913 (0.0147)
HHI	3.63e-06*** (3.89e-07)	3.57e-06*** (3.91e-07)	5.50e-06*** (1.27e-06)	5.40e-06*** (1.27e-06)	5.63e-06*** (1.27e-06)	5.56e-06*** (1.27e-06)
HHId1			7.63e-06*** (1.67e-06)	7.60e-06*** (1.69e-06)	7.09e-06*** (1.69e-06)	7.12e-06*** (1.69e-06)
HHId5			-4.94e-06*** (1.35e-06)	-4.79e-06*** (1.36e-06)	-5.02e-06*** (1.35e-06)	-4.96e-06*** (1.35e-06)
PcP	-0.0125*** (0.00254)	-0.0128*** (0.00255)	-0.0140*** (0.00522)	-0.0147*** (0.00526)	-0.0136*** (0.00524)	-0.0138*** (0.00525)
PcPd1			-0.00728 (0.00630)	-0.00673 (0.00634)	-0.00714 (0.00631)	-0.00640 (0.00632)
PcPd5			0.00612 (0.00707)	0.00666 (0.00709)	0.00556 (0.00707)	0.00575 (0.00707)
PCLF	0.0158*** (0.00223)	0.0161*** (0.00223)	0.0156*** (0.00428)	0.0163*** (0.00433)	0.0154*** (0.00432)	0.0155*** (0.00433)
PCLFd1			0.00319 (0.00525)	0.00266 (0.00532)	0.00304 (0.00530)	0.00232 (0.00530)

Table continues on page 68.

PCLFd5			-0.00612 (0.00601)	-0.00686 (0.00605)	-0.00600 (0.00603)	-0.00609 (0.00604)
MDPE	-0.000171*** (1.62e-05)	-0.000174*** (1.63e-05)	-0.000143*** (3.00e-05)	-0.000157*** (3.33e-05)	-0.000149*** (3.32e-05)	-0.000150*** (3.32e-05)
MDPEd1			-4.83e-05 (3.42e-05)	-4.11e-05 (3.99e-05)	-4.08e-05 (3.98e-05)	-4.35e-05 (3.98e-05)
MDPEd5			0.000160*** (3.96e-05)	0.000200*** (4.51e-05)	0.000192*** (4.49e-05)	0.000193*** (4.50e-05)
LFP	0.00156 (0.00395)	0.000749 (0.00397)	-0.00388 (0.00630)	-0.00886 (0.00801)	-0.00684 (0.00799)	-0.00714 (0.00800)
LFPd1			-0.00973 (0.00719)	-0.00695 (0.00987)	-0.00456 (0.00985)	-0.00546 (0.00985)
LFPd5			0.0115 (0.00795)	0.0236** (0.0105)	0.0215** (0.0105)	0.0219** (0.0105)
d1		-0.0821 (0.0500)		-0.353 (0.997)	-0.579 (0.995)	-0.475 (0.994)
d5		0.0313 (0.0588)		-2.221* (1.173)	-1.955* (1.170)	-1.986* (1.171)
P_Near_Metro					0.00706*** (0.00190)	
P_Near_Cmetro						0.00571*** (0.00173)
Constant	83.15*** (0.421)	83.34*** (0.432)	82.93*** (0.412)	83.64*** (0.812)	83.37*** (0.812)	83.40*** (0.813)
Observations	1,559	1,559	1,559	1,559	1,559	1,559
Adj. R-squared	0.698	0.698	0.737	0.738	0.740	0.739

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: F test outputs for correlates.

