DEFINING MULTIMORBIDITY SPACE: STRUCTURAL CHARACTERISTICS, SPATIAL VARIATION OF INPATIENT MULTIMORBIDITY NETWORKS (IMN), AND CORONARY HEART DISEASE

By

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ABSTRACT

TONYA E. FARROW-CHESTNUT. Defining Multimorbidity Space: Structural characteristics, spatial variation of inpatient multimorbidity networks (IMN), and coronary heart disease. (Under the direction of DR. HARRISON CAMPBELL)

Adults in the United States suffer from two or more chronic conditions at the same time (i.e. multimorbidity). Multiple chronic illnesses, such as coronary heart disease, cancer, and diabetes, dramatically shorten life expectancy and present the individual and healthcare system with numerous challenges. To date, no study has assessed multimorbidity and how it varies spatially using quantitative network analysis (QNA), exploratory spatial data analysis (ESDA), and the State Inpatient Discharge Database (HCUP SID). The goals of this study are first, to test the application of QNA as a complementary visualization and analytical tool; second, to explore the geographic variation of multimorbidity and coronary heart disease at the sub-state or county level; lastly, to examine if patterns differ based on gender, race and ethnicity. A cross sectional study design was implemented using the North Carolina HCUP SID. Visualization of multimorbidity networks was successfully demonstrated using QNA. Differences were detected between gender, race and ethnicity impatient multimorbidity networks (IMN). Relationships were observed between underlying social determinants of health and the average weighted degree of coronary heart disease. Multimorbidity varied spatially and average weighted degree of IMN was not distributed randomly; characteristics of multimorbidity space. Mecklenburg, Guilford and Wake Counties had the highest average weighted degree for non-Hispanic white and non-Hispanic black IMN. Limitations include endogeneity, quality of data, missing data, and selection bias. Causal inference cannot be made based on pattern layout of node interactions or generalization to other populations. In conclusion, QNA, network visualization and ESDA are useful exploratory and descriptive tools for studying multimorbidity. This study contributes to new measures and improved understanding of the geographic burden of multimorbidity at the sub-state level.

DEDICATION

This dissertation is dedicated to the loves of my life - my mother, who never let barriers or doubt stop her, and my husband, whose patience and humor are enduring.

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GLOSSARY OF TERMS

Average Path Length	The average network distance (shortest path length) between all pairs of nodes (Albert, Jeong & Barabási, 2000)
Betweenness Centrality	The centrality of a node is an indication of its centrality or importance in the network. Betweenness centrality is an important statistical property of a network. This is applied in real-world problems, e.g. finding influential people in a social network, finding crucial hubs in a computer network, finding border crossing points which have the largest traffic or trade flow. It describes the number of shortest paths from all the nodes to all the other nodes in the network that pass through the node under study (Brandes, 2001).
Closeness centrality	Closeness centrality indicates how long it takes for information from a given node to reach other nodes in the network. The smaller the value, the more central role the node plays in the network. The more central a node is, the lower its total distance from all other nodes. Note that in directed graphs, distances to a node are considered a more meaningful measure of centrality.
Concomitance	A "concomitant" illness, is a second illness occurring at the same time as the primary illness e.g., hypertension, chronic obstructive lung disease, diabetes, heart disease (depending on the primary illness)
Degree	The number of ties or links a node has to other nodes, number of relations (edges) of the nodes. However, in the case of the directed networks, we distinguish between in-degree (number of incoming neighbors) and out-degree (number of outgoing neighbors) of a node.
Degree Centrality	If nodes e.g. people, sexual contacts, companies, or illnesses, receive many ties, they are characterized as prominent. The idea is that many people, sexual contacts, companies, or illnesses direct ties to them—and so this may be regarded as a measure of importance. The other is out-degree centrality. Nodes that have high out-degree centrality may be able to exchange with other nodes, or disperse information quickly to many others. Nodes with high out-degree centrality are often characterized as influential.
Edges = links = ties	An edge is a line segment that joins two nodes. In geometry, an edge is a particular type of line segment joining two vertices. For example, edges can have direction and represent an attribute, in this case frequency. A

	link represents a relationship between two things or situations, especially where one thing affects the other. Therefore, nodes represent people or things and edges represent relationships among those people or things, e.g. friendship, trust, and social contact. In this analysis edges have a direction and represent the number of times each disease pair appears in the universe of patient records and is referred to as the weight. The directed edge indicates which diagnosis is primary (the primary reason why the patient was admitted) and which diagnosis is secondary; co-occurs at the time of admission or develops subsequently.
Ego	Is the node under consideration—any particular node selected for further analysis (i.e. 101 coronary atherosclerosis and other heart disease).
Graph	A diagram showing the relation between variables. In mathematics the graph refers to a set of points and lines. In computer science graph refers to data representing relationships or connections.
Modularity	Refers to community detection, the partitioning of a network into communities of densely connected nodes, with the nodes belonging to different communities being only sparsely connected. Measures the intra-links within communities. Reveals complete hierarchical community structure for the network (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Depicts the overall structure of the network and connections taking place within and between communities (Newman & Girvan, 2004).
Network	In the most general sense, networks are an arrangement of intersecting horizontal and vertical lines representing a group or system of interconnected people or things. Graphs are used to represent networks. The networks may include paths in a city or telephone network or circuit network. Graphs are also used in social networks like LinkedIn, Facebook. For example, in Facebook, each person is represented with a circle. Each circle is a structure (the arrangement of relations) and contains information like a professional colleague or friend.
Node = vertex = circle	In geometry a vertex means a point where lines meet. A node means a point where lines or pathways intersect or branch; a central or connecting point in a network. Every node is unique. The definition of a node depends on the network. For example, in this analysis each circle or node represents a disorder or diagnosis from patient hospital records. Each node contains information about the diagnosis category. Each node has a label (number in this case, it could also be a name) which describes

	the disease category (i.e. 101 is the label for coronary atherosclerosis and other heart disease).
Number of communities	Groups are viewed as communities. Community detection recognizes the inherent structure of networks (i.e. dividing a network into several communities which have high density of edges within communities and low density between them). Community detection is closely linked to graph partition and traditional clustering (Zhou, Wang, & Wang, 2012).
Number of components	The set of nodes that are connected to each other by direct or indirect paths. Alternatively, a set of nodes in a graph is a connected component if every node in the graph can be reached from every other node in the graph. Algorithms in network software detect strongly and weakly connected components. A set of nodes forms a strongly connected component (SCC) if there is a path from any node in the set to any other. A set of nodes is weakly connected under a similar definition, except that the path can follow the paths in either a forward or backward direction. In this study, components may consist of diagnoses or illnesses that point to diagnoses in the SCC, such as underlying comorbidities, pre-existing conditions that are not directly related to the principal diagnosis, infections as a secondary diagnosis (Elixhauser & Jhung, 2008); concomitant conditions that coexist at the time of admission or that develop during the stay; complications (Russo & Steiner, 2007) side effects, adverse events (disease, injury, or a symptom).
Prevalence	The number of cases of a disease that are present in a particular population at a given time, whereas incidence refers to the number of new cases that develop in a given period of time.
Weighted Degree	The ties among nodes have weights assigned to them and are summed.

CHAPTER 1: INTRODUCTION

In a real sense all life is inter-related. All men are caught in an inescapable network of mutuality, tied in a single garment of destiny. Whatever affects one directly, affects all indirectly. I can never be what I ought to be until you are what you ought to be, and you can never be what you ought to be until I am what I ought to be... this is the inter-related structure of reality.

— *Martin Luther King Jr., Letter from Birmingham Jail: Martin Luther*

Multiple chronic conditions are among the most pressing health problems facing public health, health care, and social services (Parekh & Goodman, 2013). One in four adults in the United States has two or more chronic conditions such as heart disease, cancer, chronic lower respiratory disease, cerebrovascular disease, and diabetes, according to the latest data from the Centers for Disease Control and Prevention (Ward & Schiller, 2013). More than 70% of deaths and nearly 75% of healthcare spending costs are attributable to chronic diseases. Studies show that (DuGoff, Canudas-Romo, Buttorff, Leff & Anderson, 2014) struggling with multiple chronic illnesses shortens life expectancy dramatically, especially for older Americans.

Comorbidity is defined as the presence of co-existing or additional diseases with reference to an initial diagnosis or with reference to the index condition - the subject of study (Diederichs, Berger & Bartels, 2011). Examples of comorbidity studies include chronic obstructive pulmonary disease (COPD), obesity, mental disorders, immune-related diseases, cancer, to name a few (Capobianco, 2013). Given the frequency of multiple chronic conditions this perspective appears insufficient as a framework for measuring all the chronic conditions and may be flawed from a health systems approach (Boyd & Fortin, 2010). The term multimorbidity -- capturing multiple; potentially interacting, including physical and mental conditions, is more patient-centered and perhaps a more suitable framework (Boyd & Fortin, 2010). These definitions provide the basis for the following study, which exclusively focuses on multimorbidity patterns.

Although much is known about the descriptive epidemiology of multimorbidity (Barnett, Mercer, Norbury, Watt, Wyke & Guthrie, 2012; Salisbury, Johnson, Purdy, Valderas, & Montgomery, 2011), less is known about how frequently chronic conditions occur together (Ford, Croft, Posner, Goodman, & Giles, 2013), the impact of local area characteristics, such as limited availability or accessibility of health services, infrastructure deprivation, environmental stressors (Brown, Ang & Pebley, 2007), and how they may vary geographically. Such data can inform clinicians, providers, public health professionals, policy makers, and health insurers (Ford et al., 2013).

Tailoring prevention and intervention programs to this population requires that the underlying patterns of multimorbidity are explored. Previous studies examining chronic conditions have primarily examined frequencies and prevalence. For example, Weiss, Boyd, Yu, Wolff and Leff (2007) selected 5 disease types and estimated frequencies using the National Health and Nutrition Examination Survey (NHANES). Marengoni, Rizzuto, Wang, Winblad, and Fratiglioni (2009) conducted a community-based survey estimating the observed and expected prevalence of the most frequently co-occurring pairs of conditions. The researchers calculated odds ratios, and performed a cluster analysis to evaluate patterns of comorbidity and multimorbidity. Schäfer, von Leitner, Schön, Koller, Hansen, Kolonko ... and van den Bussche (2010) identified multimorbidity patterns by using factor analysis and claims data. Their analysis was based on a list of 46 diagnosis groups of chronic diseases using ICD-10 (International Statistical Classification of Diseases and Related Health Problems, 10th Revision) codes. Van den Bussche, Koller, Kolonko, Hansen, Wegscheider, Glaeske,... and Schön (2011) used claims data and selected the most frequent conditions; grouped chronic conditions using ICD-10 codes, calculated the prevalence of chronic conditions, computed triad combinations, and the relative risk for multimorbidity. Freund, Kunz, Ose, Szecsenyi, and Peters-Klimm (2012) conducted a retrospective cohort study using claims data, classified ICD-10GM (German modification)

diagnosis codes, estimated the prevalence of 33 chronic conditions, and the ratio between observed and expected prevalence for each multimorbidity pattern. While there are studies that consider the geographic variation of comorbidity or an index condition, researchers have not explored the geographical variability of multimorbidity.

Traditional guidelines and evidence-based disease management programs focus on single diseases and treating one disease at a time. Research on multimorbidity requires a shift from a reductionist single-condition paradigm to one that considers the inherent complexity of multimorbidity (Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale ... & LeRoy, 2014). The recognition that people often have multiple chronic conditions (MCC) adds a layer of complexity to developing prevention and intervention strategies (Wolff, Starfield & Anderson, 2002; Benjamin, 2010; HHS, 2010;).

Network theory provides a useful framework for understanding and addressing public health issues such as the complexity of multimorbidity. The National Institutes of Health in an earlier funding announcement supported advances in the science of Social Network Analysis (FOA, 2010). The Department of Health and Human Services (HHS, 2011a) invited grant applications from organizations that seek to understand the different strategies in the prevention and management of chronic illness.

Network analysis is an approach to research that is uniquely suited to describing, exploring, and understanding structural and relational aspects of health. In their article, Luke and Harris (2007) review the history of network analysis, drawing on traditions in many different research disciplines including studies of disease transmission (HIV/AIDS) (Poundstone, Strathdee, & Celentano,. 2004); sexually transmitted diseases (Christley, Pinchbeck, Bowers, Clancy, French, Bennett, & Turner, 2005); social contagions (obesity) (Christakis & Fowler, 2007); social support and social capital (Szreter & Woolcock, 2004); and social ties and mental health (Kawachi & Berkman, 2001). Although it is not a new analytical tool, network analysis

provides the health sciences with a way of framing and modeling complex health problems; is a structural approach to examining patterns of connections, is grounded in empirical data, and uses computational models (Luke & Harris, 2007). For a more complete review of methods and models see texts by Scott and Carrington (2011) and Carrington and Wasserman (20005).

Multiple chronic condition literature tends to focus on clinical care, the health care system, individual factors, and rarely examines the role of the neighborhood environment on those struggling to manage their chronic conditions. Chronic disease management models, such as the Chronic Care Model, emphasize the importance of community resources (Hung, Rundall, Tallia, Cohen, Halpin, & Crabtree, 2007). Brown, Ang and Pebley (2007) argue that place and neighborhood context may differentially affect the health of those with chronic illnesses. Characteristics of local areas, such as limited availability or accessibility of health services, deteriorated infrastructure, environmental stressors, may be associated with declines in health status among adults with multiple chronic conditions (Brown, Ang, & Pebley, 2007). Without evidence based approaches and assessable tools to capture and communicate the relational aspects of multiple chronic diseases; and the extent to which area effects influence population mortality, efforts to meet the serious needs of underserved populations by policy makers, clinicians, researchers, managers, patients, are inadequate (www.opimec.org).

Understanding relations or edges, the whole network structure and function, and associated mechanisms, will help fill gaps in knowledge about multimorbidity, quality of life; as well as how to organize, provide and finance appropriate care, complex interventions, care management programs, and allocate limited resources to improve community based programs. For example, the most efficient allocation of expenditures for given intervention measures and programs may depend on the network structure and components. Network structure exists when connections between chronic conditions or groups of nodes are denser than connections between different conditions or groups of nodes (Salethe and Jones, 2010). A rich body of research

provides major insights about the measures of network structure (Watts & Strogatz, 1998; Girvan & Newman, 2002; Newman, 2003; Newman, & Girvan, 2004; Newman, & Moore, 2004). Network analysis can reveal the distribution of multimorbidity, known as the network degree distribution. Information about network structure and function may conceivably direct intervention measures and programs that will influence the topology (pattern of interactions) of multimorbidity networks.

Many studies that examine comorbidity networks can be classified into four broad categories: (1) transmission (interaction) networks, (2) social networks (relabeled "contact" for the purposes of this analysis), (3) organizational networks, and (4) symptom and molecular networks. *Transmission* networks describe interactions that are capable of transmitting information. *Symptom* networks represent latent variable networks. *Molecular* networks refer to metabolic reaction networks, biology networks and network medicine. Chmiel, Klimek and Thurner (2014) proposed a specific phenomenological comorbidity network of human disease spread (an interaction network) based on medical claims data. The network was constructed from a two-layer network, where in one layer the links represent the conditional probability for a comorbidity, and the other the links contain the respective statistical significance. Folino, Pizzuti and Ventura (2010) built a phenotypic comorbidity network and studied its structural properties in order to better understand the connections between illnesses. Moni and Liò (2014) built a comorbidity relationship network to identify significant genes. While researchers have applied major insights to comorbidity and chronic conditions, to my knowledge studies have not examined multimorbidity network characteristics and geographic variability using large patient discharge data.

Although comorbidity (or phenotypical) studies measure the ties between the diseases themselves they do not focus on the environmental influences or characteristics of the communities in which patients are embedded. In this study the multimorbidity pattern across

North Carolina counties is tested using spatial statistics. Assessable tools such as open source software (such as Pajek, GeoDa and Python) and commercial packages including (Anselin, Syabri & Kho, 2006) are engaged to capture and communicate the relational aspects of multimorbidity network spatial patterns. For this study, we look at the multimorbidity network structure of hospital inpatient data.

There is a growing trend toward more spatially extensive research in health and social science. With this trend, there is increased interest in understanding spatially varying processes in health (Congdon, 2011; Holt & Lo, 2008; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005). Spatial analysis is widely used in health geography and epidemiology, but its application to the study of multimorbidity is limited. Few studies have addressed the issue of spatial variation of multimorbidity and the association of local area characteristics.

The goal of this dissertation is to test the application of networks as a complementary visualization tool to characterize and help us understand multimorbidity patterns and assess whether population level inpatient multimorbidity can be modeled as a network. The secondary aim is to explore and build on the literature in terms of the geographic variation of multimorbidity at the sub-state level and explore whether the network measure -average weighted degree of cardiovascular/coronary heart disease networks change or vary geographically. Lastly, this dissertation examines if multimorbidity patterns differ based on gender, race and ethnicity. If differences exist, multivariate analysis are performed to determine if there is a relationship between the underlying factors and the average weighted degree of heart disease networks.

CHAPTER 2: LITERATURE REVIEW

The literature review attempts to provide the reader with a new interpretation of old material or combine new with old interpretations, trace the intellectual progression of related fields, advise the reader on the most relevant research, and identify where gaps exist in how the problem has been researched to date. The review is organized into two streams. The first stream focuses on relevant research about the silent public health crisis that motivates the dissertation. Background information regarding comorbidity and multimorbidity, multiple chronic conditions (MCC) - the primary framework for this study, and health disparities are presented. A review of the national prevalence of multiple chronic conditions (MCCs) and population characteristics are followed by the burden of chronic disease in North Carolina. Cardiovascular disease (heart disease) and the impacts on the aging population, geographic disparities and the economic burden of heart disease in North Carolina concludes this section. The literature review borrows from several conceptual frameworks, theories and models to help make research findings meaningful and generalizable, while directing and stimulating this dissertation work. The second stream begins with complexity, the relational perspective, network basics, and complex systems in health. The review closes with topics concerning network data and network modeling methodology. Let us begin now with the invisible epidemic (WHO, 2018).

Background

According to the World Health Organization (WHO, n.d.a) chronic diseases (often referred to as noncommunicable diseases or NCDs), such as heart disease, stroke, cancer, chronic respiratory diseases and diabetes, are the leading cause of mortality in the world, representing 60% of all deaths. Out of the 35 million people who died from chronic disease in 2005, half were under the age of 70 and half were women. This invisible epidemic causes poverty and delays the

economic development of many countries. Contrary to what is assumed 80% of chronic disease deaths occur in low and middle-income countries (WHO n.d.a).

In 2012, nearly half (49.8%, 117 million) of adults in the United States had at least one of ten selected chronic conditions. Among adults with at least one chronic condition, more than half (approximately 60 million) had multiple chronic conditions. Estimated prevalence of MCC varied by specific subpopulations. Women were more likely than men to have two or three or more conditions (Ward, Schiller, & Goodman, 2014). The proportion of a population with multiple chronic conditions was higher among non-Hispanic white adults, non-Hispanic black adults, and non-Hispanic adults of other races than among non-Hispanic Asian adults and Hispanic adults (Ward, Schiller, & Goodman, 2014).

Chronic conditions are an increasing concern in the United States. More than 70% of deaths in the United States and nearly 75% of healthcare spending costs are attributable to chronic diseases. From 2001 through 2010, the prevalence of persons with multiple (≥2) chronic conditions increased. Approximately 26% of U.S. adults had MCC in 2010, when 10 different conditions (e.g. hypertension, coronary heart disease, stroke, diabetes, cancer, arthritis, hepatitis, weak or failing kidneys, asthma, and COPD) were considered (Ward and Schiller, 2009).

Comorbidity vs. multimorbidity. The overarching goal of this study is to determine if there is a more effective visual tool or technique that can capture the complexity of this silent epidemic. The initial step towards that goal is to understand the terminology. There is no shortage of definitions available for these concepts. Because of the confusing and varying definitions, Ording and Sorensen (2013) proposed a more rigorous definition of the most commonly used concepts. Starting with “index disease”. The index disease is considered the main disease or condition under study, or the primary reason care is sought by the patient. The term “comorbidity” describes other medical conditions that exist when the index disease is diagnosed or occurs later, but is not a consequence of the index disease (Ording & Sorensen,

2013). According to the authors, it is not always obvious which condition should be identified as the index and which disease should be identified as the comorbid condition. Several reasons exist for this uncertainty, such as the question under study, the disease that is the main reason for admission or care, and the specialty of the attending physician. A related concept is "complication". A complication is an adverse event that either coexists or occurs after diagnoses of the index disease (Ording & Sorensen, 2013; Valderas, Starfield, Sibbald, Salisbury, & Roland, 2009). Nardi, Scanelli, Corrao, Iori, Mathieu, and Amatrian (2007) argued that a comorbidity, as a pre-existing secondary diagnosis of the admitted patient, differs from a complication, in that it is a condition acquired during a hospital stay and for that reason should not be regarded as the sum of diseases or as the coexistence of more than one disease (multimorbidity) in the same patient. It is worth mentioning that comorbidity is also commonly defined as "concomitant" (accompanying or associated with) and may reflect an unrelated condition or disease process (Davis, 2010).

In contrast, "multimorbidity" can be described as two or more chronic diseases that co-exist in an individual at the same time. According to Valderas, et al., multimorbidity has been increasingly used without any reference to an index condition. Multimorbidities are serious medical conditions that are indirectly related to the primary diagnosis itself but involve other major organ systems; are usually chronic rather than acute, and easily treated conditions (Ording & Sorensen, 2013). The concept of multimorbidity varies widely in the literature and has been used to describe the number and severity of morbidities, illnesses, diseases, etc. (Ording & Sorensen, 2013). Ording and Sorensen cite numerous definitions of multimorbidity including: predefined medical conditions or unlimited numbers and types of medical conditions, chronic conditions, or both acute and chronic conditions, physical diseases alone, or physical and psychiatric conditions.

The resource implications for addressing multimorbidity are enormous and expected to increase substantially as the U.S. population ages (US Department of Health and Human Services [HHS], 2010). Multimorbidity negatively affects quality of life, life expectancy, physical functioning and hospitalization, accounting for substantial health care spending (Freund et al., 2012). Multimorbidity is conceptualized not simply as a list of diseases with varying degrees of health risk, but as non-randomly occurring clusters of disease within populations (Lynch, Gebregziabher, Axon, Hunt, Payne & Egede, 2015). Multimorbidity has been shown to vary in different context based on socioeconomic status and race/ethnicity (O'Brien, Wyke, Guthrie, Watt & Mercer, 2014; Wang, Wang, Wong, Wong, Li, Wang, ... & Mercer, 2014). A secondary purpose of this analysis is to expand on this literature and explore how multimorbidity varies at the sub-state level. In addition to exploring the variation of multimorbidity, a complementary visualization tool is tested to characterize and help us understand multimorbidity patterns. Boyd and Fortin (2010) argued that it is important to capture the number of people with multiple occurring conditions and which specific conditions they have, in addition to characterizing the data in various ways to help us understand the information. The authors presented examples of conceptual diagrams of comorbidity and multimorbidity, shown in Figure 1 and Figure 2 respectively.

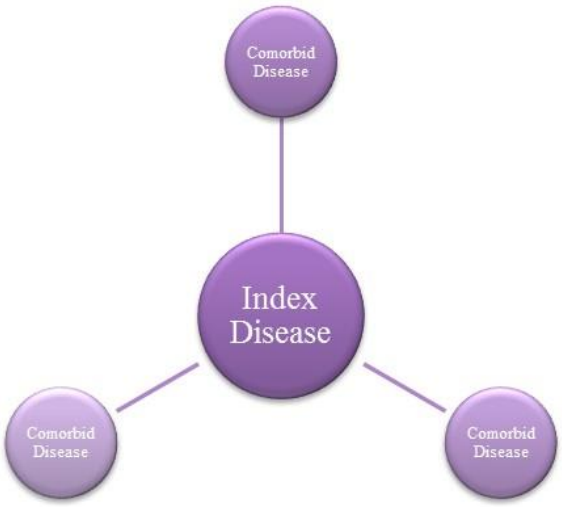


Figure 1. Conceptual Diagram of Comorbidity. Adapted from Boyd and Fortin, 2010.