Summation	Test	F (1, 1522)	Prob. > F
-0.029	PSd1+ PS=0	37.21	0.0000
-0.1335	PS+ PSd3=0	180.17	0.0000
-0.0068	POd1+ PO=0	5.58	0.0183
-0.0765	PO + POd3 = 0	63.67	0.0000
0.0194	PEd1 + PE = 0	25.20	0.0000
0.0511	PE + PEd3 = 0	76.34	0.0000
-0.04898	UnPd1+ UnP=0	9.56	0.0020
-0.0063	UnP + UnPd3 = 0	0.06	0.8027
-0.04214	InSd1 + InS = 0	6.85	0.0089
-0.05574	InS+ InSd3=0	20.01	0.0000
0.3344	SScd1+ SSc=0	83.29	0.0000
0.196	SSc+ SScd3=0	12.64	0.0004
0.0618	PbFd1+ PbF=0	72.39	0.0000
0.03904	PbF+ PbFd3=0	48.48	0.0000
1.31E-05	HHId1+ HHI=0	125.26	0.0000
5.6E-07	HHI+ HHId3=0	0.07	0.7945
-0.02128	PcPd1 + PcP = 0	37.23	0.0000
-0.00788	PcP + PcPd3 = 0	0.57	0.4485
0.01879	PCLFd1+ PCLF=0	41.71	0.0000
0.00948	PCLF + PCLFd3 = 0	2.34	0.1263
-0.00019	MDPED1 + MDPE = 0	76.11	0.0000
0.000017	MDPE + MDPed3 = 0	0.88	0.3472
-0.01361	LFPd1 + LFP = 0	14.61	0.0001
0.00762	LFP+ LFPd3=0	0.01	0.9214

APPENDIX C. : ALTERNATE ANALYSIS FOR CBSA CATEGORY 2.

This contains the analyses for the third alternate analysis performed for county categories. Large Micropolitan counties in this classification still contain a population between 25,000 and 49,999. Small Metropolitan counties are defined to include counties with populations between 50,000 and 250,000 and large Metropolitan counties in this classification are counties with a population of not less than 250,000. Figure 1 shows a map of the counties in this category. This category contained 646 large Micropolitan counties, 683 small Metropolitan counties and 231 large Metropolitan. The counties in this category are shown in Figure C.1 below.

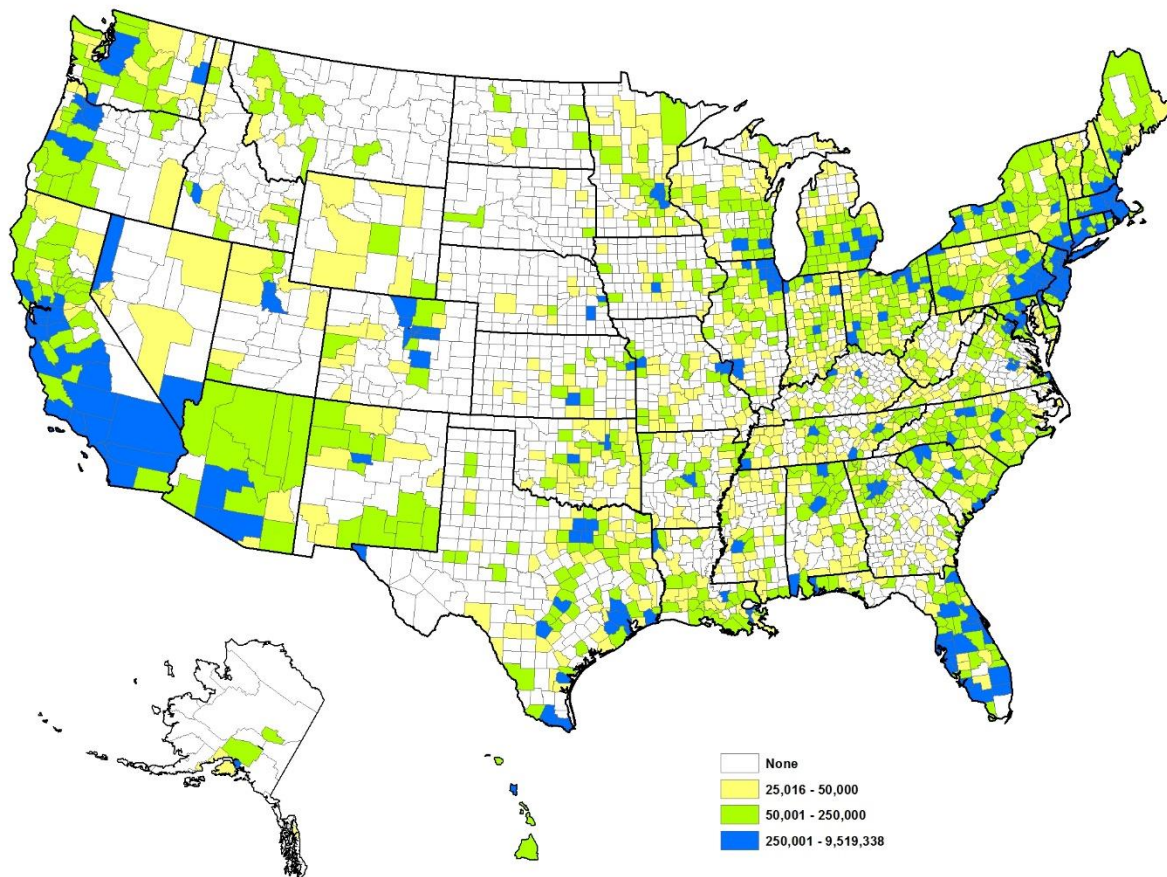


Figure C.1: Map showing counties in sample as classified by population.

ESTABLISHING SPATIAL DIFFERENCES IN LIFE EXPECTANCY.

The analyses shown in this appendix is also same as shown in Chapter 3. Spatial differences in life expectancy are first established among the three categories of counties. Tables C.1 shows the mean life expectancies in large Micropolitan, small Metropolitan and large Metropolitan counties.

Table C.1: Summary statistics for urban hierarchy life expectancy.

	Mean	Std. Dev.	Min	Max
Large Micropolitan	82.21909	1.319002	78.22048	86.63791
Small Metropolitan	82.71522	1.263284	79.15881	87.06013
Large Metropolitan	83.35535	1.207904	79.06905	85.95696

A means test for equality was conducted for the three group means, assuming homogeneity and these tests results are shown in Table C.2

Table C.2: Pairwise comparison of means for urban hierarchy.

	Large Micropolitan	Small Metropolitan	Large Metropolitan
Large Micropolitan	-		
Small Metropolitan	-.4961347*** (.0702094)	-	
Large Metropolitan	-1.136257*** (.0980511)	-.6401221*** (.0973292)	-

Table C.3 shows the income quartile level summary statistics for these three categories and a test of mean equality is performed and shown in Table C.4.

Table C.3: Summary statistics for urban hierarchy per income quartile

	Mean	Std. dev.	Min	Max
1 st Quartile				
Large Micropolitan	78.61334	1.400963	75.4583	84.34502
Small Metropolitan	78.59994	1.400465	75.45859	84.19208
Large Metropolitan	79.43685	1.859654	75.62018	83.92314
2nd Quartile				
Large Micropolitan	82.0673	1.305686	77.50161	87.39986
Small Metropolitan	82.08198	1.081567	78.85533	85.79514
Large Metropolitan	82.16611	1.01004	79.2775	85.03093
3rd Quartile				
Large Micropolitan	84.06365	1.356281	77.50368	88.24662
Small Metropolitan	84.20244	1.080824	80.23071	88.45938
Large Metropolitan	84.17102	.7932685	82.03726	86.33631
4th Quartile				
Large Micropolitan	85.65013	1.678844	76.47741	91.45098
Small Metropolitan	86.01095	1.134469	82.18167	88.92638
Large Metropolitan	86.38896	.747971	83.86246	88.56483

Table C.4: Test of means for urban hierarchy across income quartiles.

	Large Micropolitan	Small Metropolitan	Large Metropolitan
1 st Quartile			
Large Micropolitan	-		
Small Metropolitan	.013399 (.0811244)	-	
Large Metropolitan	-.8235081*** (.1132946)	-.8369071 *** (.1124604)	-
2nd Quartile			
Large Micropolitan	-		
Small Metropolitan	-.0146782 (.0642434)	-	
Large Metropolitan	-.0988068 (.0897193)	-.0841286 (.0890587)	-
3rd Quartile			
Large Micropolitan	-		
Small Metropolitan	-.1387943 (.064179)	-	
Large Metropolitan	-.1073708 (.0896293)	.0314235 (.0889694)	-
4th Quartile			
Large Micropolitan	-		
Small Metropolitan	-.3608128*** (.0739346)	-	
Large Metropolitan	-.7388268 *** (.1032536)	-.378014 ** (.1024934)	-

CORRELATES OF LOCAL AREA VARIATION IN LIFE EXPECTANCY

This section of our results looks at the base model analysis of life expectancy looking at its association with the two groups of variables. Table C.5 shows the results for the base regression model and all the model iterations. Table C.6 shows results of the F-test used to ascertain the significance of the place variations.