Figure 1 is the Conceptual Diagram of Comorbidity. Comorbidity is often studied and treated in clinical practice from the perspective of an index disease and one or more comorbid diseases may be considered. These diseases may affect treatment of the index disease (adapted from Boyd and Fortin, 2010). In this depiction, conditions in Figure 2 may include traditional diseases; reflect conditions such as disability, falls, hearing impairment, that fall outside the traditional disease model. These conditions may overlap to varying degrees (adapted from Boyd and Fortin, 2010).

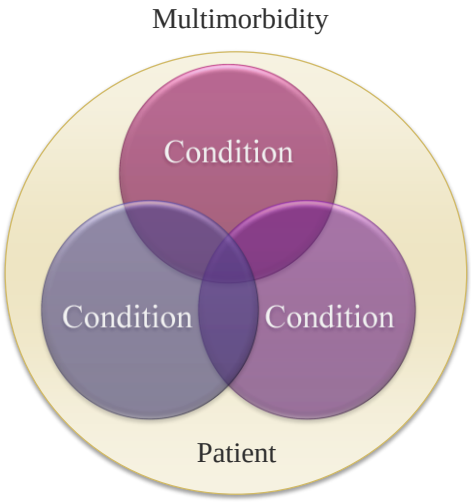


Figure 2. Conceptual Diagram of Multimorbidity. Adapted from Boyd and Fortin, 2010.

Multiple Chronic Condition (MCC) Framework. The number of individuals with multiple chronic conditions will increase dramatically in coming years. Recognizing that multiple chronic conditions are an important public health concern, the U.S. Department of Health and Human Services [HHS] proposed a strategic framework designed to improve the health of those with multiple chronic conditions (HHS, 2010). The vision that drives the department's efforts is "optimum health and quality of life for individuals with multiple chronic conditions" (HHS, 2010, p.1). The main goal expressed by the framework is to facilitate research to fill knowledge gaps about interventions and systems. Significant gaps exist in approaches to care for individuals with MCC and reinforcing research efforts will enhance characterization of the MCC population, support healthcare and providers in coordinating and managing care, and aid improvements in monitoring performance and outcomes (HHS, 2010).

To understand the epidemiology of MCC is another important goal expressed by the framework. More specifically the framework calls for more information about the "constellations

of conditions that are most prevalent and most important" (HHS, 2010, P. 14). Additional research, utilizing public programs and existing datasets, is needed to identify the most common patterns of MCC, specific intervention programs for specific populations as well as monitoring the impacts of those interventions. The framework identifies strategies for researchers to pursue, such as determining the most common dyads and triads, documenting the prevalence, structure and distribution of MCC, and develop tools to identify and target population subgroups who are at high risk for poor health outcomes.

Facilitating research to fill knowledge gaps about MCC, interventions and systems is paramount according to the framework. Significant gaps exist in approaches to care for individuals with MCC and reinforcing research efforts will enhance characterization of the MCC population, support healthcare and providers in coordinating and managing care, and improve monitoring performance and outcomes (HHS, 2010). Central to this effort, is to address disparities in multiple chronic conditions in populations. HHS expects that racial and ethnic, gender, gender identity, disability, sexual orientation, age, geographic, and socioeconomic disparities of access to care and health outcomes will persist in the MCC population, reflecting disparities in the total population. Given this likelihood, the framework recommends researchers use research findings on group -specific indicators for MCC risk and target intervention options.

Population Health Terms and Concepts

The next section discusses important terms and concepts germane to population health and is important in understanding health outcomes.

Health disparities. According to National Institute on Aging [NIA] (n.d.), health disparities are "differences in any health-related factor—disease burden, diagnosis, response to treatment, quality of life, health behaviors and access to care, …that exist among population groups". Since many of these factors are broad, complex, and interrelated, the overarching goal expressed by the framework (HHS, 2010), is to improve our understanding of the MCC

population and the approach to care by facilitating research that fills knowledge gaps (HHS, 2010, p 13). To improve the characterization of the MCC population, researchers must integrate the large and compelling body of evidence that has accumulated for decades about the influence of social factors in shaping our health across a wide range of health indicators. Health indicators are characteristics of individuals, populations, or environments used to describe aspects of the health of an individual or population (Braveman & Gottlieb, 2014).

The causes of disparities are multifactorial and perhaps the largest contributors are those related to social determinants of health external to the health care delivery system according to the authors Berkman, Kawachi, and Glymour (2014). Williams (1999) found that members of minority communities tend to be more socioeconomically disadvantaged, have lower levels of education, which increases the likelihood that the only jobs available have higher rates of occupational hazard; live in areas with greater environmental hazards than members of the majority population.

Social Determinants of Health (SDOH). Healthy People 2020 (Office of Disease Prevention and Health Promotion [Healthy People.gov].(n.d.) define SDOH as economic and social conditions that influence the health of people and communities. These conditions are shaped by the amount of money, power, and resources that people have, and ultimately is influenced by policy. Social determinants of health affect factors that are related to health outcomes such as:

- How a person develops during the first few years of life (early childhood development)
- How much education a person obtains
- Being able to get and keep a job
- What kind of work a person does
- Having food or being able to get food (food security)
- Having access to health services and the quality of those services

- Housing status
- How much money a person earns
- Discrimination and social support (Healthy People.gov, n.d..)

According to Healthy People 2020, health starts in our homes, schools, workplaces, neighborhoods, and communities. Our health is also determined in part by access to social and economic opportunities; the resources and supports available in our homes, neighborhoods, and communities; the quality of our schooling; the safety of our workplaces; the cleanliness of our water, food, and air; and the nature of our social interactions and relationships. The conditions in which we live (our communities) also explain why some Americans are healthier than others and why Americans - more generally, are not as healthy as they could be. Figure 3 summarizes the SDOH conceptual model.

Figure 3. Social Determinants of Health. Source: Healthy People.gov.

Health Insurance. According to Kirby and Kaneda (2010), millions of people in the U.S. do not have health insurance and wide differences exist across racial and ethnic groups regarding insurance coverage. For example, as cited by Kirby and Kaneda, compared with non-Hispanic whites, non-Hispanic blacks are twice as likely to be uninsured and Hispanics are three times as likely to be uninsured. This phenomenon is partly due to Hispanics and blacks experiencing a disproportionate drop in employer-based health insurance coverage since the 1970s. Racial and ethnic minorities are also more likely to rely on public programs for their insurance coverage (Roberts 2006). Lack of insurance takes a significant toll on vulnerable populations, such as less access to preventive care than the insured, higher rates of emergency department use and avoidable hospitalizations, later-stage diagnosis of cancer, and barriers to obtaining prescription medications (Andrulis, 1998). The long shadow of racism has been studied and linked to poor health outcomes among African American (Betancourt., Green, Carrillo & Owusu Ananeh-Firempong, 2016). As a result, Betancourt et al. found that members of minority groups suffered disproportionately from chronic conditions such as cardiovascular disease, diabetes, asthma, and cancer, among other conditions.

Krieger argued that a society's economic, political, and social relationships affect both how people live and where they live, and as a result shape patterns of disease distribution. Krieger maintained that an understanding of a community's distributions of health cannot be separated from politics and policy because health inequities result from how power, both power over and power to do, constrain opportunities for exercising personal agency or action. The power dynamic determines how people engage with their surroundings, their communities, the world, and ultimately determine exposures to material and psychosocial health hazards (Krieger, 2008).

Disparities in the United States are significant and persistent. According to the U.S. Department of Health and Human Services Office of Minority Health [OMH] Disparities Action Plan (2013, September), characteristics such as race or ethnicity, religion, socioeconomic status (SES), gender, age, mental health, disability, sexual orientation or gender identity, geographic location, environmental exposures, and other characteristics historically linked to exclusion or discrimination are known to influence health status. Difference in social determinants of health, such as poverty, low socioeconomic status, and lack of access to care, exists along gender, racial and ethnic lines, and contribute to poor health outcomes (OHM, 2013, September). For the leading causes of death including heart disease, cancer, stroke, diabetes, kidney disease, hypertension, liver cirrhosis and homicide, African Americans have higher death rates than whites and higher mortality across the life-course (Williams & Mohammed, 2009). Multiple chronic conditions are more likely to go undetected in low income and poor communities, resulting in even greater morbidity, diminished quality of life and lost worker productivity (HHS, 2010).

Small area studies. Several types of studies are used to examine variation in access to care, such as ecologic studies, contextual and multilevel analyses, and comparisons of small well-defined neighborhoods (Diez-Roux, 2001). For over thirty years small area studies have been performed to examine regional variations and the relationship between the socioeconomic and health characteristics of populations (Wennberg & Gittelsohn, 1973). Policy makers have used small area analysis to inform the allocation of healthcare resources between geographic areas (Mcintyre, Muirhead & Gilson, 2002). In response to rising healthcare costs, many have called for more effective regional health policy coordination (Wang & Luo, 2005). The emergence of new methodological approaches has stimulated research in this area, such as endogenous effects and system approaches, for example network analysis (Cohen-Cole & Fletcher, 2008).

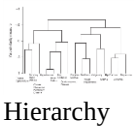
Segregation. Residential segregation is a fundamental cause of health disparities (Schwarz, 2016). Sociologists were interested in examining whether the same pattern of hyper-segregation that persisted in years prior to the 1990s extended to the 2000s (Iceland & Weinberg, 2002). Iceland and Weinberg found that despite declines in segregation observed from the 1980s to 2000, segregation was still higher for African Americans than other groups. Williams & Jackson (2005) argued that race is a marker for "differential exposure to multiple disease-producing social factors" (Williams & Jackson, 2005, p. 325). The exposure hypothesis, originating from the field of Sociology, states that individuals in disadvantaged social groups are exposed to more stressors than those that are from more advantaged social groups. The authors maintained that the residential concentration of African Americans was high and distinctive. Associated with inequities in communities, socioeconomic circumstances and medical care are important factors in causing and maintaining racial disparities in health. Williams, Jackson, & Anderson (1997) framed it this way, the quality and quantity of a wide range of resources that would improve health, including medical care, are distributed by institutions "differentially" to discriminated racialized groups. Greer, Kramer, Cook-Smith, & Casper (2014) found that segregation at the metropolitan level (MSA) was positively associated with heart disease mortality rates among blacks aged 35 or older and with stroke mortality rates among blacks aged 35–64. The authors concluded that segregation in 107 MSAs during 1990 was positively associated with heart disease mortality rates among black men and women aged 15–64 who lived in those MSAs.

Overview of Relevant Multimorbidity Literature

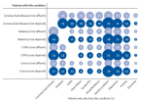
Hundreds of articles were searched and approximately 14 studies were considered and reviewed for this section of the literature review. The main objective of the search was to identify articles that stated as its purpose either of the following: to improve understanding of multimorbidity; examine multimorbidity distribution, patterns and prevalence; identify dyads and

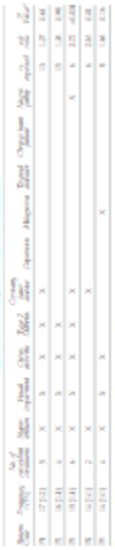
triads; analyze associations, expenditures, geographically defined populations; models or frameworks using various sources of data, designs and methodologies. This search was undertaken to 1) understand the direction of this body of research in terms of analysis of multimorbidity and methodology employed, and 2) visualization tools used to complement and explain research findings. The results of the search are contained in Table 1. Throughout the sections to follow, findings from articles featured in Table 1 is discussed in more detail.

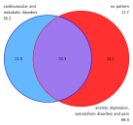
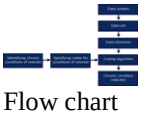
Table 1. *Overview of Multimorbidity Literature (featuring Data Visualizations)*

Article Year	**Reference [Country]**	**Purpose**	**Data**	**Methods**	**Main Results**	**Data Visualizations**
2007	Weiss, Boyd, M., Yu, Wolff, & Leff [U.S.]	Estimate patterns of major chronic disease co-occurrence in older adults	National Health and Nutrition Examination Survey (NHANES) from 3 survey waves (1999-2000, 2001-2002, 2003-2004). Sample of 4349 aged 65 yrs and older	Disease status was ascertained through the questions. Frequencies were estimated using NHANES sampling weights and masked variance units. Binomial Wald 95% confidence intervals were calculated.	Majority of participants experiencing each disease had at least 1 other coincident disease. The percentage of participants experiencing each disease alone varied from 15.2% to 47.2%.	 Table shows prevalence of major chronic disease patterns by gender. Each row is a distince pattern
2009	Marengoni, Rizzuto, Wang, Winblad, & Fratiglioni [Sweden]	Describe patterns of comorbidit y and multimorbi dity in elderly people.	Kungsholme n Project on aging and dementia conducted with 1,099 elderly subjects aged 75 and older in October 198; prospective cohort .	Diagnoses based on physicians' examinations and supported by hospital records, drug use, blood samples. Patterns of comorbidity and multimor-bidity	Visual impairments and heart failure were the diseases with the highest comorbidity (mean 2.9 and2.6 co-occurring conditions, respectively), whereas dementia had the lowest (mean 1.4	 Hierarchy displayed as a tree diagram or dendro-gram. Each object is a separate cluster.

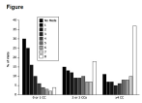
Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
			Examination included social interview, neuropsychological battery, and clinical examination	evaluated using four analytical approaches: prevalence, conditional count, logistic regression models, and cluster analysis.	comorbidities). Heart failure occurred rarely without any comorbidity (0.4%). Logistic regression analyses detected similar comorbid pairs. The cluster analysis revealed five clusters. Two clusters included vascular conditions (circulatory and cardio pulmonary clusters), mental diseases along with musculoskeletal disorders. The last two clusters included only one major disease each (diabetes mellitus and malignancy) together with their most common consequences (visual impairment and anemia, respectively).	One cluster consisted of four conditions : hyperten-sion, heart failure, chronic atrial fibrilation, and CVD.
2010	Schäfer, von Leitner, Schön, Koller, Hansen, Kolonko,... & van den Bussche, 2010 [Germany; multimorbidity patterns]	Increase knowledge specific processes multi-morbidity in elderly population	2006 Ambulatory data of German health insurance company	46 diagnosis groups; prevalence ≥1% in the age group ≥65. ICD-10 codes grouped if diseases and syndromes = pathophysiological similarity. Multimorbidity patterns were described according to factor analysis results	3 multimorbidity patterns found: 1) cardiovascular/ metabolic disorders [prevalence female: 30%; male: 39%], 2)anxiety/ depression/ somato form disorders and pain [34%; 22%], and 3) neuropsychiatric disorders [6%; 0.8%]. Patterns largely age-dependent	 Venn diagram: overlapping of multimorbidity patterns (in %) related to the total female population

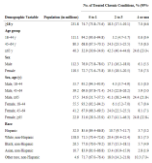
Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
2011	van den Bussche, Koller, Kolonko, Hansen, Wegscheider, Glaeske,... & Schön [Germany]	To find out which chronic diseases and disease combinations are specific to multimorbidity in the elderly.	Claims data of all insured policy holders aged 65 and older (n = 123,224). Adjustment for age and gender performed for German population in 2004.	A person was defined as multimorbid if she/he had at least 3 diagnoses out of a list of 46 chronic. Prevalences and risk-ratios calculated for multimorbid and non-multimorbid samples to identify diagnoses specific to multimorbidity and detect excess prevalences of multimor-bidity patterns.	62% of the sample multimorbid. Triads of the six most prevalent individual chronic conditions (hypertension, lipid metabolism disorders, chronic low back pain, diabetes mellitus, osteoarthritis and chronic ischemic heart disease. Gender differences minor.	 Table shows adjusted prev and prevalence rank order and O/E ratio of the 10 most prevalent triadic combi-nations of chronic conditions
2012	Barnett, Mercer, Norbury, Watt, Wyke & Guthrie, 2012 [Scotland]	Examine distribution of mult-imorbidity, and of comorbidity of physical and mental health disorders, in relation to age and socio-economic deprivation.	1 751 841 patients (Scottish population) from 314 Scottish medical practices, 2007. The dataset included age, sex, and socioeconomic status; representative of all Scottish patients	Used frequencies, percentages, cross tabulations, and graphical display for descriptive analysis: t test to analyze differences in mean number of morbidities between men and women and ANOVA for differences across age groups and deprivation deciles; $\chi 2$ test to measure differences in prevalence of multimorbidit	42·2% (95% CI 42·1–42·3) of all patients had one or more morbidities, and 23·2% (23·08–23·21) were multimorbid. Prevalence of multimorbidity increased substantially with age and was present in most people aged 65 years and older, the absolute number of people with multimorbidity was higher in those younger than 65 years (210 500 vs 194 996). Onset of multimorbidity occurred 10–15 years earlier in people living in the most deprived	 Multi-series bubble chart: Selected comorbidities in people with four common, important disorders in the most affluent and most deprived deciles

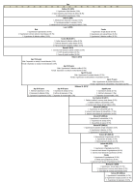
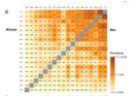
Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
				y and physical–mental health comorbidity between variables. Used binary logistic regression to examine associations between physical and mental health comorbidities, restricting analysis 16 years and older	areas compared with the most affluent, with socioeconomic deprivation particularly associated with multimorbidity that included mental health disorders (prevalence of both physical and mental health disorder	
2012	Freund, Kunz, Ose, Szecsenyi, & Peters-Klimm [Germany]	To identify and explore patterns of multimorbidity in primary care patients with high predicted risk of future hospitalizations.	Conducted a retrospective cohort study to assess insurance claims data of 6026 patients from 10 primary care practices in Germany. Analyzed insurance claims data from January 1,2007 to December 31, 2008	Multimorbidity was defined as the co-occurrence of 2 or more chronic conditions within 1 patient. Selected 33 chronic conditions from the list of chronic conditions.. All conditions counted only once if they occurred as either a hospital or ambulatory diagnosis in2007/ 2008. total numbers of chronic conditions compared by Student t –test and chi-square test (sex). Calculated single	471 (46%) out of 1013 multimorbidity patterns. High single prevalence of severe chronic conditions i.e. malignant disorders or chronic heart failure. 6 of the 10 most frequent chronic conditions intersect with the most frequent causes for hospital admissions: hypertension, coronary heart disease, type 2 diabetes mellitus, chronic heart failure, osteoarthritis of the hip/knee, and bronchial cancer.	 Table shows 10 most frequent patterns of multimorbidity

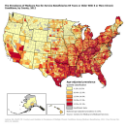
Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
				prevalence rates for all 33 chronic conditions. Calculated ratio between observed and expected prevalence of distinct multi-morbidity patterns.		
2012	Schäfer, Hansen, Schön, Höfels, Altiner, Dahlhaus,... & König, 2012 [Germany]	Analyze the association of socio-demo-graphic variables, socio-economic status with multi-morbidity with each multi-morbidity pattern.	Multimorbid patients aged 65+ randomly selected from 158 GP practices. Data collected in GP interviews and comprehensive patient interviews.	Association of patient characteristics with the number of chronic conditions is analyzed by multilevel mixed-effects linear regression analyses. Multimorbidity patterns assigned individual patients to a pattern if they had diagnoses in at least three groups with a factor loading of 0.25 or more on the corresponding pattern.	Multimorbidity associated with age (+0.07 chronic conditions per year), gender (-0.27 conditions for female), education (-0.26 conditions for medium and -0.29 conditions for high level vs. low level) and income (-0.27 conditions per logarithmic unit). Cardiovascular and metabolic disorder pattern shows associations with gender (-1.29 conditions for female); somatoform disorders and pain correlates with gender (+0.79 conditions for female), but not with age or socioeconomic status.	 Venn diagram: overlapping of multimorbidity patterns (in %) related to the female population.
2013	Goodman, Posner, Huang, Parekh & Koh, 2013 [U.S.]	Outline conceptual model for improving understand-ing; standardize approaches	5 Data systems selected: the National Health Interview Survey (NHIS);	Describe conceptual model, developed by MCC working group within the HHS Office	Conceptual model consists of 2 series of boxes. A vertical cascade of 5 boxes begins at the top with “Data system,” which leads to “Data set,”	 Flow chart (diagram) of Conceptual model

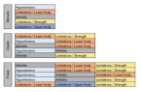
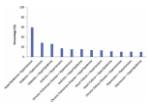
Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
		Apply standard classification scheme for chronic conditions to 5 national-level data systems in U.S.	National Ambulatory Medical Care Survey (NAMCS); Medical Expenditure Panel Survey; Nationwide Inpatient Sample of the Healthcare Cost and Utilization Project; and Medicare beneficiary enrollment and claims admini-strative data from CMS	Assistant Secretary of Health (OASH), develop list of selected chronic conditions. Provide overview of 5 data systems maintained by HHS that measure chronic conditions and illustrate model's operation applying standard classification scheme for MCC to the HHS data systems.	then "Data elements," "Coding algorithm" and "Chronic condition indicator." A horizontal series of boxes begins with "Identifying chronic conditions of interest," which leads to "Specifying codes for conditions of interest" and then intersects the vertical cascade at "Coding algorithm."	for developing and applying schemes for chronic conditions to data elements for studying and monitoring health conditions.
2013	Ward & Schiller, 2013 [U.S.]	Use NHIS to examine the prevalence of MCC by select sociodemographic groups and the prevalence of MCC dyads and triads.	2010 National Health Interview Survey (NHIS); the US adult civilian non-institutionalized population aged 18 years or older (n = 27,157).	Categorized adults as having 0 to 1, 2 to 3, or 4 or more of the following chronic conditions: hypertension, coronary heart disease, stroke, diabetes, cancer, arthritis, hepatitis, weak or failing kidneys, chronic obstructive pulmonary disease, or current asthma. Descriptive	26% adults have MCC; prevalence of MCC increased from 21.8% in 2001 to 26.0% in 2010. Prevalence of MCC significantly increased with age, significantly higher among women than men and among non-Hispanic white and non-Hispanic black adults than Hispanic adults. Most common dyad: arthritis and hypertension; combination of arthritis, hypertension, and diabetes most common triad.	 Table: 5 Most Prevalent Chronic Condition Triads for US Adults With 3 or More Chronic Conditions, by Sex and Age, National Health Interview Survey, 2010

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
				estimates; tested for significant differences.		
2013	Lochner & Cox, 2013 [U.S.]	Use U.S. Department of Health and Human Services Strategic Framework on multiple chronic conditions as a basis to examine the prevalence of multiple chronic conditions among Medicare beneficiaries.	Centers for Medicare and Medicaid Services administrative claims data for Medicare beneficiaries enrolled in fee-for-service program in 2010. Approximately 31 million Medicare beneficiaries, examined 15 chronic conditions	Included 15 chronic; ICD-9 codes and chronic conditions from the Chronic Condition Data Warehouse. Chronic conditions counted and grouped into 3 categories (0 or 1, 2 or 3, and 4 or more); multiple chronic conditions were defined as having 2 or more chronic conditions. Examined prevalence by select Medicare beneficiary characteristics: sex, age in years, dual Medicaid enrollment, and race/ethnicity.	68.4% of Medicare beneficiaries had 2 or more chronic conditions and 36.4% had 4 or more chronic conditions. Prevalence of multiple chronic conditions increased with age and was more prevalent among women than men across all age groups. Non-Hispanic black and Hispanic women had the highest prevalence of 4 or more chronic conditions, whereas Asian or Pacific Islander men and women, in general, had the lowest.	 Table shows 5 Most Prevalent Chronic Condition Dyads Among Medicare Fee-for-Service Beneficiaries, by Sex and Age Group
2013	Ashman & Beresovsky, 2013 [U.S.]	Compare physician office visits by adults with MCC with visits by adults without MCC, by selected	National Ambulatory Medical Care Survey; used 13 of the 20 conditions defined by the National Strategic Framework	Descriptive estimates generated and significant differences were tested.	326 million physician office visits, made by adults 18 years or older with MCC = 37.6% of all medical office visits by adults. Hypertension most prevalent chronic	 Bar chart of physician office visits made by

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
		patient demographic characteristics; identify most prevalent dyads and triads of chronic conditions.	on Multiple Chronic Conditions		condition that appeared in the top 5 MCC dyads and triads, by sex and age groups. The number of visits by patients with MCC increased with age and was greater for men than for women and for adults with public rather than private insurance.	patients with or without chronic conditions, by number of meds ordered or prescribed.
2013	Machlin & Soni, 2013 [U.S.]	Illustrate usefulness of Medical Expenditure Panel Survey (MEPS) data for examining variations in medical expenditures for people with multiple chronic conditions (MCC).	2009 MEPS-HC comprises a sample of approximately 14,000 households across 2 consecutive panels with a combined overall response rate of approximately 60%	Reported conditions coded according to the ICD-9 codes. Compared participants' demographic characteristics, health care use, and expenditures between people treated for MCC (defined as 2 or more) and those treated for only 1 or no chronic conditions (i.e. people not treated for 2 or more MCC). Variations in common dyad and triad combinations of treated conditions were also examined by age and sex.	One-quarter of civilian US adults treated for MCCs; 18.3% treated for 2 to 3 conditions and 7% were treated for 4 or more conditions. The proportion of adults treated for MCC increased with age. White non-Hispanic adults were most likely and Hispanic and Asian adults were least likely to be treated for MCC. Health care expenditures increased as the number of chronic conditions treated increased. Regardless of age or sex, hypertension and hyperlipidemia was the most common dyad among adults treated for MCC; diabetes in conjunction with these 2 conditions was a common triad	 Frequency table shows Number of Treated Chronic Conditions by Demo-graphics.