Table C.5: Regression results for all OLS models

VARIABLES	(1) LE	(2) LE	(3) LE	(4) LE	(5) LE	(6) LE
PS	-0.0527*** (0.00412)	-0.0534*** (0.00414)	-0.0732*** (0.00694)	-0.0732*** (0.00694)	-0.0728*** (0.00696)	-0.0725*** (0.00694)
PSd1			0.0445*** (0.00845)	0.0445*** (0.00845)	0.0429*** (0.00860)	0.0447*** (0.00857)
PSd5			-0.102*** (0.0194)	-0.102*** (0.0194)	-0.102*** (0.0197)	-0.102*** (0.0197)
PO	-0.0227*** (0.00350)	-0.0218*** (0.00352)	-0.0375*** (0.00615)	-0.0375*** (0.00615)	-0.0369*** (0.00619)	-0.0364*** (0.00617)
POd1			0.0307*** (0.00733)	0.0307*** (0.00733)	0.0297*** (0.00742)	0.0303*** (0.00739)
POd5			-0.0344* (0.0201)	-0.0344* (0.0201)	-0.0349* (0.0202)	-0.0354* (0.0201)
PE	0.0276*** (0.00279)	0.0270*** (0.00281)	0.0393*** (0.00415)	0.0393*** (0.00415)	0.0411*** (0.00464)	0.0411*** (0.00462)
PEd1			-0.0199*** (0.00489)	-0.0199*** (0.00489)	-0.0230*** (0.00586)	-0.0223*** (0.00584)
PEd5			0.0141* (0.00842)	0.0141* (0.00842)	0.0131 (0.00936)	0.0131 (0.00932)
UnP	-0.0436*** (0.0151)	-0.0449*** (0.0151)	-0.0290 (0.0209)	-0.0290 (0.0209)	-0.0221 (0.0224)	-0.0213 (0.0223)
UnPd1			-0.0190 (0.0269)	-0.0190 (0.0269)	-0.0321 (0.0300)	-0.0418 (0.0300)
UnPd5			-0.0116 (0.0532)	-0.0116 (0.0532)	-0.0128 (0.0584)	-0.0136 (0.0582)
InS	-0.0113 (0.00722)	-0.0214** (0.00882)	-0.0303*** (0.0110)	-0.0303*** (0.0110)	-0.0305*** (0.0110)	-0.0287*** (0.0110)

Table continues on page 76.

InSd1			-0.0119 (0.0218)	-0.0119 (0.0218)	-0.0112 (0.0218)	0.00310 (0.0220)
InSd5			-0.0215 (0.0221)	-0.0215 (0.0221)	-0.0209 (0.0221)	-0.0227 (0.0220)
SSc	0.298*** (0.0218)	0.301*** (0.0219)	0.264*** (0.0311)	0.264*** (0.0311)	0.263*** (0.0311)	0.267*** (0.0310)
SScd1			0.0702 (0.0434)	0.0702 (0.0434)	0.0726* (0.0434)	0.0653 (0.0433)
SScd5			-0.123* (0.0745)	-0.123* (0.0745)	-0.123* (0.0746)	-0.128* (0.0743)
PbF	0.0493*** (0.00470)	0.0486*** (0.00485)	0.0409*** (0.00869)	0.0409*** (0.00869)	0.0405*** (0.00870)	0.0404*** (0.00866)
PbFd1			0.0210* (0.0123)	0.0210* (0.0123)	0.0213* (0.0123)	0.0233* (0.0123)
PbFd5			-0.0101 (0.0126)	-0.0101 (0.0126)	-0.00946 (0.0127)	-0.00933 (0.0126)
HHI	3.63e-06*** (3.89e-07)	3.54e-06*** (3.93e-07)	3.97e-06*** (7.70e-07)	3.97e-06*** (7.70e-07)	4.00e-06*** (7.71e-07)	4.08e-06*** (7.68e-07)
HHId1			9.18e-06*** (1.34e-06)	9.18e-06*** (1.34e-06)	9.00e-06*** (1.35e-06)	8.64e-06*** (1.35e-06)
HHId5			-3.50e-06*** (9.62e-07)	-3.50e-06*** (9.62e-07)	-3.51e-06*** (9.64e-07)	-3.60e-06*** (9.60e-07)
PcP	-0.0125*** (0.00254)	-0.0128*** (0.00255)	-0.0157*** (0.00404)	-0.0157*** (0.00404)	-0.0153*** (0.00405)	-0.0148*** (0.00404)
PcPd1			-0.00560 (0.00536)	-0.00560 (0.00536)	-0.00606 (0.00538)	-0.00593 (0.00536)
PcPd5			0.0146* (0.00807)	0.0146* (0.00807)	0.0141* (0.00812)	0.0135* (0.00808)
PCLF	0.0158*** (0.00223)	0.0161*** (0.00223)	0.0171*** (0.00343)	0.0171*** (0.00343)	0.0168*** (0.00346)	0.0164*** (0.00344)
PCLFd1			0.00158 (0.00459)	0.00158 (0.00459)	0.00215 (0.00463)	0.00211 (0.00461)