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
2014	Violan, Foguet-Boreu, Flores-Mateo, Salisbury, Blom, Freitag,... & Valderas, 2014 [Italy]	Review studies of the prevalence, patterns and determinants of multimor-bidity in primary care.	Systematic review of literature published between 1961 and 2013 and indexed in Ovid (CINAHL, PsychINFO, Medline and Embase) and Web of Knowledge	Studies were selected according to eligibility criteria of addressing prevalence, determinants, and patterns of multimorbidity in primary care	9 eligible publications describing studies that included a total of 70,057,611 patients in 12 countries. The number of health conditions analyzed per study ranged from 5 to 335, with multimorbidity prevalence ranging from 12.9% to 95.1%. All studies observed a significant positive association between multimorbidity and age (odds ratio [OR], 1.26 to 227.46), and lower socioeconomic status (OR, 1.20 to 1.91). Positive associations with female gender and mental disorders were also observed. The most frequent patterns of multimorbidity included osteoarthritis together with cardiovascular and/or metabolic conditions.	 Table shows hierarchy - most frequent pairs of health conditions
2014	Rocca, Boyd, Bobo, Rutten, Roger,... & Sauver, 2014 [U.S.]	Describe prevalence multi-morbidity 20 selected chronic conditions geographic ally defined US population	Rochester Epidemiolog y Project records linkage system; residents from Olmsted County, Minnesota,	Electronically extracted ICD-9 codes associated with all health care visits (5-year capture frame). Defined 20 common chronic	38.9% study participants had 1 or more conditions (n=54,012), 22.6% had 2 or more conditions (n=31,444), and 4.9% had 5 or more conditions (n=6853). Prevalence of	 Heat map of burden of multimor-bidity by absolute frequency.

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
		by age, sex, and racial/ethnic differences	April 1, 2010, 138,858 study participants, 52.4% were women (n=72,732)	conditions recommended by the US DHHS. Counted only persons who received at least 2 codes for a given condition separated by more than 30 days, and calculated age-, sex-, and race/ethnicity-specific prevalence of multimorbidity.	multimorbidity (≥2 conditions) increased steeply with older age, 77.3% at 65 years and older. Absolute number of people affected by multimorbidity was higher in those younger than 65 years. Prevalence of multimorbidity similar in men and women overall, most common dyads and triads of conditions varied by sex. Compared with white persons, the prevalence of multimorbidity slightly higher in black persons and slightly lower in Asian persons.	Number in each square % co-occurrence in overall population (all ages combined). 18 conditions listed on the X and Y axes by frequency.
2015	Lochner, K. A., & Shoff, 2015 [U.S.]	Perform geographic information system (GIS) analysis to describe county-level prevalence patterns of Medicare beneficiaries with 6 or more chronic conditions.	Centers for Medicare & Medicaid Services (CMS) administrative enrollment and claims data for 100% of Medicare beneficiaries enrolled in the fee-for-service program in 2012	Calculated prevalence estimates by dividing the number of beneficiaries with 6 or more of the 17 chronic conditions by the total number of beneficiaries in our fee-for-service population, expressed as a percentage. Age-adjusted all prevalence estimates to the 2000 US standard population aged 65 or older	15% of aged Medicare beneficiaries had 6 or more chronic conditions. Prevalence varied geographically by county; 87 counties had estimates at least 1.5 times higher than the national average; 3 counties had prevalence estimates at least twice the national average. Counties in the Northeast and Southeast generally had a higher prevalence of aged beneficiaries with 6 or more chronic conditions	 Map shows counties with the highest prevalence of Medicare bene-ficiaries with 6 or more chronic conditions located in southern states and north-eastern states

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
2017	Koroukian, Schiltz, Warner, Sun, Stange, Given & Dor, 2017 [U.S.]	Analyze patterns of conditions constituting multimor-bidity (CCMM) and expenditure s in a US representa-tive sample of midlife and older adults (50–64 and ≥65 years of age, respectivel y).	2010 HRS and linked Medicare data from 2010 to 2011. HRS biennial survey of adults aged 50 years or older. Approximatel y 30,000 older adults surveyed; includes sociodemogr aphic; self-reported chronic conditions, functional status, cognitive status, and depressive symptoms variables	Multimorbidity self-reported chronic conditions and functional limitations and geriatric syndromes. Survey weights account for the complex survey design of the HRS; descriptive analysis identify patterns of CCMM count in the sociodemo-graphic strata. Reported median expenditures for CCMM. Used association rule mining (ARM) to identify the most common monads, dyads, triads, etc. Identified five most frequently observed specific CCMM that were identified in each of the count categories.	Large representations of participants within specific CCMM categories were not observed; however, functional limitations and geriatric syndromes were prominently present with higher CCMM counts. Among fee-for-service Medicare beneficiaries aged 50–64 years, 26.7% of the participants presented with ≥10 CCMM, but incurred 48% of the expenditure. In those aged ≥65 years, these percentages were 16.9% and 34.4%, respectively.	 Table shows 5 most frequently observed monads, dyads, triads, etc. appearing in combina-tions of conditions constitutin g multimor-bidity among adults aged ≥65 years
2017	Tisminetzk y, Bayliss, Magaziner, J. S., Allore, Anzuoni,	Describe the prevalence of, and patient characteris-	TRACE-CORE used a multisite prospective cohort design to recruit and	Included most common Multimor-bidities, defined as frequency >/=	Most common cardiac-related morbidities: hypertension, hyperlipidemia, and diabetes	 Multi-bar chart of

Article Year	Reference [Country]	Purpose	Data	Methods	Main Results	Data Visualizations
	Boyd... & Hornbrook, 2017 [U.S.]	tics associated with, cardiac- and non-cardiac-related multimor-bidities in patients discharged from the hospital after an acute coronary syndrome.	follow a cohort of 2174 eligible and consenting adults hospitalized with an acute coronary syndrome at 3 medical centers in Worcester, Mass, 1 in Macon, Ga, and 2 in Atlanta, Ga between April 2011 and May 2013	3%. Information from hospital medical records. 8 most prevalent cardiac-related conditions and 8 most prevalent non-cardiac-related conditions examined. Categorized patients into having none or any 1, 2, 3, or 4 or more chronic conditions. Estimated overall prevalence of individual morbidities and multiple cardiac related, non-cardiac-related morbidities. Calculated tetra choric correlation to determine more prevalent dyads. Analysis of variance and the chi-squared test performed	(76%, 69%, and 31%, respectively). Arthritis, chronic pulmonary disease, and depression (20%, 18%, and 13%, respectively) most common non-cardiac morbidities. Patients with >/= 4 morbidities slightly older and more frequently female than those with 0-1 morbidity; more likely to be cognitively impaired (26% vs 12%), have symptoms of moderate/severe depression (31% vs 15%), high perceived stress (48% vs 32%), a limited social network (22% vs 15%), low health literacy (42% vs 31%), and low health numeracy (54% vs 42%).	Dyads of cardiac- and non-cardiac-related morbiditie s in patients hospital-ized with an acute coronary syndrome by decreasing prevalence .

National MCC Tends, Dyads, Future of Data, Standards and Codes

Researchers have responded to HHS's call to fill gaps in knowledge regarding measurement, characterization (dyads and triads), data capability, sub-state analysis, and the geographic distribution and variation of the Multiple Chronic Condition (MCC) population. This section discusses key research findings in these areas. The studies presented below focus on two groups – the noninstitutionalized, civilian US adult population and Medicare beneficiaries.

MCC trends, gender, and race/ethnic prevalence. The Centers for Medicare and Medicaid Services [CMS] (2014), prepared a chartbook describing chronic conditions among Medicare beneficiaries, highlighting the prevalence of chronic conditions among this population. The prevalence and costs of chronic health conditions among Medicare beneficiaries have far-reaching implications for the health care system. Most beneficiaries have multiple chronic conditions (defined as two or more chronic conditions) and conditions such as high blood pressure, high cholesterol, heart disease and diabetes were most prevalent. The data used for the report comes from the 2010 CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service (FFS) program. Results in the chartbook revealed that chronic conditions increase as beneficiaries age. Women live longer than men and as a consequence the prevalence of specific and multiple chronic conditions was higher for women, and the specific chronic conditions differ. For example, women were about 1.7 times as likely to have arthritis or depression while men were 1.3 times more likely to have ischemic heart disease (CMS, 2014, p. 6). Similarly, chronic conditions tend to be more prevalent among beneficiaries eligible for Medicare and Medicaid benefits. This population is known as "dual eligible" beneficiaries and is considered particularly vulnerable because they are either disabled, 85 years of age and older, or both.

Unexpectedly, CMS found that the number of chronic conditions varied little across racial and ethnic beneficiary groups. Overall, the most frequent number of chronic conditions by

race and ethnicity were 0 to 1 conditions (between 31% and 34%) followed by 2 to 3 conditions (between 28% and 33%), and 4 to 5 conditions (nearly 23%). The least frequent number of conditions among beneficiaries was 6 or more (between 11% and 16%). In 2010, Hispanics were more likely to have 0 to 1 conditions (34%) than non-Hispanic whites (31%), non-Hispanic blacks (31%), and Asians and Pacific Islanders (Asians/PI) (32%). Asians/PI and non-Hispanic whites were equally likely to have 2 to 3 conditions at 33%, while non-Hispanic blacks (30%) and Hispanics (28%) were less likely.

Lochner and Cox (2013) examined the Centers for Medicare and Medicaid Services (CMS) administrative enrollment and claims data for Medicare beneficiaries for the prevalence of multiple chronic conditions by similar Medicare beneficiary characteristics as defined by HHS. Among beneficiaries 65 and older, 69.1% of men had multiple chronic conditions compared with 73.4% of women. The authors also found that race/ethnicity did not explain the variation between men and women. The prevalence of multiple chronic conditions was 81.2% for non-Hispanic white, 9.6% for non-Hispanic black, 5.7% for Hispanic, and 2.2% for Asians/PI (Lochner & Cox, 2013, p. 2).

Ward, Schiller, and Goodman (2014) used the 2012 National Health Interview Survey (NHIS) to update and generate estimates of multiple chronic conditions for the noninstitutionalized, civilian US adult population and demographic characteristics. The authors observed that prevalence for MCC varied by specific subpopulations. Women were more likely than men to have 2, 3 or more conditions, consistent with earlier findings. However, the authors found that the prevalence of MCC was higher among non-Hispanic white adults, non-Hispanic black adults, non-Hispanic adults of other races, and that the prevalence rates for non-Hispanic Asian adults and Hispanic adults were actually lower. While Ward et al.'s observed that the prevalence of Hispanic adults were lower than non-Hispanic whites and blacks (in contrast to Lochner and Cox's findings), the authors' conclusion that the percentage of adults with MCC

(both 2 and ≥3) increased with age (Ward, Schiller, & Goodman, 2014) was consistent with earlier findings.

Gerteis, Izrael, Deitz, LeRoy, Ricciardi, Miller, and Basu (2014) used the Household Component of the 2010 and 2006 Medical Expenditure Panel Survey (MEPS), a nationally representative survey administered by The Agency for Healthcare Research and Quality (AHRQ). The authors observed similar results in terms of gender prevalence, women were more likely than men to report multiple chronic conditions (34.7% for women compared to 28.2% for men). Below is a summary of the evidence regarding the presence of gender, race and ethnic disparities in the MCC population (national adult population):

- More women had more multiple chronic conditions compared with men, women were more likely than men to have 2, 3 or more conditions. Women were nearly 2 times as likely to have arthritis or depression while men were less so. However, men were more likely to have ischemic heart disease (in the Medicare population)
- Chronic conditions tend to be more prevalent among dual eligible beneficiaries
- Among Medicare beneficiaries, chronic conditions varied less across racial and ethnic groups. The most frequent number of chronic conditions by race and ethnicity were 0 to1 conditions, followed by 2 to 3 conditions
- Hispanics were more likely to have 0 to 1 conditions. Asians/Pacific Islanders and non-Hispanic whites were equally likely to have 2 to 3 conditions
- Among Medicare beneficiaries, the prevalence of MCC was higher among non-Hispanic white adults, non-Hispanic blacks, and non-Hispanics of other races. Non-Hispanic Asian adults and Hispanic adults had lower prevalence rates respectively
- The percentage of adults with MCC (both 2 and 3 or more conditions) increased with age

- Among the noninstitutionalized, civilian U.S. adult population, the prevalence of MCC was higher among non-Hispanic white adults than non-Hispanic black adults, and non-Hispanic adults of other races. Non-Hispanic Asian adults and Hispanic adults had lower prevalence rates respectively. While chronic conditions varied less across racial and ethnic groups in the Medicare population, that was not observed among the noninstitutionalized civilian U.S. adult population.

A stated goal of the framework was to improve the health status of the total population and fill knowledge gaps about the MCC population. To do so, researchers performed population studies (as compared to clinical studies) frequently using national datasets, such as the National Health Interview Survey (NHIS), the Medical Expenditure Panel Survey (MEPS) or CMS administrative claims data for Medicare beneficiaries.

MCC dyads and triads. Research on adults with chronic conditions generally focus on a single disease or condition, such as hypertension or diabetes, rather than on multiple chronic conditions (MCC) according to Ashman, & Beresovsky (2013). Researchers have responded to the recommendations made by the framework and conducted studies on the prevalence of MCC and the most common MCC dyads and triad combinations (combinations of chronic conditions) by selected demographic characteristics such as sex and age groups (Ward & Schiller, 2013; Ashman, & Beresovsky, 2013). Ward and Schiller conducted a review of the literature and the following data sources were used: Medicare and Medicaid beneficiaries (Lochner & Cox, 2013), MCC medical expenditures for adults (Machlin & Soni, 2013), Centers for Medicare and Medicaid Services (CMS) administrative enrollment and claims data, the National Health Interview Survey (NHIS) (Ward & Schiller, 2013), Nationwide Inpatient Sample (NIS) of the Healthcare Cost and Utilization Project (HCUP) (Steiner, & Friedman, 2013), the National Ambulatory Medical Care Survey (Ashman, & Beresovsky, 2013), and the Medical Expenditure Panel Survey (MEPS) data (Machlin & Soni, 2013). Table 2 displays the results of Ward and

Schiller's review of the literature regarding the most prevalent chronic condition combinations with two (dyads) or more chronic conditions. The authors found that for both women and men ages 45 to 64 years and 65 years and older, arthritis/hypertension and diabetes/hypertension were the most prevalent dyadic combinations followed by diabetes/hypertension dyad. The third most prevalent disease combinations differed by age and gender. For working age men and women CHD/hypertension and arthritis/diabetes were the third most prevalent dyadic combinations respectively. For men and women 65 years and older, the third most prevalent dyads were CHD/hypertension for men and Arthritis/diabetes for women.

Table 2. *The five most prevalent condition dyads for US adults with 2 or more chronic conditions by sex and age.*

National Health Interview Survey, 2010 (adapted from Ward & Schiller, 2013).	
Sex, Age, and Dyad	**% (95% Confidence Interval)**
Men	
45–64 y	
Arthritis/hypertension	46.9 (43.71–50.17)
Diabetes/hypertension	29.7 (27.02–32.50)
CHD/hypertension	16.4 (14.27–18.71)
Arthritis/diabetes	14.7 (12.70–17.05)
Cancer/hypertension	11.3 (9.50–13.43)
≥65 y	
Arthritis/hypertension	49.3 (46.29–52.32)
Diabetes/hypertension	29.5 (26.81–32.42)
Cancer/hypertension	27.6 (24.91–30.40)
CHD/hypertension	24.8 (22.05–27.84)
Arthritis/diabetes	21.2 (18.75–23.83)
Women	
45–64 y	
Arthritis/hypertension	49.9 (47.24–52.55)
Diabetes/hypertension	23.6 (21.50–25.87)
Arthritis/diabetes	17.3 (15.38–19.37)
Asthma/hypertension	16.7 (14.72–18.89)
Arthritis/asthma	16.6 (14.79–18.63)
≥65 y	
Arthritis/hypertension	63.0 (60.46–65.51)
Diabetes/hypertension	25.4 (23.27–27.71)

Arthritis/diabetes	20.4 (18.39–22.50)
Cancer/hypertension	21.8 (19.78–24.02)
Arthritis/cancer	21.0 (19.05–23.07)

Future of data and technology challenges

This is an ideal place to briefly note that tabular forms of data display, such has Table 2, that are traditional visualization tools to convey information. Tabular forms are straightforward, suitable and certainly a common approach but they are limited in how much complexity they can show in the data. The more complex the data is, the harder it is to understand. For example, consider how the information contained in the table might be presented to show the interaction of the conditions? The use of simple networks combined with the patterns described here can complement research findings, making it easier to understand the complexity and perhaps generate novel insights (Merico, Gfeller, & Bader, 2009).

As discussed prior, researchers have at their disposal large national data sets to explore and examine issues related to MCC. According to Khan, Yaqoob, Hashem, Inayat, Mahmoud Ali, Alam,... and Gani (2014), the rapid growth of volume, variety, value, management of national data sets and electronic health records represent new issues and challenges with respect to data management and analysis. As cited in Khan et al., information increases rapidly at a rate of 10xs every five years and the computing size of general-purpose computers increases annually at a rate of 58%, lagging the rate of information growth. This is the new world of "Big Data". It is reasonable to expect that national health datasets will evolve to include data from electronic health records and devices in the near future. The magnitude of data cannot be processed using existing technologies and methods according to the authors. The generation of large datasets where tabular forms of display are used such as in the fields of science, business, geography and health, are no longer effective. Data analytics, procedures and tools, designed to search and

analyze large datasets are in their infancy but the frontier is waiting for researchers to explore data analytics and system approaches to unlock the intricacies of multiple disease states in vulnerable populations where environments shape health and distributions vary geographically.

Framework standard set of conditions, HIPPA and Codes

In their study, Lochner, Goodman, Posner, and Parekh, (2013) described state-level variation of MCC among Medicare beneficiaries, by focusing on six or more conditions using data for 2011 from the CMS Chronic Condition Warehouse database which includes pre-defined indicators for 27 chronic conditions. The authors used the set of 15 conditions (the standard set promoted by HHS) including: arthritis, Alzheimer's and related dementia, asthma, atrial fibrillation, cancer (breast, colorectal, lung, and prostate), chronic kidney disease, chronic obstructive pulmonary disease (COPD), depression, diabetes, heart failure, hyperlipidemia, hypertension, ischemic heart disease, osteoporosis, and stroke to characterize whether Medicare beneficiaries had MCC. Diagnosis codes from Medicare claim forms were used to count the number of conditions from the set of 15 conditions.

HIPAA and ICD-9-CM codes. Medicare claims contain codes that are generally used in determining coverage and payment amounts. According to Medicare Claims Processing Manual (the manual) (2017, February), CMS accepts only HIPAA approved ICD-9-CM or ICD-10-CM/ICD-10-PCS codes, depending on the date of service. HIPAA is the Privacy Rule, a Federal law that gives individuals rights over their personal health information and sets rules and limits on who can look at and receive their health information (HHS, 2017, February). ICD-9-CM codes are the official codes used in medical diagnoses. Chapter 23 of the manual describes how and what providers must report when reporting the principal diagnosis on the inpatient claims. As stated in the manual, the principal diagnosis is the condition determined after review to be primarily responsible for the admission. Even though another diagnosis may be more severe than

the principal diagnosis, the principal diagnosis, as defined above, should be entered (Medicare Claims Processing Manual, 2017, February).

The Case of State Patterns of Multimorbidity

In their study, Lochner and colleagues found state-level variation in the prevalence, healthcare utilization, and Medicare spending for beneficiaries with multimorbidity (used hence forth in place of multiple chronic conditions for ease of interpretation). The authors argued that current evidence about multimorbidity have come primarily from analyses of national level data sets and hence the need to explore state level variation. The authors were the first to examine state-specific patterns of multimorbidity among a large population and observe state-level variability in multimorbidity prevalence, healthcare utilization, and expenditures across the United States. Lochner et al. acknowledged limitations of their approach, for example estimates of multimorbidity were influenced by the number and type of conditions that were used in studies like this. Although the researchers included common chronic conditions, they excluded several behavioral and mental health disorders, such as substance abuse disorders and schizophrenia because they were unavailable as pre-defined chronic conditions from the Medicare claims data source. HHS (2010) recommends researchers focus on the most common chronic conditions for a more consistent and standardized approach to measuring the occurrence of chronic conditions in the United States (HHS, 2010; Goodman, Posner, Huang, Parekh, & Koh, 2013). Lochner et al. recognized the limitations of the standard approach advocated by HHS and attributed the omitted variable bias to exclusions of conditions and the number and types of conditions as influencing their results. The authors concluded by recommending that future research include conducting similar analyses at sub-state levels that are more local, including counties and communities where strategies, interventions, and other health care services can be tailored to specific populations with multimorbidity.

So far the review illustrates how researchers discovered important information about the prevalence of multiple chronic conditions among populations and detected the most common dyads and triads by counting a limited set of chronic conditions and grouping them into categories. The terms dyad and triads suggest that chronic condition combinations have some relationship, or describe some interaction. The framework identifies a specific structure to understand the epidemiology of multimorbidity, however further understanding of the structure and function requires more knowledge about both structure and function of these interacting conditions. To extend our understanding and support the objectives of the framework, presented is a systems approach to characterizing the pattern of the relationships and interactions and explore the geographic variation of multimorbidity in North Carolina.

Additionally, HHS's framework seeks to "catalyze change" and usher in a "paradigm shift", while motivating researchers to discover the "constellations of conditions" (e.g., dyads and triads) (HHS, 2010, p.1). My aim is to build on these earlier contributions by examining county-level patterns using county-level data, with less exclusion, and present a technique for observing constellations of multimorbidity conditions. It is my contention that in order to target specific interventions for specific populations, it is important to understand the structural properties of interaction between populations burdened with multimorbidity and the context or environment that these interactions occur. Put another way, I am motivated to study context to understand the interactions and relations among multiple chronic conditions.

The Role of States, Sub-State Data and Regional Differences

The function of the agency. Understanding the national implications of this growing crisis is critical. A broader function of the federal agency is to establish national health objectives that serve as the basis for the development of state and community plans (HHS, 2010, p.5). Federal policymakers and health researchers have long recognized that the amount and quality of health care services that populations receive vary substantially across different regions of the

United States (Black & Schiller, 2016). Figure 4 shows that in 2014, 17.3% of adults aged 18 to 64 did not have a usual place of medical care. The percentage ranged from 2.8% in Vermont to 26.7% in Nevada. Nine states (Nevada, Idaho, Texas, Oregon, Wyoming, Kentucky, Arizona, Alaska, and Florida) had a higher percentage of adults without a usual place of medical care compared with the national average (17.3%). North Carolina, South Carolina and Georgia were at or above the national average with 16.2%, 18.7%, and 17.4% respectively.

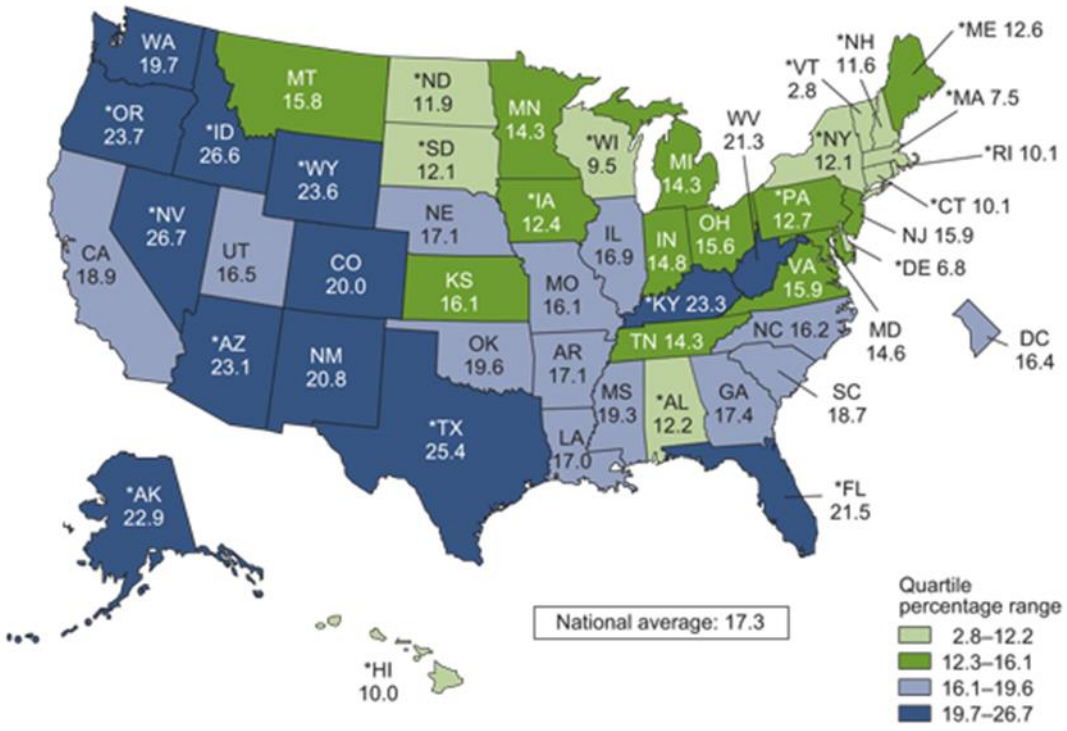


Figure 4. The Percentage of Adults aged 18-64 Without Place of Medical Care by State, 2014. Source: Black & Schiller (2016).

Until now the discussion has centered on research using national data sets. To understand the distribution of multimorbidity demographic characteristics at a sub-state level it is

important to examine county-level patterns. From a policy perspective, states are increasingly playing a key role in the financing, regulation, and delivery of health care and little is known about differences in healthcare use and spending across counties for populations with multimorbidity. To build and strengthen state health department capacity to effectively prevent chronic disease and promote health, all 50 states engaged in a partnership with the Centers for Disease Control and Prevention (CDC) (NC Department of Health and Human Services, Public Health, Chronic Disease and Injury [CCDIHP], 2013).

State Inpatient Data (SID). The Healthcare Cost and Utilization Project [HCUP] (2017) State Inpatient Database (SID) can facilitate discovery with data from hospital inpatient and ambulatory (emergency room) settings. State inpatient data permit investigations at the sub-state level and comprise the universe of hospital discharge abstracts for participating states. Inpatient discharge data are used in a wide range of applications. For example, hospital discharge data provide critical information for disease surveillance, chronic disease prevention and control programs; facilitate the assessment of racial and ethnic disparities and allows researchers to examine patterns of inpatient care for a specific area (Healthcare Cost and Utilization Project [HCUP], 2017). SID enables the identification of services that are lacking in a community and facilitate development of plans for allocation of resources (Schoenman, Sutton, Kintala, Love, & Maw, 2005). The State Inpatient Database are large data sets and allow researchers to drill down to the community level to understand differences, such as gender and racial and ethnic groups disparities, and the influence of various health indicators and risk factors. Patient zip-codes allow linkages to other databases that contain health indicators, risk factors, social factors and other measures of access and utilization, therefore enhancing research capabilities.

While studies have documented disparities among groups (less so for Hispanics and other racial/ethnic groups due primarily to data issues), often they do not simultaneously compare groups within a single study. The proportion of elderly people within Hispanic and other

racial/ethnic groups is expected to increase more quickly than that of non-Hispanic whites and blacks (HHS, 2010). By focusing on the powerful role of social factors in shaping health across a wide range of health indicators, settings, and populations, this research "more clearly elucidates" (HHS, 2010, p. 15) gender and racial/ethnic differences in the multimorbidity population at the county level. This dissertation examines racial/ethnic differences and a wide range of health indicators, risk factors, social factors and other measures of access and utilization using HCUP's State Inpatient database.

Understanding state differences in multimorbidity can help state health officials establish disease prevention goals, priorities, and strategies. Few researchers have assessed North Carolina's multimorbidity population. The following section reviews state variation of multimorbidity and provides an overview of the burden of chronic disease in North Carolina.

Regional Multimorbidity Prevalence and Burden

In a subsequent study by Lochner, Goodman, Posner, & Parekh (2013), the researchers described state-level variation of multimorbidity among Medicare beneficiaries, focusing on those with 6 or more conditions. According to the researchers, multimorbidity burden among this population was remarkable because the 14% of beneficiaries with 6 or more chronic conditions accounted for almost half of total Medicare spending (Centers for Medicare & Medicaid Services [CMD], 2012). Lochner et al. (20130 recognized that while studies highlighted the important issue of multimorbidity for healthcare, characterizing geographic variations were effective for targeting service delivery, resource projections, and program planning. In their study, the authors used CMS administrative data for 2011. They followed the same standard as described earlier for determining the prevalence of conditions from a set of 15 conditions and the conditions were identified using diagnosis codes on the claims. Diagnosis codes were also present on the patient's discharge record in SID.

Lochner et al.'s (2013) study population included fee-for-service beneficiaries residing in the U.S. Figure 5 shows the rates of beneficiaries with six (6) or more chronic conditions. Prevalence rates were lowest in Alaska and Wyoming (7%) and highest in Florida and New Jersey (18%). North Carolina's prevalence rate was 12.3%, lower than the national prevalence rate (14%). However, for 2 to 3 conditions, Virginia (34.0%), North Carolina (34.4%) and South Carolina (34.9) were among the states with the highest prevalence. The state with the lowest prevalence (2 to 3 conditions) was Wyoming (28.3%) and the state with the highest prevalence was Hawaii (35.3%). The authors argued that for states in the Pacific and Mountain West, and for most states in the Midwest, the prevalence of beneficiaries with more than 6 conditions was below the national average. Generally, the prevalence was higher in the Northeast and South (not the case for North Carolina). Lochner et al. concluded that findings such as these highlight the need for further study of state variations in multimorbidity identifying specific factors underlying patterns, such as differences in distributions of underlying risk factors, combinations and types of conditions. This dissertation focuses on prevalence patterns of multimorbidity across counties in North Carolina and underlying risk factors.

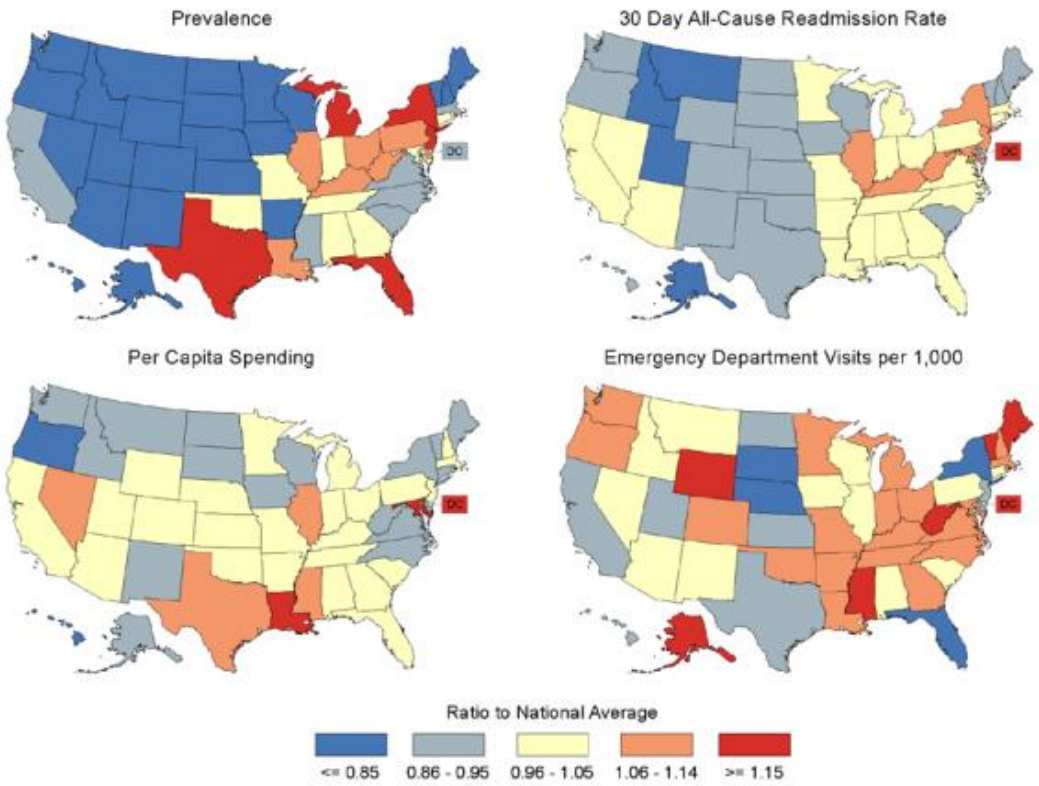


*Figure 5.*U.S. Maps of Prevalence, Hospital Readmissions, ED Visits, and Medicare Spending for Medicare Beneficiaries with 6 or more Chronic Conditions by state, 2011. Source Lochner, Goodman,Posner and Parekh (2013).

NC Multimorbidity Trends, CVD, Geographic Disparities and Economic Burden

In collaboration with the CDC and other partners, North Carolina developed the North Carolina Chronic Disease, Injury, and Health Promotion State Plan as part of its participation in the CDC's Coordinated Chronic Disease and Health Promotion Program (NC Department of Health and Human Services, Public Health, Chronic Disease and Injury [CCDIHP], 2013). The funding for CCDIHP came from the Patient Protection and Affordable Care Act (2010). The Affordable Care Act, President Obama's signature health care reform law, emphasized disease prevention. Many of the 10 major titles in the law, especially Title IV, Prevention of Chronic Diseases and Improving Public Health (Protection, P., & Act, A. C., 2010), supported a

prevention theme through a wide variety of initiatives and funding efforts (Koh & Sebelius, 2010). Funding was provided to states, such as North Carolina, to "build and strengthen state health department capacity to effectively prevent chronic disease and promote health" (NC Department of Health and Human Services, Public Health, Chronic Disease and Injury [CCDIHP], 2013). Each of the states was required to develop a Coordinated State Chronic Disease Prevention Plan (State Plan). Among the goals of the NC State Plan were to address health disparities and health equity. The NC CCDIHP includes detailed descriptions of the burden of chronic disease in North Carolina (in addition to injury), co-morbid chronic conditions and risk factors to explain the burden and reveal chronic disease disparities in the state (CCDIHP, 2013, p. 3).

NC cardiovascular disease trends. Around the world, the occurrence of death from cardiovascular and circulatory diseases rose by one third between 1990 and 2010 (Go, Mozaffarian, … Roger, 2013). According to (WHO, n.d.a), an estimated 17.7 million people died from CVD in 2015, representing 31% of all global deaths. Of these deaths, an estimated 7.4 million were due to coronary heart disease and 6.7 million were due to stroke. WHO (n.d.a) estimated that most cardiovascular diseases can be prevented by addressing behavioral risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol if population-wide prevention and interventions strategies are used. Epidemiologic studies have played an important role in explaining the factors that predispose individuals to cardiovascular disease (Mahmood, Levy, Vasan, & Wang, 2014).

Cardiovascular (CVD) disease is the most common cause of mortality in developed countries. The Centers for Disease Control and Prevention [CDC] (2017a) estimates that nearly 610,000 people die of heart disease in the United States every year, representing 1 in every 4 deaths. Heart disease is the leading cause of death for both men and women. More than half of the deaths due to heart disease in 2009 occurred in men. Coronary heart disease (CHD) is the

most common type of heart disease, killing over 370,000 people annually. Figure 6 shows the geographic variation by county. Counties such as Scotland, Pitt, Columbus and Bladen in North Carolina had the highest rates (per 100,000) of death for adults 65 years and older (indicated by dark red). Table 3 shows the percentages of all deaths caused by heart disease by ethnicity in 2008.

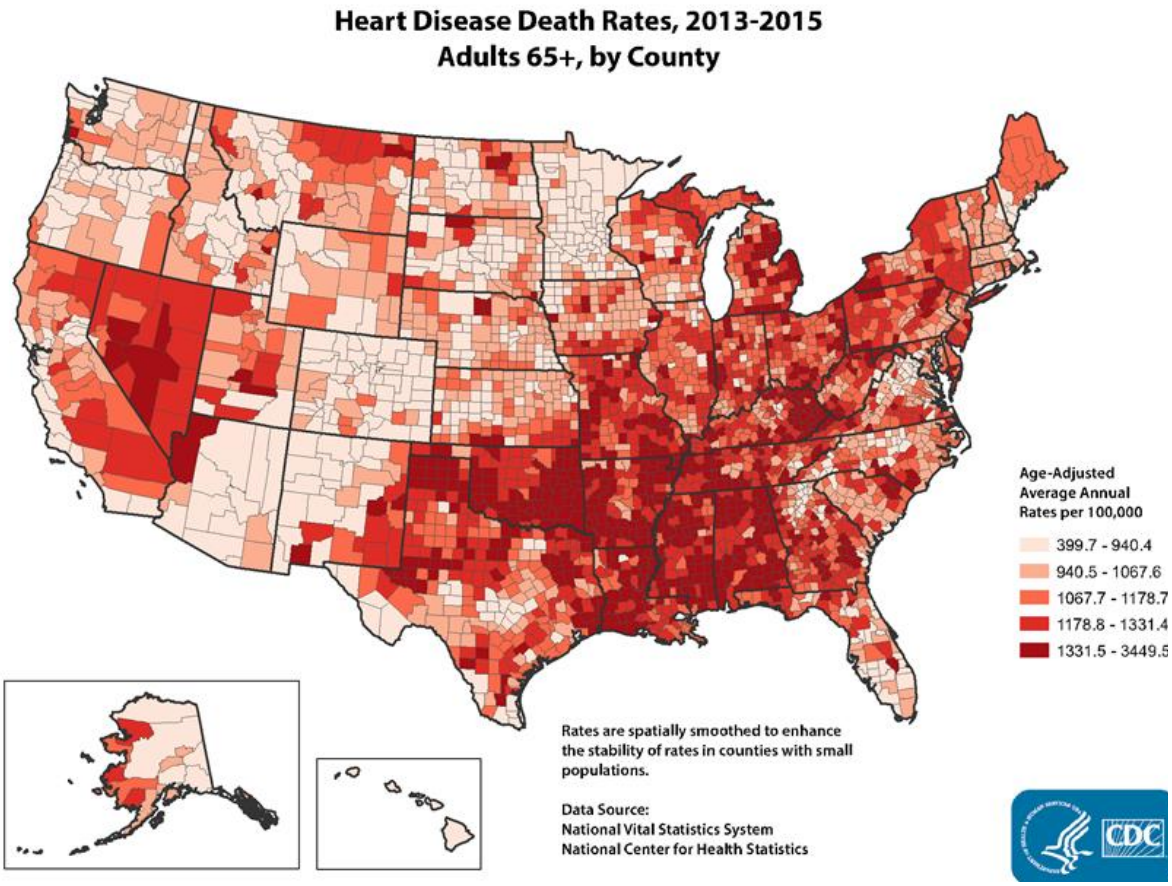


Figure 6. Heart Disease Death Rates, Adults 65 years and older by county, 2013 to 2015. Source: CDC (2017b)

Table 3. *Heart Disease Deaths Vary by Race and Ethnicity.*

Below are the percentages of all deaths caused by heart disease in 2008 by ethnicity. Source: CDC (2017a).

Race or Ethnic Group	**% of Deaths**
American Indians or Alaska Natives	18.4
Asians or Pacific Islanders	22.2
Non-Hispanic Blacks	23.8
Non-Hispanic Whites	23.8
All	23.5

Heart disease mortality and geographic disparity. According the CDC (2017a), heart disease is the leading cause of death for people of most ethnicities, including African Americans, Hispanics, and whites. For American Indians or Alaska Natives and Asians or Pacific Islanders, heart disease is second only to cancer. Casper, Kramer, Quick, Schieb, Vaughan, and Greer (2016) observed dramatic changes in the geographic patterns of heart disease mortality from 1973 to 1974, 2009 to 2010 for those aged 35 years and older. The authors detected that a substantial shift occurred in the concentration of high-rate counties from the Northeast to the Deep South. Although counties in the South experienced a slow-decline, a nearly 2-fold increase in geographic inequality among counties was observed (as shown in Figure 7). Casper et al. (2016) maintained that studies have not monitored changes in the pattern of geographic disparities in heart disease mortality among US communities during this time period. Small-area surveillance of heart disease mortality is important because it can reveal patterns that are masked at the national level, and provide communities the historical context for understanding their current burden of heart disease (Casper et al., 2016).

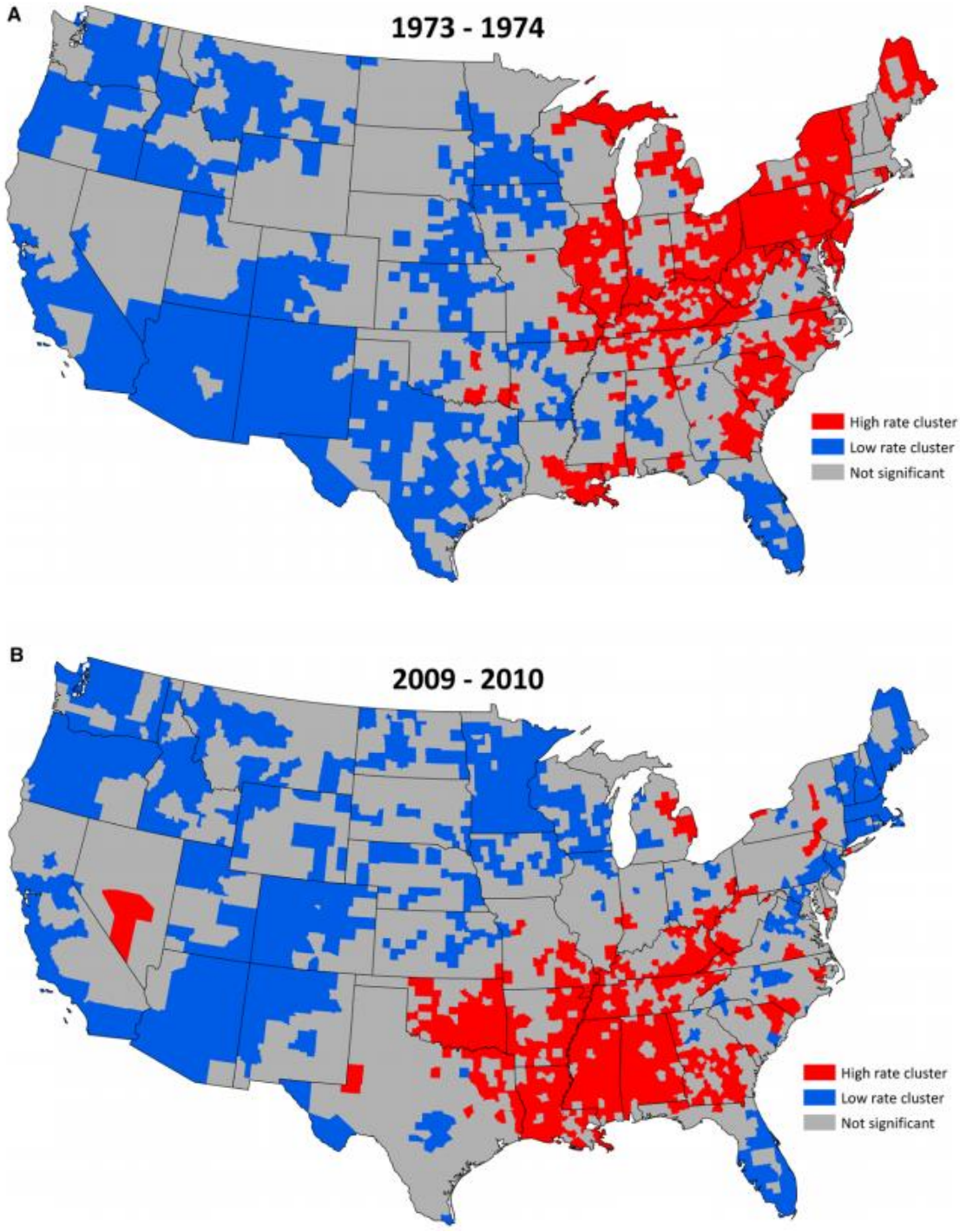


Figure 7. Clusters of county-level age-standardized heart disease death rates, ages ≥35 for the beginning (1973–1974, A) and end (2009–2010, B). Source: Casper et al (2016).

Each day in North Carolina in 2010, approximately 144 residents died because of a chronic disease. The NC CCDIHP examined mortality rates by race, overall across all cause of death, and reported that non-Hispanic African Americans have rates that are approximately 1.2 times higher than non-Hispanic whites (984 vs. 797.3). Within chronic disease, non-Hispanic blacks had higher rates than non-Hispanic whites for all but chronic lower respiratory diseases, chronic liver disease and Alzheimer's disease. The only chronic disease or injury where non-Hispanic white rates were more than two times higher than that of non-Hispanic blacks, was suicide (14.9 vs 4.8) (CCDIHP, p. 53). The NC CCDIHP reported that chronic disease mortality patterns also differ geographically in North Carolina. Except for chronic lower respiratory diseases, the eastern regions of the state and the southern Piedmont regions (between the Atlantic Coastal Plain and the Appalachian Mountains) tend to consistently have the highest age-adjusted mortality rates. According the NC CCDIHP, these same counties (in the eastern part of North Carolina) often have high concentrations of poverty (as shown in Figure 8) and larger minority populations. No mortality rates were reported to assess gender disparities.