Table continues on page 77.

PCLFd5			-0.0148** (0.00727)	-0.0148** (0.00727)	-0.0143* (0.00729)	-0.0138* (0.00726)
MDPE	-0.000171*** (1.62e-05)	-0.000175*** (1.63e-05)	-0.000120*** (2.37e-05)	-0.000120*** (2.37e-05)	-0.000111*** (2.57e-05)	-0.000107*** (2.56e-05)
MDPEd1			-6.96e-05** (2.90e-05)	-6.96e-05** (2.90e-05)	-8.70e-05** (3.39e-05)	-8.35e-05** (3.38e-05)
MDPEd5			0.000221*** (4.80e-05)	0.000221*** (4.80e-05)	0.000218*** (5.40e-05)	0.000214*** (5.38e-05)
LFP	0.00156 (0.00395)	0.000766 (0.00397)	-0.00152 (0.00498)	-0.00152 (0.00498)	0.00106 (0.00580)	0.00231 (0.00579)
LFPd1			-0.0117* (0.00626)	-0.0117* (0.00626)	-0.0169** (0.00819)	-0.0138* (0.00820)
LFPd5			0.0104 (0.00900)	0.0104 (0.00900)	0.00998 (0.0129)	0.00874 (0.0129)
d1		-0.0921* (0.0474)			0.856 (0.869)	0.541 (0.870)
d5		0.0697 (0.0724)			0.119 (1.379)	0.287 (1.374)
P_Near_Metro						0.00692*** (0.00189)
P_Near_Cmetro						
Constant	83.15*** (0.421)	83.36*** (0.432)	82.87*** (0.407)	82.87*** (0.407)	82.43*** (0.648)	82.26*** (0.647)
Observations	1,559	1,559	1,559	1,559	1,559	1,559
Adj. R-squared	0.698	0.698	0.737	0.737	0.739	0.739

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.6: F test outputs for correlates.

Summation	Test	F (1, 1522)	Prob. > F
-0.0287	PSd1+ PS=0	34.23	0.0000
-0.1752	PS+ PSd5=0	93.85	0.0000
-0.0068	POd1+ PO=0	2.77	0.0965
-0.0719	PO + Pod5 = 0	14.06	0.0002
0.0194	PEd1 + PE = 0	33.89	0.0000
0.0534	PE + PEd5 = 0	49.77	0.0000
-0.048	UnPd1+ UnP=0	6.37	0.0117
-0.0406	UnP + UnPd5 = 0	0.66	0.4151
-0.0422	InSd1 + InS = 0	5.06	0.0247
-0.0518	InS+ InSd5=0	7.36	0.0067
0.3342	SScd1+ SSc=0	121.60	0.0000
0.141	SSc+ SScd5=0	4.82	0.0387
0.0619	PbFd1+ PbF=0	50.46	0.0000
0.0308	PbF+ PbFd5=0	11.37	0.0008
1.32E-05	HHId1+ HHI=0	142.53	0.0000
4.7E-07	HHI+ HHId5=0	0.67	0.4120
-0.0213	PcPd1 + PcP = 0	36.16	0.0000
-0.0011	PcP + PcPd5 = 0	0.02	0.8854
0.01868	PCLFd1+ PCLF=0	37.06	0.0000
0.0023	PCLF + PCLFd5 = 0	0.14	0.7106
-0.00019	MDPED1 + MDPE = 0	86.70	0.0000
0.000101	MDPE + MDPED5 = 0	5.50	0.0191
-0.01322	LFPd1 + LFP = 0	6.50	0.0109
0.00888	LFP+ LFPd5 =0	1.12	0.2906

VITA

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