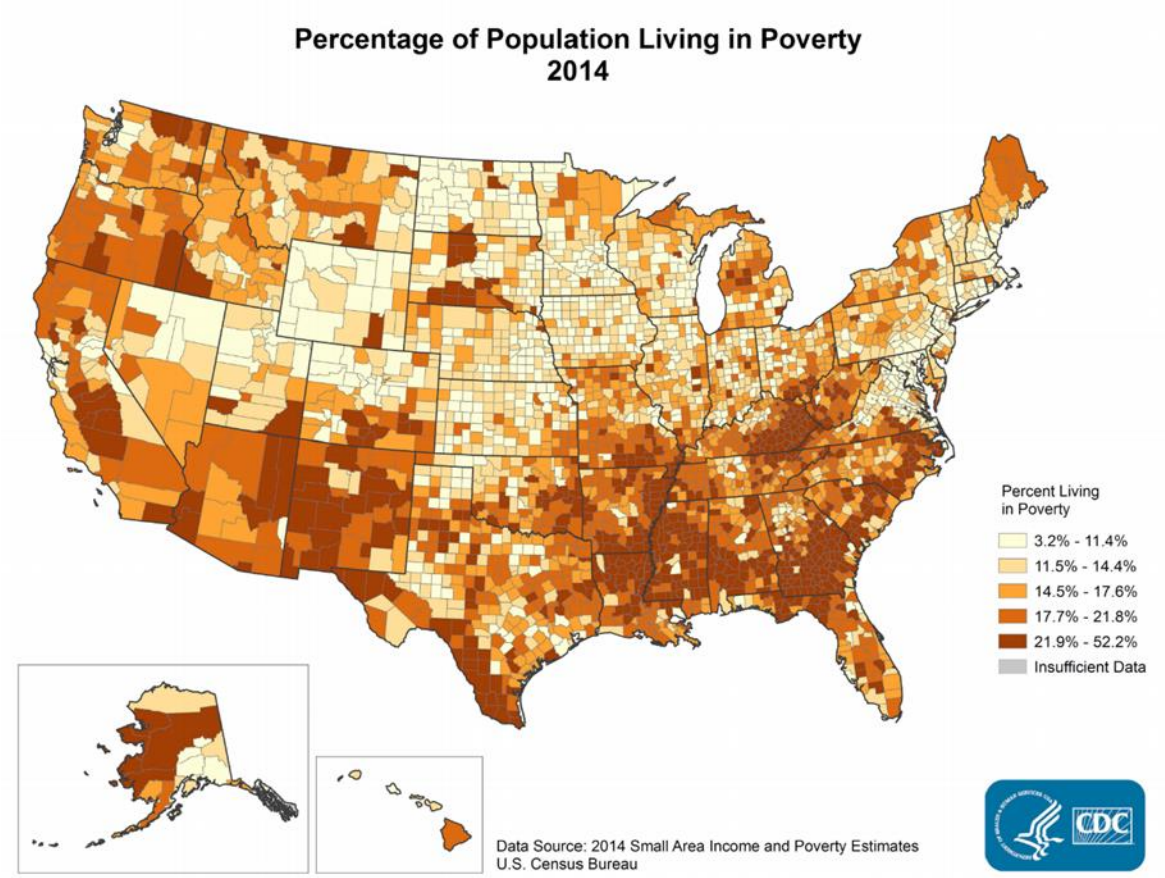


Figure 8. Percentage of Population Living in Poverty, 2014. Source: CDC (2017c).

Hospitalization rates by race. The NC CCDIHP examined North Carolina's inpatient hospitalization rates by race (Table 4). They found that non-Hispanic black hospitalization rates were higher than non-Hispanic whites (overall), for asthma, diabetes, kidney disease, and cardiovascular disease. The Native American population had the highest hospitalization rates for chronic obstructive pulmonary disease (COPD). The only diagnostic category where hospitalization rates were higher for non-Hispanic whites compared with all other racial groups were arthropathies (i.e. arthritis). Hospitalization rates for gender were not provided.

Table 4. *2010 North Carolina Resident Inpatient Hospital Utilization Rates for Chronic Diseases by Race.*

Population per 10,000. Source: CCDIHP, 2013.

Selected Primary Diagnosis Categories	White Rate	African American/Black Rate	Native American Rate	Other Non-White Rate
Cardiovascular & Circulatory Disease	159.9	183.9	156.5	126.8
Chronic Obstructive Pulmonary Disease (excl. Asthma)	22.6	15.0	39.0	7.9
Asthma	7.0	20.0	18.3	24.3
Cancer	32.3	31.3	19.5	36.4
Diabetes	12.7	35.1	21.2	23.4
Chronic Liver Disease/Cirrhosis	2.5	1.8	2.2	3.8
Nephritis, Nephrosis, Nephrotic Synd. (disorders that affect the major organs like kidneys)	12.5	21.7	13.3	13.5
Arthropathies (arthritis) and Related Disorders	34.1	23.3	26.9	18.0
Injury & Poisoning	81.9	71.9	70.2	107.2

CVD prevalence ranking. According to the NC BRFSS survey, almost one in ten North Carolina adults (9.0%) reported a history of cardiovascular disease (heart attack, coronary heart disease or stroke) in 2010. North Carolina's cardiovascular disease (CVD) prevalence rate ranks among the states with the highest CVD rates in the country and remains significantly higher than the national 2010 CVD rate of 7.9%. The North Carolina Behavioral Risk Factor Surveillance System (NC BRFSS) is a random telephone survey of state residents aged 18 and

older in households with telephones and is conducted monthly and analyzed annually, BRFSS was initially developed in the early 1980s by the Centers for Disease Control and Prevention (CDC) in collaboration with state health departments and is currently conducted in all 50 states (including D.C.) and most territories (CCDIHP, 2010). The NC BRFSS was used to determine the percentage of adults who reported being told by a health professional that they have angina or coronary heart disease (pre-2011 BRFSS methodology).

Cardiovascular disease (CVD) prevalence by gender revealed that males (9.6%) had slightly higher rates of CVD than females (8.3%) according to NC CCDIHP (2010). Reported rates of CVD did not differ significantly between non-Hispanic whites (9.5%) and non-Hispanic blacks (9.2%), and CVD rates increased with age as noted earlier. Education was inversely related to CVD prevalence in North Carolina. As education levels increased, reported prevalence of CVD decreased. NC CCDIHP reported that among other risk factors, 2010 CVD rates were significantly higher for North Carolina adults without health insurance (10.1%), for obese adults (10.6%), adults with asthma (16.4%), and adults with diabetes (26.9%). Risk factors may predispose individuals to chronic disease. Risk factors for chronic disease include unhealthily diet, physical inactivity and tobacco use. These factors are considered modifiable because individuals may control them by altering their behavior according to the CCDIHP (CCDIHP, p. 62).

Economic burden of CVD. In North Carolina adults are somewhat more likely to smoke, have sedentary lifestyles and be obese, compared with all US adults according the NC CCDIHP (CCDIHP, p.63). The estimated annual economic costs associated with preventable causes and unhealthy lifestyles were estimated at $57.4 billion (North Carolina State Center for Health Statistics [NCSCHS], 2010). NCSCHS reported that North Carolina's chronic disease burden was not distributed equally among its counties, making geography associated with disease burden an indicator for selected health determinants (e.g., socioeconomics, personal behaviors,

and environments). According to NCSCHS, counties with a larger percentage of the population living below the federal poverty level had a disproportionate burden of heart disease, whereas more affluent counties had a higher mortality burden of cancer. Metropolitan or urban counties such as Mecklenburg and Wake, were more affluent and had higher burdens of cancer, whereas counties with a lower socioeconomic status such as counties in the eastern and western part of the state, suffered disproportionately more years of life lost (YLLs) due to heart disease. The percentage of a population's YLLs caused by a specific condition is often used to measure the relative burden for a disease on a population (NCSCHS, 2010).

WHO (n.d.b) defines one DALY (Disability-adjusted life years) as one lost year of "healthy" life. The sum of DALYs across the population, or the burden of disease, measures the gap between current health status and good health – where good health means the entire population lives longer, free of disease and disability. DALYs for a disease or health condition are calculated as the sum of the Years of Life Lost (YLL) due to premature mortality in a population (WHO, n.d.b).

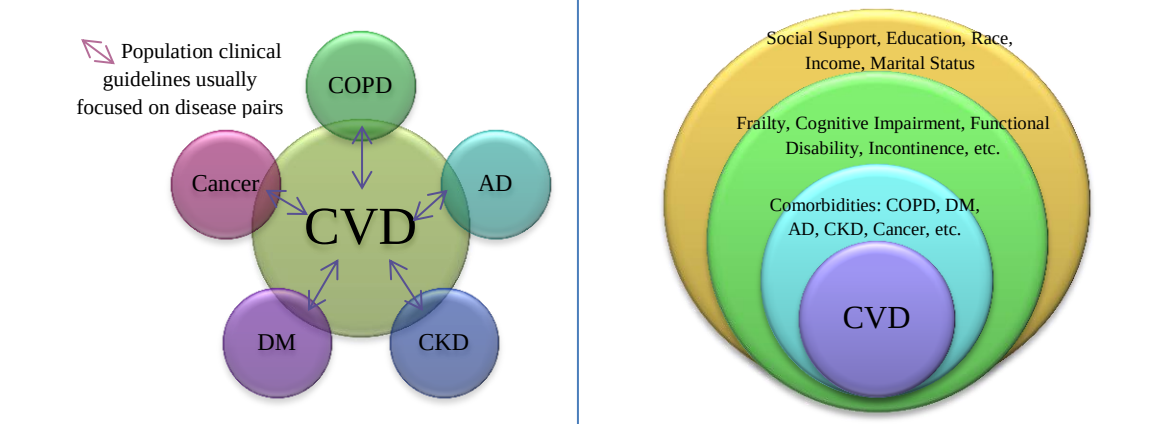
Conceptual Frameworks

Bell and Saraf conceptual framework. According to Bell and Saraf (2016), the increasing prevalence of co-existing disease processes in the aging population adds to the complexity and challenges facing patients with CVD and the providers that care for them. The authors maintain to properly diagnose and manage CVD in older adults requires the following:

- a thorough understanding of the intersection between patient differences (heterogeneity)
- the accumulation and interactions of chronic and acute conditions
- functional ability of individuals
- therapeutic use and reaction to medications (pharmacology), and
- socioeconomic factors

Bell and Saraf argue that the accumulation of chronic conditions because of genetics, lifestyle choices, environmental factors, treatment of prior conditions and aging itself accumulated in older adult populations, requiring management of multiple medical problems. The authors found that combinations of chronic diseases were different in men and women with men more likely to have the presence of cancer, CVD and cardiovascular risk factors (e.g. obesity and diabetes mellitus, cigarette smoking, dyslipidemia—high cholesterol, and hypertension) as compared to women who had a higher occurrence of arthritis and depression. In older adults with ischemic heart disease, heart failure, stroke and atrial fibrillation (irregular heart beat) the most common connected or related conditions were arthritis, anemia and diabetes. Other common chronic conditions included chronic kidney disease, cognitive impairment, chronic obstructive lung disease and depression, each of which must be considered when developing individual treatment strategies for the management of CVD.

The authors developed a multimorbidity conceptual framework (shown in Figure 9) that compares the traditional single disease focused conceptual framework (shown in panel A) with a more patient centered multimorbidity model (as shown in panel B). The conceptual framework demonstrates a more patient-centric approach to managing CVD and multiple chronic conditions, geriatric syndromes, functional status and social determinants of health (panel B) As factors accumulate, the CVD component diminishes – becoming the smallest component when managing patients with increasing complexity.



A. Common Comorbidities with CVD as Index Disease

B. Multimorbidity, Geriatic Syndromes and Social Factors Experienced vy the Individual Patient

Figure 9. Comorbid and Multimorbidity Conceptual Framework - traditional disease-centered approach to understanding disease processes. Adapted from Bell & Saraf, 2016.

AHRQ Multimorbidity Conceptual Model. The Agency for Healthcare Research and Quality (AHRQ, 2014) developed the conceptual model of complexity and healthcare for patients with multimorbidity (not shown). The 3 goals of the model are:

1. Define the concept of complexity in patients with multimorbidity
2. Describe patient, health system, and other contextual factors that influence complexity
3. Review implications of the model for patient care, research, and health policy

The AHRQ multimorbidity conceptual model is an ecological model that emphasizes the interconnectedness of component elements. At the center, "complexity" is defined as the gap between the major system components, for example, an individual's needs and the capacity of healthcare services to support those needs. Because this model focuses on health care, this relationship is the heart of the conceptual model. However, health and healthcare are always influenced by the broader context, for instance, social determinants of health and healthcare policies that create economic incentives or disincentives. As part of its ongoing effort to improve care for patients by multimorbidity through evidence-based research, AHRQ has funded 14 grants in 2014 for researchers to use existing large data sets for research concerning the multimorbidity population and to develop and test methods for improving research on this patient population (Agency for Healthcare Research and Quality [AHRQ], 2015)

Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy (2014) build on the AHRQ multimorbidity model and their version is shown in Figure 10. Contextual factors and their influence are represented with dashed line, boxes and arrows. The authors described the size of the need-services gap as related to patient needs, system capacity, and the interaction between them. On the person and social support side (left side of Figure 10), the number, severity, and duration of a person's chronic conditions affect the level of need, as well as other conditions. The authors argue that characteristics such as age, gender, socioeconomic status,

race, ethnicity, values, and preferences, impact the need even further. Often self-management is compromised for individuals with multimorbidity. Self-management is essential for optimal health outcomes and with inadequate social support, needs increase. The authors concluded that prevalence of multimorbidity is not distributed randomly but is instead concentrated in older individuals, families, and vulnerable communities (Grembowski et al., 2014).

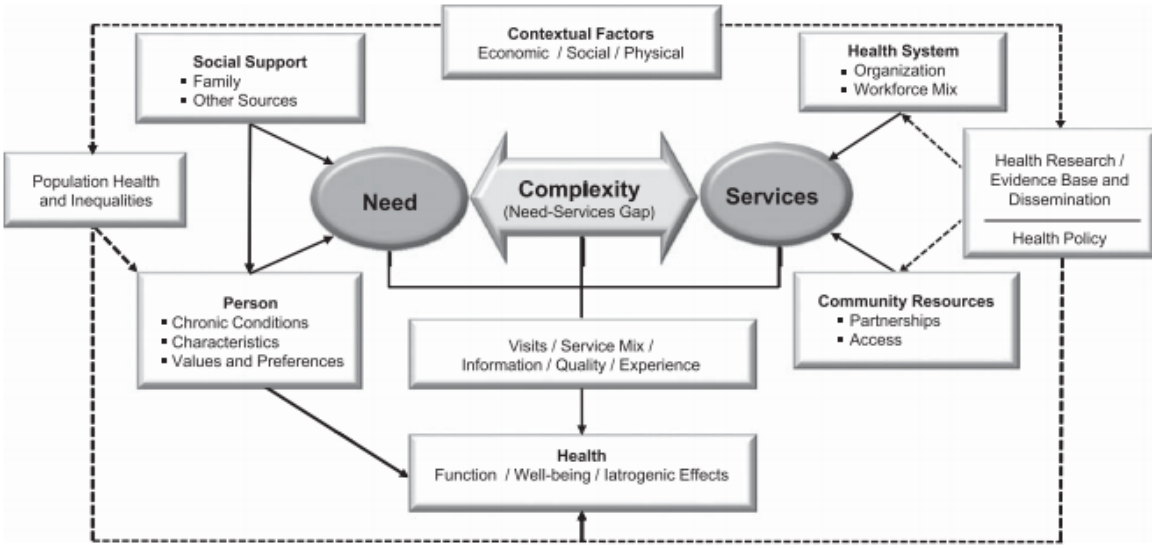


Figure 10. Grembowski, et al. conceptual model of the role of complexity in the care of patients with multiple chronic conditions. Source: Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy (2014).

In summary, the first stream of the literature review borrowed from several frameworks and models to add meaning and direction to research having to do with multimorbidity . First, the conceptual diagram of comorbidity and multimorbidity by Boyd and Fortin (2010) was introduced to distinguish between how comorbidity is often studied and treated in clinical practice as compared to multimorbidity. This distinction was necessary as part of the background in order to give a clear perspective and lay the foundation for HHS's strategic framework -- the multimorbidity framework. The multimorbidity framework placed each work in the context of its contribution to understanding the research problem. The goal expressed by the framework was to facilitate research and reveal any gaps that exist in the literature. Among gaps identified were approaches to enhance our understanding of multimorbidity patterns and its "constellations".

Concluding the first stream of the literature review was the Bell and Saraf conceptual framework and the AHRQ multimorbidity (further developed by Grembowski et al.) conceptual model. Bell and Saraf's framework expanded on the initial diagrams by Boyd and Fortin by focusing on disease pairs, such as CVD and diabetes mellitus, or CVD and chronic kidney disease, and illustrated the patient-centric approach to managing CVD in the context of multiple chronic conditions. The diagrams, frameworks and models all help summarize the various dimensions of this very complex problem.

The terms dyad and triads, introduced in the first stream, suggest that chronic condition combinations have some relationship, or describes some interaction. Research that identified multimorbidity dyads and triads represented progress in measuring multimorbidity. Just as Bell and Saraf and Grembowski et al., expanded on the models traditional disease centered approach, incorporating complexity and patient centeredness, what was proposed in this study were approaches that expand on our understanding of multimorbidity patterns. The next stream of this review reinterprets traditional "social network analysis" and uses this methodology as a technique to explore the structure and function of multimorbidity. The goal was to construct a

representative model, not unlike the diagrams, frameworks and models presented earlier; characterizing the patterns, relationships and interactions among multimorbidity and explore the geographic variation in North Carolina.

What follows are the basics of networks and a brief introduction to graphs, complexity and the network perspective. Background information including types of networks, network structure, measures and topology; network visualization as an exploratory tool, and a comparison of related terms are presented. Network perspectives and applications in health are discussed followed by an overview of the broad categories of networks. The significance of network data and centrality; distinctions between egocentric and global networks, and peculiarities of network theory and boundary specifications are all addressed. Closing the discussion on network analysis is network modeling methodology. The literature review concludes by locating this research within the context of health geography by way of the relational perspective and describing the application of exploratory spatial data analysis.

Points, Lines and Reasons for Graphs

Consider a graph with points and lines. The points correspond to multiple chronic conditions, and the lines correspond to the prevalence or frequency the chronic conditions occur in a patient population. Put simply, this is what my research proposes. But what will that give us? As Broder, Kumar, Maghoul, Raghavan, Rajagopalan, Stata, and Wiener, (2000) explain, various properties of graphs including its diameter, degree distributions, connected components, and macroscopic structure can be studied. Since the problem under study is a public health related issue, reasons borrowed from the field of epidemiology to explain the utility of graphs (Centers for Disease Control and Prevention [CDC], 2006) are appropriate. As noted by CDC, Network graphs are an effective visualization tool to:

1. Identify actual illnesses and health problems in the community
2. Determine where illnesses and problems occur (with some labeling)

3. Recognize groups that are at increased risk (with labeling)
4. Detect how problems evolve over time (if temporal data is collected)
5. Represent the size of the problem
6. Describe the patterns and how they relate to the distribution
7. Provide information to support effective action
8. Contribute to heath professionals' and providers' understanding
9. Portray the emergence of important new phenomena

As I review topics from this literature stream, discussion and examples will provide additional evidence and support for the reasons given.

Complexity and a Network Perspective

Jayasinghe, (2011) maintains that a complexity perspective takes a more holistic view of systems. For example, systems within systems are interconnected, and their interactions are non-linear and lead to self-organizing and emergent properties. In recent years, social epidemiologists -- who explore population health and health inequalities, have moved closer to this perspective. The author described how theoretical frameworks such as "epi+demos+cracy and the Eco social approach" (p. 2) to health have incorporated some of these concepts of dynamic interacting sub-systems. Jayasinghe explained that multiple levels of sub-systems or factors from sub-cellular levels; individual, community, social group, country and global levels interact with exposure, susceptibility and resistance and accumulates. With a complexity perspective, we can view population health outcomes as an emergent property of these dynamic interconnected systems of people with disease. An example of a construct that captures this phenomenon is health disparities and health impacts due to employment or work.

Multimorbidity creates a real challenge for research because of its complexity. The aging of the population and the stress involved in creating and adhering to multifaceted treatment programs, makes managing multimorbidity a complex problem for patients, their families as well

as for clinicians and systems that serve them (Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy, 2014). Guidelines and evidence-based disease management programs focus on single diseases. Therefore, research on multimorbidity requires a shift from a reductionist single-condition paradigm to one that accounts for the inherent complexity of multimorbidity (Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy, 2014).

Complexity is inherently difficult to define, measure, or predict which creates challenges for analysis and problem solving (Shippee, Shah, May, Mair & Montori, 2012). Emerging development of patient centered models of complexity help translate gaps in how we understand interactions between multiple occurring conditions, quality of life; as well as how to organize, provide and finance appropriate care, complex interventions, care management programs, and allocate limited resources to improve community based programs (Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy, 2014). Socioeconomic, cultural, behavioral, and environmental circumstances also contribute to complexities which have not received similar attention (Safford, Allison & Kiefe, 2007). Social and environmental factors continue to disrupt access, utilization, and self-care (Shippee, Shah, May, Mair & Montori, 2012). Directing programs to communities at highest risk for cost-intensive care offers the greatest opportunity to improve quality of care and reduce healthcare costs (Freund, Kunz, Ose, Szecsenyi, & Peters-Klimm, 2012).

System based approaches are likely to play an important role in uncovering the interactions underlying multiple chronic conditions. For example, biological networks occur on many different levels such as cells, organs, organisms, and social systems (Lusis & Weiss, 2010). A network perspective may reveal connected targetable nodes or conditions that can be an effective approach to develop combination therapies, interventions and programs (Lusis & Weiss, 2010). Network analysis tries to depict the entire burden of disease by collecting data on multiple occurring conditions within a defined population (Marsden, 1990). Such data permit calculation

of network structural statistics or properties that allow the researcher to discover additional insights into the mechanisms through which the connections and interactions of multiple chronic conditions occur and the socioeconomic, cultural, behavioral, and environmental circumstances in which they are embedded.

Introduction to Networks

Now that we have more or less an orientation, we now move away from the explanations used earlier (i.e. dots and lines) and refer to terms used more often to describe networks. A network is a set of elements, which we call vertices or nodes, with connections between them, called edges (Newman, 2003). Networks occur all around us, in nature and society. Typical examples include large communication systems (the Internet, the telephone network, the World Wide Web), transportation infrastructures (railroad and airline routes), biological systems (gene or protein interaction networks), connections between individuals, organizational networks and networks of business relations between companies, neural networks, metabolic networks, food webs, distribution networks such as blood vessels or postal delivery routes, networks of citations between papers, and the list goes on (Newman, 2003).

Newman positions the rise of graph theory and explains the geniuses of this body of knowledge. For starters, many newcomers generally come with the knowledge that networks have been studied primarily in the social sciences. In the 1930s, sociologists realized the importance of the patterns of connection between people to help them understand how human society functions. The typical network study in sociology involves questionnaires, where people are asked questions about their interactions with others. The responses are then documented in order to reconstruct a network in which nodes represent individuals and edges represent the interactions between them. Typical social network studies address issues of centrality (which individuals are best connected to others or have the most influence) and connectivity (whether and how individuals are connected to one another through the network) (Newman, 2003).

As Newman and others have documented, the field has changed dramatically over the last 20 years and there is a substantial new effort underway in network research. The focus has shifted away from the analysis of small graphs and the properties of a few individual vertices or edges to large-scale graphs with millions of nodes and edges. The availability of computers and communication networks has largely driven this new effort. As discussed earlier, the rapid growth and variety of data represent new issues and challenges with respect to data management and analysis. This is the new world of "Big Data". Are you on Facebook or Twitter? Computers allow us to gather and analyze data on a scale far greater than previously imagined. Where analysts looked at networks of maybe tens or a hundred cases, now analysts can consider networks with millions or even billions of nodes. The change in magnitude forces us to change our analytic approach. How did analysts do it before, by using our eyes. The networks were so small we could visually see the relationships. With a network of a million or a billion vertices, this approach is simply not possible. Researchers can no longer eyeball a network (like a table of numbers) and draw a meaningful picture of a million nodes. Direct analysis in that way is no longer possible. As a result, analytical and technological approaches were developed to address this issue. Statistical methods were developed to quantify large networks and permit researchers to perform network analysis in this new age of Big Data. Newman described how statistical methods answer what a huge network looks like. The body of theory that focuses on statistical properties, such as path lengths and degree distributions, characterize the structure and behavior of networked systems and suggest appropriate ways to measure these properties.

Types of Networks. The simplest form of a network is a set of nodes joined by edges. According to Newman, networks can be much more complex. For instance, there may be more than one different type of node in a network, or more than one different type of edge. And nodes or edges may have a variety of properties, numerical or otherwise, associated with them. For example, in a social network of people, the nodes may represent men or women, people of

different ethnicities, locations, ages, gender roles, or many other things. Edges may in fact represent any kind of relationship – familial or professional, emotion or geographical proximity for example. What is certainly intriguing is that the edges can carry weights, representing intensity or frequency. The categorization of networks has more to do with the nature of the interaction.

The term network is used in many applications and to avoid misinterpretation, the application of network analysis proposed is explained further. The reference to networks is different and distinct from Bayesian networks, using a multivariate methodology (see for example, Ramoni, Himes, Sale, Furie, & Ramoni, 2009) or physician hospital networks, which include empirically defined networks around a hospital or catchment area (see for example, Bynum, Fisher, Skinner & Chandra, 2010). Most network research is based on graph theory. In graph theory, a network in its most basic form is a set of nodes and edges (Zalesky, Fornito, & Bullmore, 2010). Researchers begin with a set of identifiable units such as individuals, places, published papers or diseases. Each unit is called a node. The relationships between the nodes are presented by edges. The network is represented by a graph, which is defined as a set of nodes (Butts, 2009).

Network structure, measures and topology. Since we can no longer just look at a network and estimate its size, statistics are used to approximate the network's size and other features. Statistics, referred to as measures or properties, are used to define the structure of networks. Measures of overall network structure include: the number of nodes and edges, graph density (size), network diameter, number of communities, number of components, average degree, clustering, path length for starters. Measurers define network structure. Measures such as degree and betweenness are concepts that explain a nodes location in the network, centrality, importance and influence. Network measures are actually computed using statistics.

In this study, degree and betweenness are the measures used to characterize multimorbidity. Degree is traditionally defined as the number of connections a node has. In this analysis degree refers to the number of connections a condition or diagnosis has to other diagnoses. Identifying which diagnoses are connected and which are central enhances our ability to characterize the interactions between and among conditions, complementing traditional analytical techniques and potentially discovering new insights. The actual pattern layout of the interactions between the nodes is referred to as topology. The analysis of patterns of relationships is conducted on the graph, which is merely a representation of the data.

Information from measures such as degree and betweenness define the network structure and function, and are suitable inputs for health promotion strategies designed to build healthy public policy, create supportive environments for health, strengthen community action for health, develop personal skills, and re-direct health services(WHO, n.b.c); altering the topology of multimorbidity network (i.e. feedback loop). In a complex system, a feedback loop is where change in a variable results in either increase (positive feedback) or a decrease (negative feedback) of that change (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, ... & Lai, 2012). By focusing resources on developing both community and individual capacity to address the unique needs of those with multimorbidity, intervention measures and programs can increase capacity resulting in improved self-management and connection of individuals, family and friends to available resources (positive feedback). Therefore, measuring network structure and studying degree has implications for targeting intervention measures and programs, improving efficiency and effectiveness.

Network visualization as an exploratory tool. Shneiderman (1996) pioneered the idea of trying to understand the variety and richness of information visualizations. The author described how humans have extraordinary perceptual abilities and our capacity to absorb information visually far exceeds that of other senses. Users can scan, recognize, and recall

images quickly; detect changes in size, color, shape, movement, or texture. In cases where relationships among items cannot be conveniently represented in tabular or graphic form, it is useful to have items linked to a number of other items (Shneiderman (1996). Network visualization is an old and at times imperfect technique because of the complexity of relationships, but it is a very useful exploratory tool. As an abstract of reality, networks have been used for decades to represent relationships, leading to useful discoveries (Wasserman, S., & Faust, 1994; Shneiderman, 1996; Scott, 2017; De Nooy, Mrvar, & Batagelj, 2011.). Figure11 shows a diagram of 40 AIDS patients in 10 cities linked by sexual contact. This representation was among the first evidence that AIDS was an infectious disease and was transmitted through sexual contact (Auerbach, Darrow, Jaffe, & Curran, 1984). In their diagram, Auerbach et al. describe the sexual contacts among homosexual men with AIDS. Each point represents an AIDS patient. Edges connecting the points represent sexual exposures and the city or state as the place of residence of a patient at the time of diagnosis. A "0" represents "patient zero", believed to be the primary case for AIDS in the United States. Networks are well suited to describing, exploring, and understanding structural and relational aspects of health (Luke & Harris, 2007).

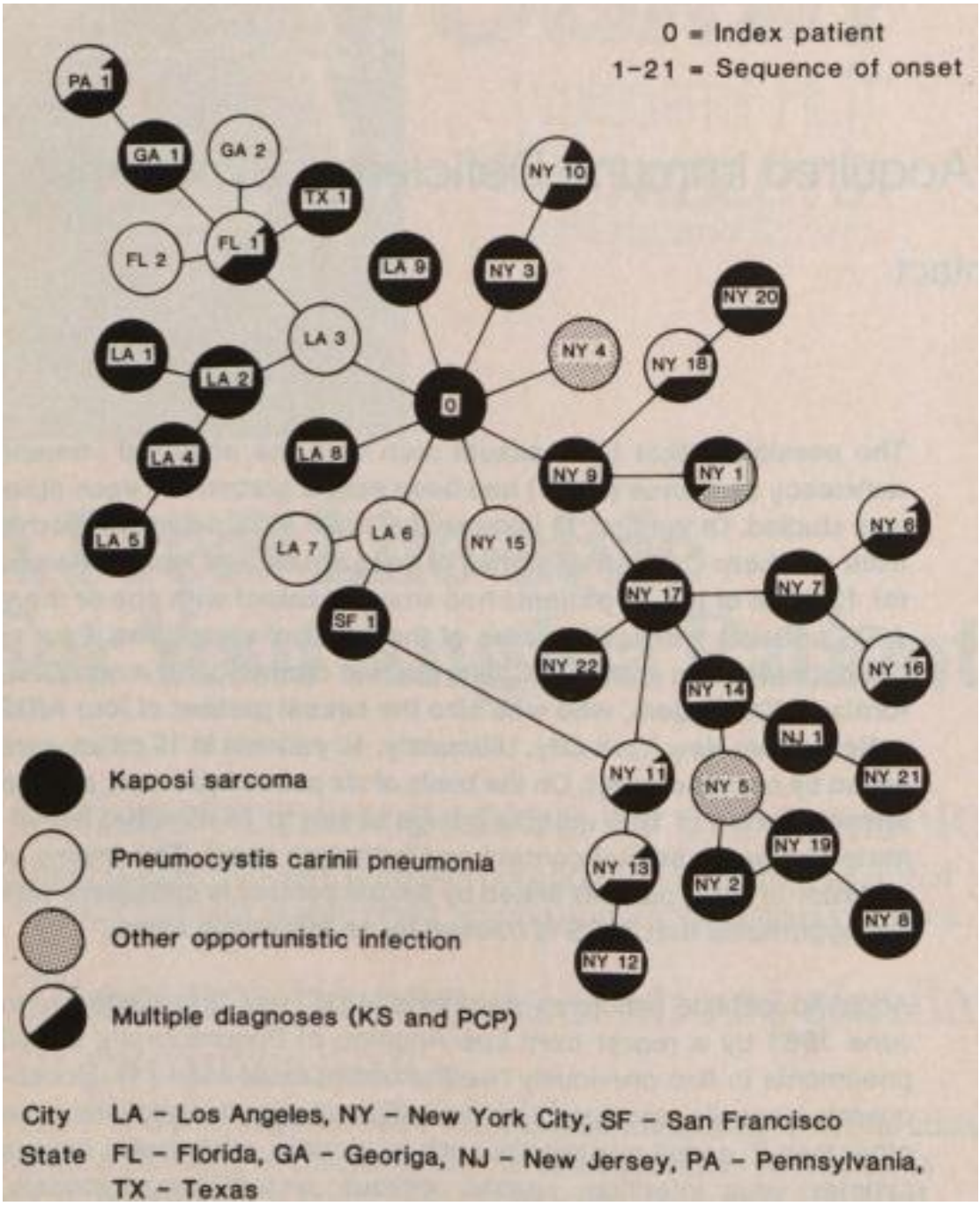


*Figure 11.*Diagram of 40 AIDS patients in 10 cities linked by sexual contact. Source: Auerbach, Darrow, Jaffe, Curran (1984).

Visualization of networks consists of presenting network information in a graphic format. The nodes represent individual elements. The node stores the actual data of that particular element and connects to another node. The example in Figure 12 shows this clearly with shading and numbers. Network software programs today, store this information as attributes. Figure 12 shows a tree structure (a particular type of network). This network is undirected (no arrows indicating direction of the edges). In contrast, a network with arrows pointing in a direction is called a directed graph (which this dissertation explores). A directed network is distinguished by in-degree, the number of incoming diagnoses (or secondary diagnoses) and out-degree, the number of outgoing diagnoses (or the primary diagnoses).

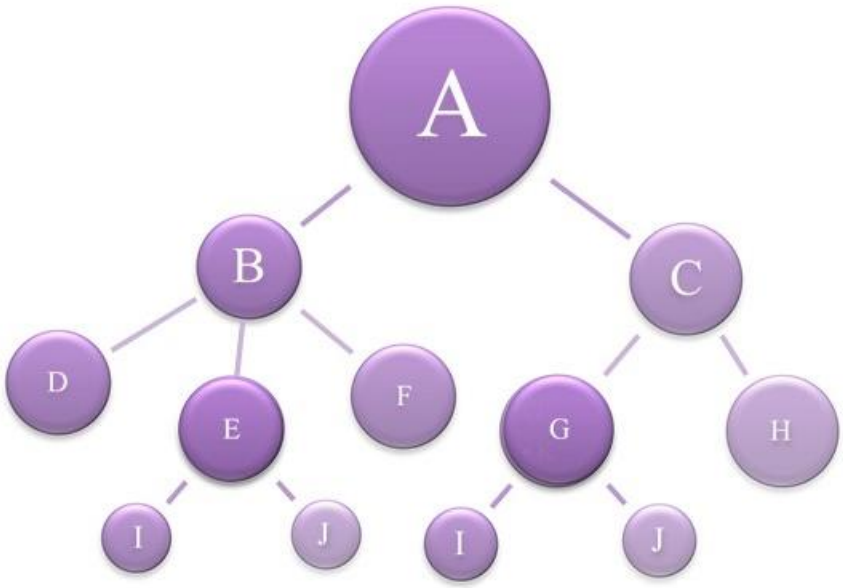


Figure 12. Network information in a graphic format. In this example, degree of B is 3, A has degree 2, and F has degree 0 (no nodes originating from it). Source: Farrow-Chestnut (2018).

Key Concepts and Word Comparison

In the review -- comorbidity, concomitant, dyads and triads, and node have been used to contrast or characterize multimorbidity and propose a new approach to measuring multimorbidity. Figure 13 features five (5) word clouds (a visualization technique) to summarize and compare the most important terms that define these concepts. The five clouds (differentiated by color) represent the concepts: node (upper left cloud), comorbidity (the middle smaller cloud), multimorbidity (the cloud below and between the node cloud and comorbidity cloud), dyads/triads (upper right could), concomitant and complication (lower right cloud). The words in each cloud are scaled to approximate their level of importance (based on the description of the concepts used in the literature review). The printed words are arranged without overlap and tightly packed into a pentagon shape. For example, the cloud on the far left prominently features the word ‘node’ and less prominent words such as ‘network degree’, ‘number’, and ‘graph centrality’ appear in the cloud. How these words are drawn in the clouds suggest that they are linked semantically. Integrating different literature domains can be overwhelming and Figure 13 is an attempt to highlight the more important features of these concepts for review and comparison.

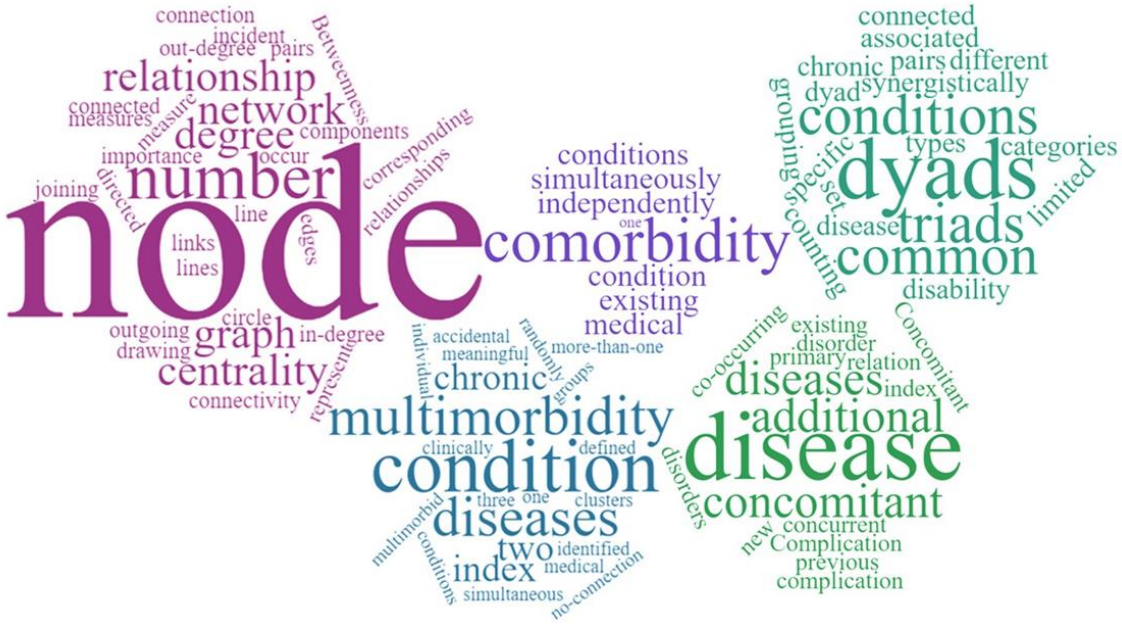


Figure 13. Key terms and network, comorbidity, multimorbidity, dyad/triad and concomitant Text Comparison. Source: Word Cloud generator Wordclouds.com by Zygomatic.

Network Perspective in Health

Central to the concept of population health and disease, is that the health of individuals and populations are expressed through a system in which biology interacts with the environments (Diez Roux, 2011). Complex systems theory is increasingly invoked in the health sciences literature such as: epidemiology, health social science, and health geography (Diez Roux, 2011). Diez Roux's (2007) argues that a systems model approach views social and biological factors as entangled, "modifying both functional and structural aspects of biology," and "are not only antecedents [precursors] of modifiers but actually become embodied in them" (Diez Roux, 2007, p. 567). Under the systems model the social-biological is interrelated and social experience alters both the structure and functioning of biological systems. The environment is critical to understanding the functioning of the system (Diez Roux, 2007).

A complex systems perspective emphasizes relationships (Gatrell, 2005), the number of parts that interact, the effect on the characteristics, and behavior of the whole system (Rickles, Hawe & Shiell, 2007). As well, a systems framework incorporates a relational understanding of how place influences health into empirical analysis (Gatrell, 2005, p. 2665). The proposed research incorporates a relational understanding of how multimorbidity in counties throughout North Carolina influences population morbidity and the burden of disease.

Network applications in health (and biology). Scientific study of social networks has had a long history and the last decade has seen tremendous growth in its application in public health. Every health topic can be viewed through the network perspective according to Valente (2010). Some of the major areas of network study include:

- HIV/STDs via sexual contact networks (Wohlfeiler & Potterat, 2005; Fujimoto, K., Kim, Ross, & Williams, 2016)
- Substance abuse including injection drug use (Johnson, Gerstein, Cerbone, & Brown, 2002; Valente, Gallaher, & Mouttapa, 2004; Strathdee, Hallett, Bobrova, Rhodes, Booth, Abdool, & Hankins, 2010)
- Smoking (Ennett & Bauman, 1993; Christakis & Fowler, 2008; Cobb, Graham, & Abrams, 2010)
- Suicide (Pescosolido & Georgianna, 1989; Bearman & Moody, 2004; Mueller & Abrutyn, 2015)
- Romantic relationships (Connolly, Furman, & Konarski, 2000; Utz & Beukeboom, 2011; Backstrom & Kleinberg, 2014)
- Physician Behavior (Christakis and Fowler, 2011; Barnett, Landon, O'malley, Keating, & Christakis, 2011)
- Contraceptive use (Valente, Watkins, Jato, Van Der Straten, & Tsitsol, 1997; Behrman, Kohler, & Watkins, 2002; Perkins, Subramanian, & Christakis, 2015)

- Obesity (Cohen-Cole & Fletcher, 2008)

Network analysis is an approach to research that is uniquely suited to describing, exploring, and understanding structural and relational aspects of health. In their article, Luke and Harris (2007) review the history of network analysis, drawing on traditions in many different research disciplines from the study of disease transmission (HIV/AIDS) (Auerbach, Darrow, Jaffe, & Curran, 1984); sexually transmitted diseases (Christley, Pinchbeck, Bowers, Clancy, French, Bennett, & Turner, 2005); social contagions (obesity) (Christakis & Fowler, 2007); social support and social capital (Szreter & Woolcock, 2004); and social ties and mental health (Kawachi & Berkman, 2001). Although it is not a new analytical tool, it provides the health sciences with a way of framing and answering important health questions, is a structural approach that focuses on patterns of connections, is grounded in empirical data, and uses computational models (Luke & Harris, 2007).

The next section offers an overview of the broad categories of networks. The categorization of networks has more to do with the nature of the interaction, whether they are flows or influenced based. Figure 14 shows the broad categories and examples of each. Luke and Harris (2007) suggested that the use of network analysis in public health falls into four groups: (1) transmission networks, (2) social networks (relabeled "contact" for the purposes of this analysis), (3) organizational networks (not reviewed here), and (4) symptom and molecular networks. The discovery of the human genome and work in behavioral health has created an exciting new category– system and molecular networks (shown in Figure 14).

Transmission networks. A common use of network analysis in public health is transmission networks. According to the authors, transmission networks are social systems that structure the flow of some tangible element (i.e. where the flows between actors in a network are

emphasized). Naturally, the focus in public health has been on two major types of transmission networks: disease transmission networks and information transmission networks.

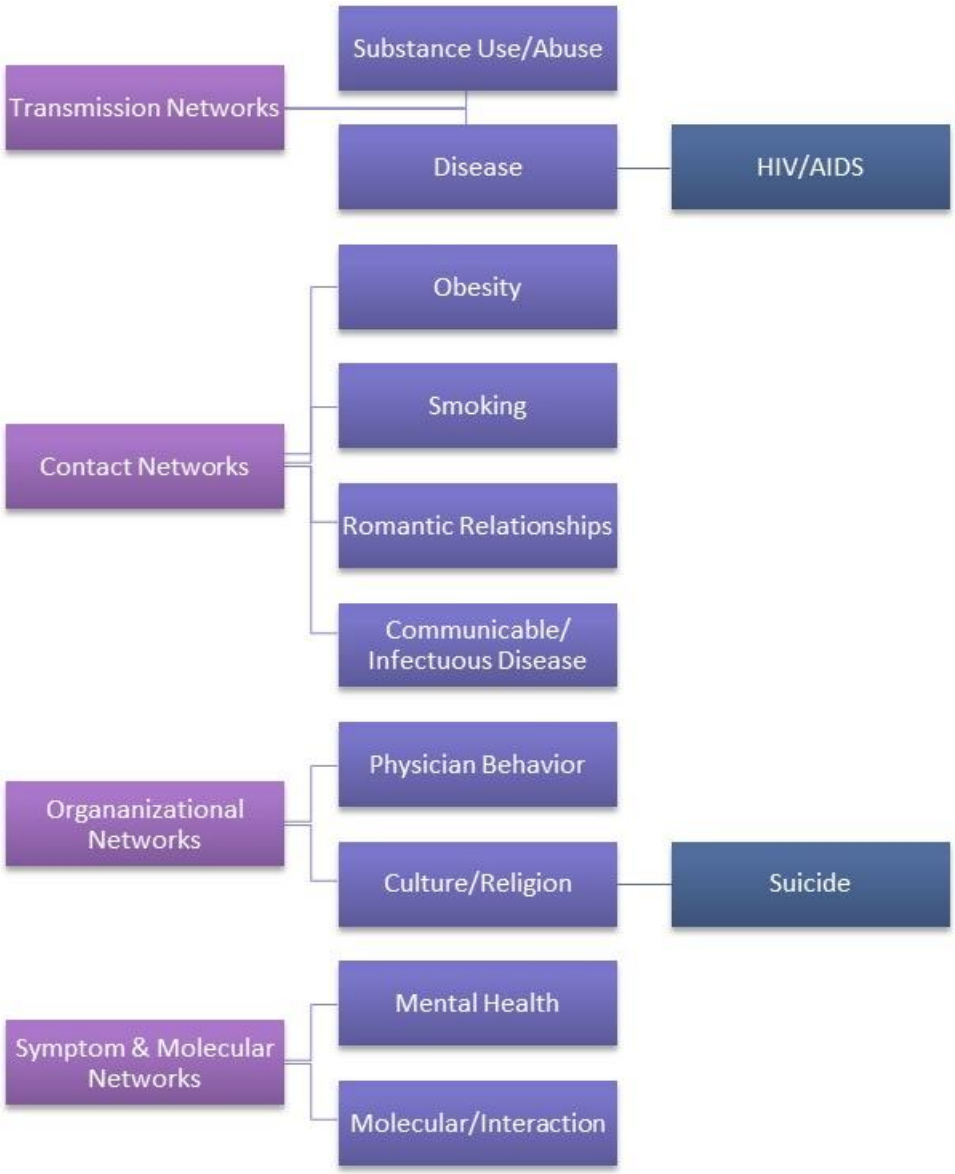


Figure 14. Network analysis applications in public health (adapted from Luke and Harris, 2007).

Contact networks (formally social networks). There is a large body of literature on how social networks and population structures may affect the spread of communicable diseases and influence the design of optimal control strategies (Cauchemez, Simon, Achuyt Bhattarai, Tiffany, Marchbanks, Ryan, … Swerdlow, 2011). Such work often makes use of detailed data on populations (e.g., demographics in households, schools, and workplaces; mobility and land-use data; contact surveys; or time-use data) which is time consuming and requires considerable financial support. While researchers have applied major insights extensively to their effects on infectious disease epidemics (Salathé, Kazandjieva, Lee, Levis, Feldman, & Jones, 2010), systems biology (Lusis & Weiss, 2010), comorbidities of an infection (Moni & Lio, 2014) and chronic conditions (Teljeur, Smith, Paul, Kelly & Dowd, 2013), to my knowledge studies have not examined the degree of multimorbidity and the spatial variation of interactions.

Symptom and molecular networks. Previous work using a network approach includes studies about mental disorders (Cramer, Waldorp, van der Maas, & Borsboom, 2010) and molecular interaction networks (Lee, Park, Kay, Christakis, Oltvai, & Barabási, 2008). Molecular interaction network studies focus primarily on a single disease in examining the interrelationships between genes and proteins. The proposed research takes a conceptually different approach to analyzing multimorbidity patterns at the population level by exploring both a global view of multimorbidity and an egocentric view --where a single node is the focal node of the study). The egocentric view explores the index condition, coronary heart disease and its interactions.

Studies by researchers that have published in –the between space of symptom and molecular networks, are summarized in Table 5. This space is referred to as “symbolic”. While no study to date applies the novel approach proposed here, the survey identifies areas of prior scholarship, points the way for additional research, and provides clarity on where this work fits within the existing literature. Shown in Table 5 are primarily comorbidity studies. While not

featured in Table 5, Goh, Cusick, Valle, Childs, Vidal, and Barabási (2007), Lee, Park, Kay, Christakis, Oltvai, Barabasi (2008) and Hidalgo, Blumm, Barabási, and Christakis, (2009) are pioneers of the application of networks analysis in molecular gene studies. This work formed the foundation for later work by researchers applying network analysis to characterize comorbidity. Characteristics of studies in this research space (between space of symptom and molecular networks) are:

- **Data-** inpatient records, claims containing diagnosis codes (ICD-9 & 10), PHDN, GDN database
- **Study designs -** cross sectional or retrospective
- **Network model/theory** – network diffusion or unstated
- **Methods and analysis** –prevalence, association, relative risk, correlation, PHDN, GDN, linear regression, t-test
- **Key findings** – multimorbidity clusters – CVD and metabolic disorders, kidney disorder, breast cancer, osteoporosis and heart disease associated with SARS; degree increases from childhood to adulthood, female/male network structure evolve over time, three distinct phases across lifetime; most common chronic condition pairs with type 2 diabetes
- **Structure/topology** – scale free, degree distribution follows power law, heterogeneous structure – some disease highly connected, others unconnected
- **Network visualization** – nodes are the diseases and edge represents the relationship between two nodes when comorbid; statistically significant edges represent relative risk

A review of selected studies in this research space follows. Chmiel, Klimek and Thurner (2014) proposed a specific phenomenological comorbidity network of human disease spread (an interaction network) based on medical claims data. The network was constructed from a two-layer network, where in one layer the links represent the conditional probability for comorbidity, and the other the links contain the respective statistical significance. Moni and Liò (2014) built a comorbidity relationship network to identify significant genes. Rijken, van Kerkhof, Dekker and Schellevis (2005) assessed the separate and joint effects of co-occurring chronic diseases on both physical and mental functioning. Teljeur, Smith, Paul, Kelly and O'Dowd (2013) used a study cohort to construct individual chronic diseases and chronic disease pairs, ranking them by frequency of occurrence to examine the nature of multimorbidity. A network diagram was used to illustrate the most common disease pairs.

While these studies demonstrate how this research space has evolved, the general omission of theoretical models or frameworks, and a reviews of literature in adjacent fields (that motivated the adaptation of network science) was glaring. While researchers have applied major insights to comorbidity and chronic conditions, to our knowledge studies have not examined multimorbidity network characteristics and geographic variability using patient discharge data. Although phenotypical and comorbidity studies measure the ties between the diseases themselves they do not focus on the environmental influences or characteristics of the communities in which patients are embedded.

Table 5. *Overview of Diagnosis Network Literature*

Author	**Data**	**Study design**	**Analysis**	**Type of Network**	**Sample of basic network position and structural properties**	**Network visualization**
Folino, Pizzuti & Ventura, 2010	Italian medical records of 1462 patients Disease codes defined by ICD-9-CM	Retrospective study, panel 13 years 1990 to 2009	Association analysis performed to discover hidden relationships.	Built a network by selecting only the statistically significant edges having RR > 20, and another network by discarding all the edges having $\varphi \leq 0.06$	Degree distribution disease network indicates network is a scale-free network, i.e. the degree distribution follows a power-law	Nodes are the diseases and a link between two nodes occurs when a comorbidity relation appears. The edges were labelled with the number of patients showing both the illnesses.
Schäfer, Kaduszkiewicz, Wagner, Schön, Scherer, & van den Bussche, 2014	German adults aged 65 years older. Morbidity based on 46 diagnosis groups of chronic diseases from ICD-10 codes	Cross sectional study using claims data set from 2006.	Information from (1) triads and multimorbidity clusters from factor analysis. Disease position computed by multidimensional scaling procedure.	Diseases grouped into multimorbidity clusters i.e., "cardiovascular and metabolic disorders"	Cardiovascular and metabolic - hypertension: degree centrality females 13 (6.5%); males 9 (5.2%)	Edge list used to visualize disease networks. Two diseases linked by edge are diagnosed together.
Chmiel, Klimek & Turner, 2014	Cross sectional study using complete medical claims data in years 2006 & 2007	Compute prevalence of all diseases within age group	Phenotypic human disease network analysis (PHDN). Network diffusion model based on age and gender specific comorbidity relations recorded in PHDN	The number of nodes N with at least one link increases in both network layers from childhood into adulthood and levels off at higher ages. Average degrees $\langle k \rangle$ increase over age.	Disease networks O across lifetime presented for males and females. Structural reorganization in the disease networks clearly visible across age. Nodes represent diseases & proportional to disease prevalence.	Three distinct phases of diseases networks across lifetime.

Author	Data	Study design	Analysis	Type of Network	Sample of basic network position and structural properties	Network visualization
Teljeur, Smith, Paul,, Kell, & O'Dowd, 2013	cohort of patients with type 2 diabetes attending general practice in Ireland. Medical conditions were recorded by practice nurses; chronic conditions reported in medical records and patients were asked to report chronic conditions. Conditions reported were coded using primary care specific ICPC-2 for coding illnesses.	A cohort of 424 patients with type 2 diabetes enrolled in a cluster randomized controlled trial based in Irish general practice was examined. Patients ' chronic conditions were determined from list of unique conditions generated by combining practice recorded and self-reported chronic conditions. Acute conditions and those that were considered complications of another chronic condition were excluded	Individual chronic diseases and chronic disease pairs were ranked by frequency of occurrence to examine the nature of multimorbidity. From the linear regression model, three patient level characteristics were statistically significant predictors of HbA1c: patient age (P 0.02).	Circles are proportional to number of patients with condition, width of connecting nodes proportional to number of patients with disease pairing. For example, 53 patients had arthritis and hypertension.	A network diagram was used to illustrate the most common disease pairs, otherwise not structural properties given	Network diagram of most common chronic condition pairs in a cohort with type 2 diabetes. Only pairings observed in 10 or more patients were shown.
Moni & Lio, 2014	Retrospective study of elderly patients 1990 to 1993	Compared the gene expression profiles of SARS, HIV and other diseases. Used the reactome knowledge base of human biological pathways database for pathways association analysis, employed a linear regression approach to obtain a combined t-test statistic between two conditions.	Bipartite graph consists of two disjoint sets of nodes, where one set corresponds to all known genetic disorders and the other set corresponds to all of our identified significant genes for SARS and HIV-1 infections.	Ccorrelation strength and distance between pair of diseases and infections presented. Showed some diseases (such as kidney disorders, breast cancer, osteoporosis and heart failure) more associated with SARS infection.	In the GDN, nodes represent disease class or genes, and two disorders are connected to each other if they share at least one gene in which mutations are associated with both diseases groups.	Phenotype disease network (PDN) has a heterogeneous structure where some diseases are highly connected while others are hardly connected at all. Showed that disease progression can be represented and studied using network methods

"Symptom Space" and "Disease Space" as Descriptive Metaphors

Cramer, Waldorp, van der Maas and Borsboom's (2010) study is not included in Table 5 because their work uses as its framework the latent variable model and symptom networks (neither of which is germane to this study). However, it is informative in terms of the authors' perspectives, the thread that links their work to the multimorbidity framework; and how they and others use "symptom space" and "disease space" as descriptive metaphors. The commentary concerning contradictions and weaknesses of the latent variable model are particularly instructive.

Cramer, Waldorp, van der Maas and Borsboom's (2010) focused on the property of network centrality, in which the nodes are symptoms. In their study, the authors argued that a latent variable (hidden, unobserved) perspective encounters serious problems in the study of comorbidity and offer a radically different conceptualization in terms of a network approach. Earlier in the first stream of the literature review, the goal expressed by the multimorbidity framework was to understand the epidemiology of multimorbidity and gather more information about the "constellations of conditions that are most prevalent and most important" (HHS, 2010, P. 14). Cramer et al. used the same phrase in their description of the problem that motivated their study, that the problem of comorbidity research lies in the "…latent variable theory, in which a mental disorder is viewed as a latent variable that causes a constellation of symptoms" (p. 137). At last, an explanation for the use of the phrase --"constellations of conditions." While the authors were concerned with problems associated with multiple mental disorders, the inclusion of this phrase in the multimorbidity framework does highlight how important it is to address the mental health aspects of this crisis.

Cramer et al. hypothesized that comorbidity occurs from direct relations between symptoms of multiple disorders. The authors proposed a method to visualize comorbidity networks, based on an empirical network for major depression and generalized anxiety. Their claim was that this approach generates realistic hypotheses about pathways to comorbidity,

overlapping symptoms, and diagnostic boundaries. Besides discovering the source of the intriguing phrase used in the multimorbidity framework, Cramer et al.'s alternative conceptualization of the relation between symptoms and disorders offered a natural way of explaining comorbidity. The authors asserted that disorders are networks that consist of symptoms that are connected through a dense set of strong causal relations and claimed this network approach represented a radically different conceptualization of comorbidity, in terms of direct relations between the symptoms of multiple disorders. The authors described their network model as representing symptoms as nodes in a graph and the relationships between them as edges (similar to what is proposed here). There were also symptoms that did not clearly belong to one or the other disorder, because they were overlapping symptoms or "bridge symptoms". The authors hypothesized that "bridge" symptoms play a crucial role in explaining co-occurring disorder. The authors argued that bridge symptoms can be tested within a network framework, and they claimed that "non-symptom causal processes" (p. 140) partly explain relations between symptoms. Such processes may involve pathways that contain some of the other symptoms in the network; for instance, a lack of sleep may lead to a loss of concentration via fatigue (p. 140).

Bridge symptoms. While Cramer et al.'s work flowed from the field of psychology and was itself a critique of the latent variable model (a statistical model that contains latent or unobserved variables), their discussion of "bridge" symptoms is useful when explaining co-occurring disorders and may have application to our understanding multimorbidity. In addition, Cramer et al. argued that some pathways to comorbidity through the "symptom space" are more likely than others; those pathways generally have the same direction (i.e. from symptoms of one disorder to symptoms of the other). Overlapping conditions may in part suggest that co-occurring conditions play an important role in multimorbidity and boundaries between diagnostic categories are necessarily "fuzzy" (p.145). The metaphor -- "system space", is intriguing and was considered further.

Symptom Space. A brief search of the phrase symptom space produced the paper by Croft and Machol (1974). In their work, the authors presented mathematical models for diagnosing diseases. The authors explained that information gathered could be used to create symptom patterns to build models. For future research, they proposed personalized diagnostic models, perhaps a precursor to personalized medicine. A subsequent literature search discovered the paper by Torres, Oliveira, Tate, Rath, Cumnock, and Schneider (2016). The authors used the phrase in their work regarding disease tolerance; measuring the pathogenesis of infectious diseases in populations. Torres et al. imagined a multidimensional space or plot using quantitative measurements of disease symptoms as axes. This space followed the path of patients as they grew sick and then recovered. All three references produced ideas for how this metaphor can be applied in current and subsequent multimorbidity studies using networks analysis.

Disease space, multimorbidity space. After surveying the use of symptom space in the literature, I recalled that my mentor and an advisor suggested early on using either phrase: "disease space" or "diagnoses space" as metaphors for this work, and encouraged the use of metaphors as an effective means of presenting abstract concepts. Since this work sits in the in between space, "disease space" or multimorbidity space" seem appropriate. These phrases change what is familiar to something interesting and different, and easily captures the essence of the research, without extraneous or irrelevant details. A more definitive rational will be developed for future publications.

Returning to the assertions by Cramer et al., the authors argued that pathways generally have the same direction. Based on research findings discussed earlier and genetic work occurring in molecular biology, disorders in the symptom space may share pathogenesis, the development of disorders and the chain of events that lead to multimorbidity. In their commentary, Danks, Fancsali, Glymour, and Scheines (2010) challenged Cramer et al.'s view and argued that symptoms cannot also influence one another. How does this relate to this study? If the analysis

were to estimate associations, then Danks et al.'s reasoning would by extension suggest that additional conditions cannot influence one another in the case of other chronic conditions. Danks et al. also maintain that models can have both unobserved causes and direct influences on measured variables. For example, this is the case of confounding in observational studies. Although all symptoms have the same variance, or the same dependence on any unobserved variables according to Danks and his colleagues, each of these claims is violated in many latent variable models in the social sciences. This commentary is instructive and explains why theory is critical to explain the behavior observed and why analyst must not infer causality from the pattern layout of the interactions. Even simple associations cannot, according to Dank et al., be used reliably to estimate causal relations; they ignore the assumption of conditional independent relations, generate measurement errors, confounding, and they give no direction to causal relations when they exist. Conditional independence is the assumption that all outgoing edges are independent from the rest of the attributes (the other nodes), given the parent or index (e.g. see Figure 8, node A) (Friedman, Geiger, & Goldszmidt, 1997). Regardless, the conditional independence assumption is rarely true in most real-world applications (Danks, Fancsali, Glymour, and Scheines, 2010).

Analyzing Network Data – Centrality

The four most commonly used centrality properties of networks are degree (Freeman, 1979), closeness, betweenness, and Bonacich's (1972) measure of eigenvector centrality. Freeman's articles in the 1970s are generally regarded as the preferred design for network data (Marsden, 2002). Freeman (1979) described the centrality concept as referring to the locations of positions or points in networks, as it applies to the overall structure of a network. Measures based on degree, betweenness, and closeness were defined for sociocentric (global) network data that provided information on relationships about all nodes within a "bounded" network (Marsden, 2002). Freeman (1978) described a graph as consisting of a set of nodes and a set of edges

connecting pairs of points and "degree" as the number of other nodes that are connected (Freeman,1978, p.218). A "path" is defined as a sequence of one or more steps or edges, passing through intermediate nodes, ending eventually. When every node is reachable from any other node the graph is called "connected" (Freeman,1978, p. 218). These characteristics are typically studied by network scientists. This work focusses on the network measure -- *degree*.

Egocentric vs. global networks. Marsden (1990) described how before the advent of big data (data sets so large and complex that it becomes difficult to process using personal computers, database management tools or traditional data), network data were obtained via surveys and questionnaires, archives, observation, diaries, electronic traces, and experiments. Network studies which all or nearly all of the individuals in a community are surveyed are called sociometric studies (Marsden, 1990) or global networks. Global network studies were data intensive and as a result fewer studies involved global network analysis. Without global network data, the macrostructure of chronic illness and multiple occurring chronic conditions cannot be mapped and studied. However, much of those concerns were addressed with algorithms that process large amounts of data.

Valente (2010) explained that three different types (only two are relevant to this discussion) of studies can be conducted with network data. First, an egocentric study with data on an individual (person, place, thing or object) and second, a global study with one or a few networks analyzed entirely in a network program. According to Valente (2010), network data provide measures at both the individual and the network level (Valente, 2010). Individual measures indicate an individual's position in the network relative to others in the network, while network-level measures describe overall properties of the network. Various centrality measures can be computed both for individual nodes and the whole network.

The difference between egocentric network and global network analyses is relevant. Egocentric networks can be mapped by gathering information about a node alone, or starting with

the global network and "filtering". Global networks require that all medical conditions are directly observed, which requires both sets of observational units when modeling the network--individual conditions that are connected to other conditions, and the other conditions. This analysis explores both, a) the global disease diagnosis network to model area multimorbidity and b) an egocentric network representing a specific chronic condition – coronary heart disease.

Network theory v. theory of networks. Borgatti and Halgin (2011) were motivated to clarify the concept of social network and identify characteristic elements of social network theorizing. Although network as a methodology is presented in this analysis, the objective is not to perform a social network study where the patients are represented by nodes. This distinction is important because not all the mechanisms used in network theory as Borgatti and Halgin explained, are relevant to this study. However, where the mechanisms and processes do relate, I will point this out.

As Borgatti and Halgin explained, network theory encompasses two domains, network theory and the theory of networks. At first glance this appears to be a distinction without a difference but there are some interesting and applicable nuggets. The authors begin by explaining what Network theory refers to -- the mechanisms and processes that interact with network structures and produce an outcome. Network theory is more about the outcome or consequences of the interactions. For example, interactions result in perhaps one node being centrally located. On the contrary, the Theory of Networks is more concerned with the processes that determine why networks have the structures they do. For example, who or what in this study forms the edges and who or what becomes central in addition to the overall characteristics of the network (e.g., network structural characteristics). This study uses both perspectives. That is, the analysis focuses on demonstrating how the outcome or consequences of the interactions can provide insights into multimorbidity, and the frequency of occurrence of multiple occurring diseases; coronary heart disease and conditions that are central in the network. Another view is that a

network theory perspective considers all the edges formed between all the nodes. In this case, the diseases and diagnoses originate from the universe of patient records of all hospital admissions in North Carolina. In making this choice, edges of one specific diagnosis are not made a priori (earlier).

Borgotti and Halgin emphasized two points which are worth reiterating. The first point answers the question what exactly is a network? Touched on throughout the review, a network contains a set of nodes along with a set of edges that connect them. Now, the ties (to simplify the discussion) are of a specified type usually. The ties interconnect like neighborhood streets connecting places of residence to form a path. For example, one can walk taking short cuts, to take the shortest path to a destination. As Borgotti and Halgin explained, the patterns of ties in a network create a particular structure and the nodes or in this example, the residences occupy positions within this structure. So the wealth of this analysis consists of describing the network structures and node positions and relating these to the node and diagnosis.

The second point made by Borgotti and Halgin, the researcher chooses the set of nodes and the type of edge (alluded to in the discussion of Table 5). To use the example above, it is the builder or developer who is in the residential construction business and the nodes are the units or structures. In this analysis, the nodes are essentially chosen by the data and the edges are defined by how often they occur or their frequency, a unique pair of diagnoses appears in the universe of patient records. Both the nodes and the edges define the network. To appreciate this point, let's consider the boundary question.

Boundary specification and generalization. According to Borgotti and Halgin, a common problem researchers faced is the problem of identifying boundaries on the set of nodes that are included in the network. Marsden (1990) referred to this as boundary specification. Boundary specification relates to the general problem of defining the population which is used for generalizing the results. As in geography (for somewhat different reasons), the notion of

boundary are importance in network studies. Network analysis focus explicitly on the assumption of interdependency among the particular nodes or units studied. As Marsden (1990) points out, excluding relevant elements or an arbitrary description of boundaries, leads to misleading or contrived results. Borgatti and Halgin (2011) argued that specifying the network boundary becomes problematic because networks are often confused with "groups", who or what is in or out. Therefore, when studying groups of things, it is reasonable to be concerned with establishing the boundaries of the group. However, Borgatti & Halgin maintain that networks do not have "natural" boundaries and therefore do not have to be connected.

Luke and Harris (2007) offered a different view. They argued that network data collection is complete or bounded because it is based on identifying all network members a priori. The authors argued that when boundaries are clear, network identification is straightforward. Another view offered by Marsden (1990) is that the boundary specification problem concerns determining operationally which other nodes or units are regarded as part of a given (i.e. individual, place, or thing, etc.) network. While Butts (2009) argued that the purpose (of boundaries) is to serve as an approximation of the structure of a complex system.

Clarification of boundary specification is important because a disconnected network occurs when some nodes cannot reach others by any path, meaning that the network is divided into fragments known as components. Networks do not have to be connected. By allowing the network to be disconnected, researchers can trace how connections change over time. Borgatti and Halgin (2011) recommended that analyst ask what specific properties of the network, such as the level of fragmentation or path length, change over time, as opposed to what are the circumstances that produce a particular structure. Take the example of the builder with projects in a high growth area. Initially as the builder(s) construct units, shopping areas, etc., everything is disconnected and fragmented. Eventually, the community becomes connected into a single

component in which every residence, Food Lion and Walgreen can be reached from every other by at least one path.

This analysis focuses explicitly on the assumption of interdependency among the particular nodes or diagnosis. The assumption is that multimorbidity networks approximate the structure of a complex system and is defined operationally as containing pairs of diagnoses which form the networks. In addition, networks are allowed to be disconnected, not necessarily to trace the evolution over time (reserved for future analysis) but rather to discern differences between groups such as gender, race and ethnicity (to answer questions of disparity) or disease classes (as in the case of this study).

A closely related issue is what is counted as an edge. Borgatti and Halgin (2011) suggested the research question addresses that issue. No matter how the edge is defined, all pairs of nodes in the sample define the network, and each network has its own structure and implications for the nodes involved. For example in this analysis, a node representing a condition relating to cardiovascular disease may have different implications than a node representing say, pregnancy (causality is not inferred). In practice, network theorists tend to be interested in edges that are either states (persistent relationships) or events (transactional or transitory) (Borgatti & Halgin, 2011). Ultimately this translates to some type of flow between nodes. Flows refer to what actually passes between nodes as they interact, such as information, a pathogen or contagion. While this characterization is important in other network studies, the concept of flows does not characterize the nature of the interactions (as discussed in the section about network applications). The next section frames the question of what ties are considered, by redirecting the discussion back to how researchers measure the occurrence of chronic disease.

Patterns. As mentioned earlier in the section, Goodman, Posner, Huang, Parekh, & Koh (2013) identified a specific set of 20 common conditions to foster a more consistent and standardized approach to measuring the occurrence of chronic conditions in the United States.

Given this standardized approach, the authors acknowledge that the exclusion of such conditions influenced the findings by the number and types of conditions included in their study. Schäfer, von Leitner, Schön, Koller, Hansen, Kolonko, ... & van den Bussche, (2010) argued that many possibilities emerge when studying the distribution of diseases in multimorbidity. All diseases are to some extent statistically associated with each other therefore, there has to be a guide or standard set. Schäfer et al. (2010) maintained that having a standard has merit and proposed a new approach of disease clustering to identify complex interrelations between chronic conditions using German ambulatory data. The authors assumed that there were a limited number of multimorbidity patterns (i.e. clusters of diagnoses groups that were significantly associated with each other). Some diseases were associated with other diseases, while others were independent of other diseases. The authors found that all patterns increased with the age of patients and that three patterns emerged: 1) cardiovascular/metabolic disorders, 2) anxiety/depression disorders and pain, and 3) neuropsychiatric disorders. The researchers concluded that about 50% of all persons belonged to at least one of those patterns. Consistent with the literature, Schäfer et al (2010) acknowledged that gender differences are not always easy to explain and might account for the different pattern compositions i.e. rheumatoid arthritis belongs exclusively to the female pattern. They concluded that more research is needed concerning the impact of different patterns.

When performing network analysis, the researcher does not make assumptions, limiting the number of patterns. This is related to the boundary problem discussed earlier. The purpose (of boundaries) is to serve as an approximation of the structure of a complex system. A network theory perspective maintains that all edges among all conditions diagnosed for the entire universe of hospital admissions in North Carolina, put another way, edges of one specific diagnosis were not made based on theoretical deduction. Prados-Torres et al maintains, techniques can explore novel and potentially (clinically and statistically) relevant patterns or associations of diseases without stating a priori.

Network Modeling Methodology

Modeling is a useful tool for network analysis. Robins, Snijders, Wang, Handcock, & Pattison (2007) present a general methodology for modeling the structure of a complex network. The authors argue that to make the underlying basis of a model explicit, it is important to ground models conceptually. Not only is the reasoning explicit, but it helps to form hypotheses about the underlying processes generating network structure (Robins, Snijders, Wang, Handcock, & Pattison (2007). In this analysis, processes refer to potential interrelationships among disease, environment and social influences. Robbins et al.'s (2007) rationale for network modeling are summarized below.

1. Interactions and connections are complex, and stochastic (showing randomness) models permit researchers to capture both the regularities in the processes, generating network ties and recognize there is variability which is difficult to model with any detail.

2. Statistical models allow inferences about whether certain structures are commonly observed in the network than might be expected by chance. Hypotheses can be developed about the underlying processes that potentially produce specific properties.

3. Different underlying processes may make similar qualitative predictions about network structures and it is only through careful quantitative modeling that differences in predictions can be evaluated. However, Golbeck (2013) argued that there are 2 levels of analysis – graph and node. To know more about the underlying process, researchers must focus the study at the node level, which may require qualitative investigations.

4. An unsolved puzzle in network analysis is how localized social processes and structures combine and form global network patterns, and if localized processes are sufficient to explain global network properties. The authors argued that it is difficult to investigate such questions without a model (Robbins et al., 2007).

The observed network. Robbins et al. (2006) describe the observed network as the data that the researcher collected for the analysis. The observed network is regarded as one realization from a set of possible networks with similar characteristics (i.e. number of nodes), that represents the outcome of some stochastic process. Alternatively, the observed network represents a pattern of ties out of a large set of possible patterns. The stochastic process generating the observed network is unknown. The goal in formulating a model is to propose a plausible and theoretically based hypothesis for the process (Robbins et al., 2007).

For instance, Robbins et al. (2007) suggested that a research question may explore whether in the observed network there are significantly more, or less, structural characteristics than expected by chance. In the case of the proposed network, the observed network may show a strong tendency for certain diseases (represented by diagnoses codes) to co-occur showing a higher prevalence (frequency) of occurrence over and above the chance appearance of diseases that co-occur less frequently, than if the relationship occurred completely at random. Put another way, do diagnoses (codes) in the observed network tend to exhibit certain structural properties as measured by network properties (i.e. degree)? Here the structural characteristic (edges between diagnoses) is the outcome of a social process. For example, processes and interactions occurring among people and places over time (that are important for health). According to the authors, the structural characteristics in question help to shape the model form or topology. An assumption of processes generating the underlying multimorbidity structure and pattern leads to the hypothesis that a stochastic network model with two parameters, one that reflects the tendency for edges between diagnoses to occur at random and one that reflects an additional tendency for edges between diagnoses not to occur.

As an example, consider patient diseases diagnosed and recorded in hospital discharge records in a given county in North Carolina. The observed network is the network where the relations between primary and secondary diagnoses have been measured. There are many

possible networks that could have been observed for that particular county. The observed multimorbidity structure -- for the county in the context of all possible network structures for the county are examined. Some structures in the county may be likely and others less so.

The assumption is, as Robbins et al. (2007) argued, that the network is generated by a stochastic process in which relational edges exist in ways that may be shaped by the presence or absence of other ties (and other possible node-level attributes). In other words, the network is conceptualized as a self-organizing system of relational edges. There are local processes that generate dyadic relations, and these processes may depend on the surrounding social and physical environment. For example, in this study of multimorbidity networks, it is assumed that patients develop multiple co-occurring conditions, and at some point the edges between primary and secondary diagnoses is formed. In addition to the assumption of stochasticity, this description is implicitly temporal and dynamic.

Costa, Rodrigues, & Cristino (2008) argued that the success of complex networks can be attributed to their natural ability to represent virtually any discrete system. Networks are unlimited in their capability to represent connectivity in a diverse real way, integrating several aspects, including the inter-relationships between structure and events (Economides & White, 1994). A significant limitation of network methods is that they are basically descriptive. Network data is non-independent and traditional parametric models (containing probability distributions or assumptions of normality) require independence among observations (Luke & Harris, 2007).

Place Matters – A Relational Perspective

Researchers within geography, sociology and epidemiology are engaged with the idea that place is relevant when explaining health variation because it comprises both social relations and physical resources. Cummins, Curtis, Diez-Roux, and Macintyre (2007) proposed an alternative view, using a "relational" (Cummins et al., 2007, p. 1835) perspective to illustrate how place affects population health. Examples of empirical research investigating associations

between place and health that implicitly incorporate relational views were presented by the authors. Cummins et al. (2007) suggested three ways to incorporate relational understanding into empirical analyses. First, recognize there is both a reinforcing and reciprocal relationship between people and place. Cummins et al. (2007) suggest that places can be viewed as nodes in networks rather than as separate and distinct "bounded [containing boundaries] spatial units" (Cummins et al., 2007, p. 1827), containing multiple connections. Human practice and interaction form the connections which extend beyond the traditional notion of place. The relational view of space implies that individuals influence and are influenced by multiple places; areas and spaces are socially constructed; maintained by the activities of actors, who operate individually or as populations across a broad range of geographical scales (local to global). Cummins et al. (2007) suggest that these actors can be thought of as individuals, community organizations, firms and businesses, regional and national governments and institutions, peer-networks and families; regulatory structures or processes.

The authors propose that the second way to incorporate a relational understanding into empirical analyses is to recognize that context and place varies in time and space. Place is dynamic, occurs daily, and over the life-course. When we can chart an individual's personal geography through multiple places over time, we greatly improve measures to help us understand which environments are the most important for health. The third way suggested by Cummins et al. (2007), is to incorporate scale into the analysis. Understanding the appropriate level, where actors operate and the spatial scale where their impacts are expressed is important to deliver effective interventions.

There is increased interest in understanding spatially varying processes in health (Congdon, 2011; Holt & Lo, 2008; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005). Investigating associations between place and health that implicitly incorporate a relational perspective is widely used in health geography, but its application to the study of multimorbidity

is limited. Few studies have addressed the issue of the interactions of multimorbidity and the locations in which it is embedded. Rather than nodes representing places, in this study, nodes represent diagnoses from inpatient records where the place of residence on the record indicates the county or location of the networks. This dissertation uses a novel approach to characterizing multimorbidity by using network structure, measures such as degree and topology (the patterns of interactions).

The current work demonstrates how tools such as quantitative network analysis, spatial analysis and Geographic Information Systems (GIS) can be utilized to analyze structure and information about networks of multimorbidity. A GIS promotes investigations of spatial relationships (i.e. linking people to place), communicates spatial information using cartography and visualization along with spatial statistics and multivariate statistical analysis (Nykiforuk & Flaman, 2011). In this study GIS integrates and analyzes spatially referenced data, visually represents spatial patterns of network measures (e.g. degree) and the underlying macro-social determinants of health.

Exploratory spatial data analysis (ESDA)

There is a growing trend toward more spatially extensive research in health and social science. With this trend, there is increased interest in understanding spatially varying processes in health (Holt & Lo, 2008; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005). And so, the secondary goal of this analysis is to "explore" how multimorbidity varies at the sub-state or county level. As suggested, this study is exploratory in nature (or inductive). The first step to understanding the characteristics or attributes of counties and how they might influence the distribution of multimorbidity in North Carolina, is to convert the data and map it using GIS. This stage of data exploration is performed using exploratory spatial data analysis or ESDA. Anselin (1994) defined ESDA as a series of techniques designed to visualize spatial distributions, identify unusual locations (e.g. spatial outliers), discover patterns of spatial association (spatial clusters), and spatial non-stationarity (variation). According to Knigge and Cope (2006), ESDA and visualization using GIS and other visualization software (e.g. network software) are approaches used by researchers to analyze data, identify themes and processes, and raise new questions. Figure 15 shows the general process for performing ESDA and confirmatory spatial data analysis. Both are discussed in turn.

Spatial autocorrelation and spatial association. There are two important spatial concepts of ESDA and they are spatial autocorrelation and spatial association. Anselin (1994) described spatial autocorrelation as the phenomenon whereby a set of spatial features and their associated data values are clustered together in space. The spatial locations are discrete points or areal units (e.g. counties) and the spatial data represented are actual observations of a spatial stochastic process (phenomenon that varies spatially). For example, if estimated prevalence of multimorbidity by specific subpopulations varied geographically. Spatial autocorrelation is captured by Tobler's observation that "Everything is related to everything else, but near things

are more related than distant things" (Tobler, 1970). Griffith (1987) argued that positive spatial autocorrelation means that geographically nearby values of a variable tend to be similar on a map: high values tend to be located near high values, medium values near medium values, and low values near low values. The second concept involves local and global indicators of spatial association. Global indicators, such as Moran's I and Geary's c spatial autocorrelation statistics, summarize the overall pattern of dependence in the data into a single indicator. Given a set of features such as a county, and an associated attribute-- the prevalence of multimorbidity, the Moran's I statistic evaluates whether the pattern expressed is clustered, dispersed, or random. Local indicators of spatial association are commonly referred to as LISA statistics. According to Anselin (1995), LISA statistics serve two basic purposes. On one hand, they may be interpreted as indicators of local hot spots, representing local pockets of nonstationarity where the underlying process is not constant, similar to the Gi and G*i statistics (Getis & Ord, 1992). According to Anselin, LISA statistics also may be used to assess the influence of individual locations and to identify "outliers" (Anselin, 1995). For example, LISA statistics may indicate which specific counties represent hot spots or outliers where women have two or three or more conditions. Visualizing local patterns of spatial association in GIS increases our abilities to both understand underlying processes and implement effective intervention programs for specific populations as well as monitoring the impacts of those interventions.

Exploratory questions and questions that generate hypotheses. ESDA techniques have a wide range of applications and are appropriate for exploring point data as well as continuous spatial data. The techniques that are used in this analysis test for significant clustering among the locations of events (multimorbidity) and independence between different types of events (e.g. poverty, education, income) as well as spatial autocorrelation. Research questions that grow out of ESDA are exploratory by nature. One or two questions are designed to generate hypotheses that are typically reserved for future study but they are tested in this analysis (e.g.

multimorbidity by gender, race and ethnicity do not vary spatially). Therefore, the last section of the review contains two types of research questions, exploratory questions and questions that generate hypotheses. Hypotheses are given for the questions that generate hypotheses and are stated in the familiar fashion reflecting the parametric statistical methods that is appropriate. Methods that use parameters, for example the mean and standard deviation, are called parametric methods because we estimate the parameters of the distribution using the data. Parametric methods that are commonly used include t-tests, analysis of variance for comparing groups, and Ordinary Least Squares regression-OLS, commonly referred to as linear regression (simple or multiple depending on the number of explanatory variables), and correlation for studying the relationship between variables (Altman & Bland, 2009). All of these methods are applied in this study.

Spatial regression analysis. In the case of least squares regression analysis, Lopes, Brondino, and Silva (2007, July) described that the objective is to find a good fit between predicted and observed values of the dependent variable in the model, and identify which of the variables significantly influences the linear relationship. The standard hypothesis is that the observations are not correlated, the residuals in the model follow a normal distribution, have constant variance, are independent, and uncorrelated with the dependent variable. Lopes et al. argued it is very unlikely with spatial data that the standard hypothesis of uncorrelated observations is true. More commonly, the residuals exhibit spatial correlation and spatial regression is necessary. Spatial regression analysis allows the incorporation of the spatial effects.

Lopes et al. describe two basic types of modeling presented by Anselin (2002), the Spatial Auto Regressive (SAR) or Spatial Lag Model and the Conditional Auto Regressive (CAR) or Spatial Error Model. If spatial dependence is observed then spatial regression is necessary using the models described. The spatial data analysis panel in Figure 15 highlight the final stages of the process.

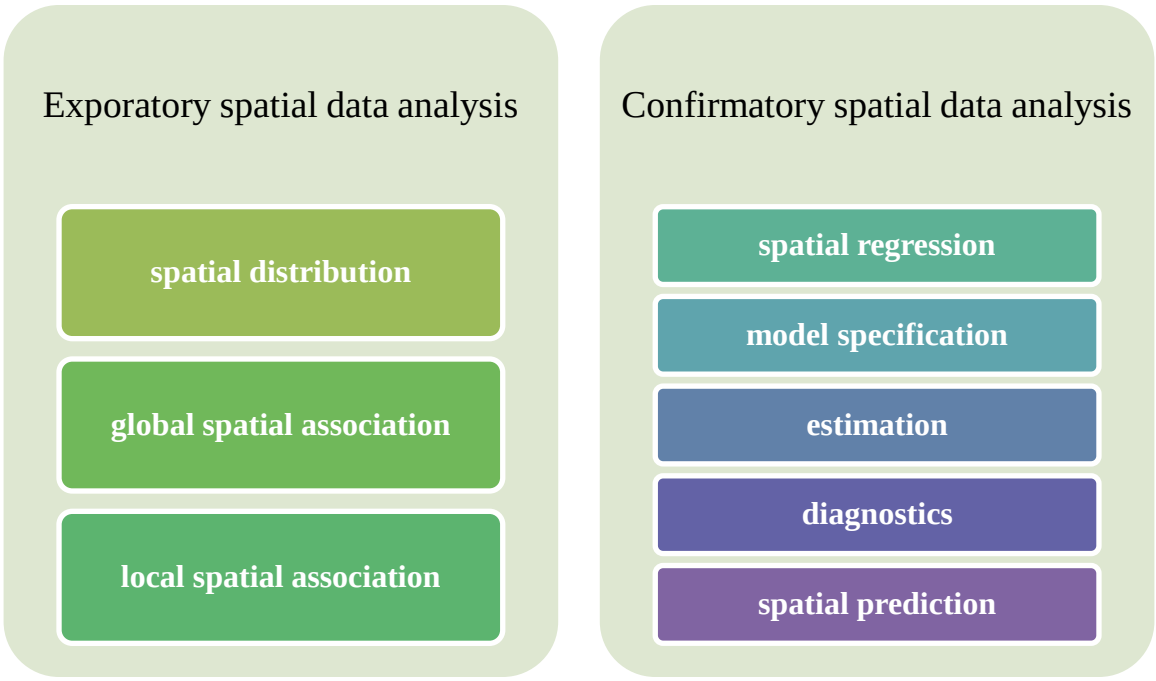


Figure 15. ESDA and Spatial Analysis. Adapted from Anselin (1999).

Conceptual framework

The conceptual framework in Figure 16 was adapted from Zulman, Asch, Martins, Kerr, Hoffman and Goldstein (2014). This framework depicts the influence of gender, race, ethnicity; social determinants of health (SDOH); population and county characteristics; quality of care, and the influence of the comorbidity number on the average weighted degree of multimorbidity.

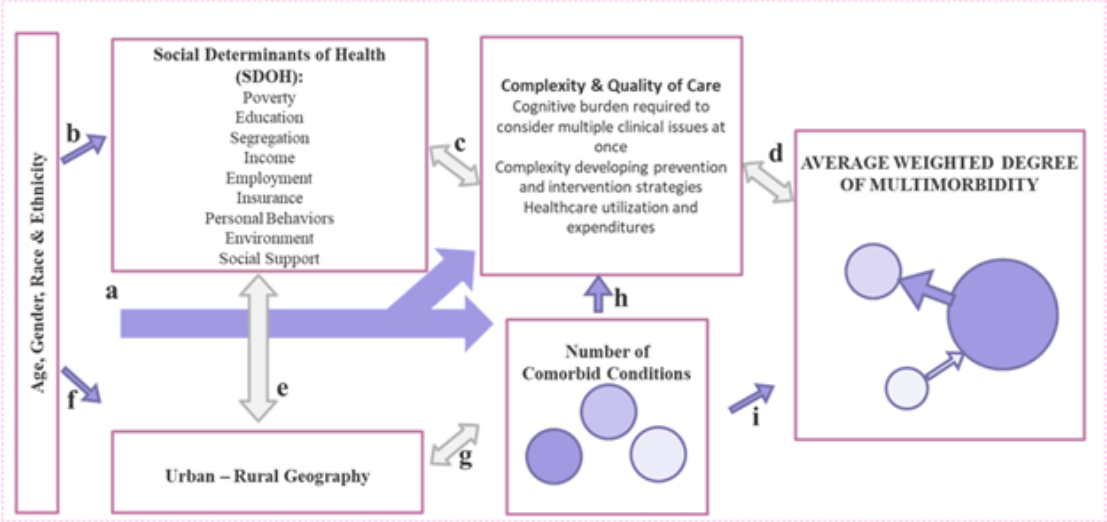


Figure 16. Multimorbidity Average Weighed Degree Conceptual Framework. Source: Farrow-Chestnut 2018.

In the proposed framework, the relationship between patient gender, race and ethnicity, SDOH, rural and urban geography, complexity and quality of care, and the patient's number of chronic conditions, increases multimorbidity average weighted degree. Disease combinations (and prevalence) differ by age and gender (a). Patient's age, gender, race and ethnicity interact with SDOH because members of minority communities tend to be more socioeconomically disadvantaged have lower levels of education, which increases the likelihood that the only jobs available have higher rates of occupational hazard; live in areas with greater environmental hazards than members of the majority population (b). In addition, difference in poverty, low SES, and lack of access to care, exists along gender, racial and ethnic lines (b, c). Residential concentration of African Americans is associated with inequities in communities, socioeconomic circumstances; and medical care (a, b, c, e, f). SDOH shapes complexity and quality of care because the amount of money, power, and resources that people have, influences access to health services and the quality of those services (c). SDOH interacts with the quality of care (c) and quality of care influences multimorbidity negatively and positively (d). There is a positive association of multimorbidity and use (costs) and use significantly increases with each additional

condition and the number of conditions adds a layer of complexity to developing prevention and intervention strategies (h).

Chronic disease burden is not distributed equally among rural and urban counties, making geography associated with disease burden an indicator for selected health determinants (e.g., socioeconomics, personal behaviors, and environments) (e) and the prevalence of chronic conditions (g). With an increase in number of conditions, there is an increased likelihood that one or more conditions occur more frequently (e.g., dyads and triads), which increases the complexity and generates quality of care challenges (h). These characteristics also increase the likelihood of conditions interacting with one another in ways that affect decisions, related to multimorbidity (i, d). Multiple, potentially interacting, including physical and mental conditions, determine multimorbidity patterns (i). Less is known about how frequently multiple conditions occur together; the impact of local area characteristics, such as limited availability or accessibility of health services, infrastructure deterioration, environmental stressors (Brown, Ang & Pebley, 2007), and how they may vary geographically (e, c, g, h).

Justification

The review raises important questions. What is the structure and function of multimorbidity networks? If social determinants of health, geographic location, socioeconomic status, and environmental factors affect health, what influence do area characteristics have on the distribution patterns of multimorbidity? What is the spatial distribution pattern of multimorbidity in North Carolina?

The primary goal of this dissertation is to explore the application of network analysis to multimorbidity. Multimorbidity greatly increases the complexity of managing disease, suffering, expense and quality of life of those burdened with multimorbidity and those that care for them. A better understanding of the interaction pattern of multimorbidity attributes and behavior may

result in new insights. After careful examination of the literature on this topic, no studies were found that employed quantitative network analysis and ESDA to explore how multimorbidity varies at the sub-state or county level. This novel approach evaluates the structure of multimorbidity globally (the universe of NC hospital inpatient data) and tests its application using cardiovascular/coronary heart disease. Gephi, an open source network visualization software, is used to explore the underlying structure and visualize multimorbidity networks. The secondary goal is to perform ESDA to visualize distributions and study geographic patterns of multimorbidity among North Carolina counties. Differences among gender and racial/ethnic groups, the influence of social determinants of health, geographic location, socioeconomic status, and environmental factors underlying network formation are examined.

Such work often makes use of detailed data on populations (e.g., demographics in households, schools, and workplaces; mobility and land-use data; contact surveys; or time-use data) which is time consuming and requires considerable financial support. Geographic Information Systems (GIS) such as GeoDa (open source software) and commercial packages including ArcGIS (Anselin, Syabri & Kho, 2006) are used to capture and communicate the relational aspects of multimorbidity and multimorbidity network spatial patterns.

Research Questions

The research is guided by exploratory and hypothesis related questions and is discussed below.

Exploratory Questions:

1. Can networks characterize multimorbidity? If so, what is the content and structure of multimorbidity networks?
2. What does an egocentric network study of cardiovascular/coronary heart disease reveal?

3. What do centrality measures such as betweenness reveal about the relative importance of conditions?
4. How does the network measure -average weighted degree of multimorbidity change or vary geographically?
5. How does average weighted degree of cardiovascular/coronary heart disease networks change or vary geographically?
6. How might the structure of multimorbidity or networks influence interventions and programs?
7. What directions might future research on multimorbidity networks and health in low income communities take?

Hypothesis Driven Questions:

8. Are there gender and racial/ethnic differences in cardiovascular/coronary heart disease networks?

   H0: No difference in gender and racial/ethnic networks

   HA: Difference is detected in gender and racial/ethnic networks

9. What is the relationship between the underlying factors and the average weighted degree of heart disease networks?

   H0: No relationship exists between underlying factors and the average weighted degree of heart disease networks.

   HA: Relationship exists between underlying factors and the average weighted degree of heart disease networks.

CHAPTER 3: METHODS

Data for the dissertation were drawn from four sources: (1) the 2010 North Carolina State Inpatient Database (SID), (2) the 2011/2012 Area Health Resource File (AHRF), (3) the CMS Chronic Condition Data Warehouse (CCW), and (4) the Population Studies Center at The University of Michigan. All provide annual estimates reported for U.S. Counties.

Sources of Data

Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost and Utilization Project [HCUP] (2013) is a comprehensive source of hospital inpatient data. HCUP provides, including information on in-patient stays, ambulatory surgery and services visits, and emergency department encounters. Among the most reliable and affordable databases for studying important health care topics are the State Inpatient Databases (SID) provided by HCUP. The SID are state specific files that contain inpatient care records and are used by researchers, insurers, policymakers and others to study health care delivery and patient outcomes over time, and at the national, regional, state, and community levels (Agency for Healthcare Research and Quality (AHRQ), 2014). The database contains information from inpatient records. Each record consists of the date of visit, and up to 25 diagnoses, all specified by ICD-9-CM codes of up to 5 digits. The SID include discharge-level data on inpatient stays from most, if not all, hospitals in a state. The SID include all types of inpatient stays, including transfers from another acute care hospital and stays that originated in the hospital's emergency department (ED). The SID are used to investigate questions unique to one state, or to compare data from two or more states. The first three digits specify the main disease category and the last two provide additional information about the disease. The entire ICD-9-CM classification consists of 657 different categories at the 3-digit level and 16,459 categories at 5 digits.

The 2010 SID. The 2010 North Carolina SID inpatient records were compiled from community hospitals to carry out the cross-sectional analysis of 1,129,367 million records from 123 community hospitals. Community hospitals are defined as nonfederal, short term, general and other specialty hospitals, academic medical centers and specialty hospitals, short term rehabilitation, orthopedic, and pediatric hospitals (AHRQ (2017). The data source for the networks are the SID. The 2010 NC SID contain diagnoses on all patients, and all persons are included regardless of payer, including persons covered by Medicare, Medicaid, private insurance, and the uninsured. Each data set record consists of clinical and non-clinical attributes for each visit. Nonclinical attributes include patient demographics (age at admission, race, and gender), admission date, HCUP hospital information, patient zip code (place of residence), length of stay in the hospital-- in days (LoS). Clinical attributes include diagnosis codes, diagnosis categories and procedure information. As noted by AHRQ (2017), demographic variables such as age and gender do have roles in assessing disparities, however limited.

Age and gender are well populated while race and ethnicity are more variable. North Carolina resumed providing the race and ethnicity variable beginning in 2010. Beginning fourth quarter 2010, the race and ethnicity data values changed. This presented a problem because many counties did not have values for patients identified as American Indian/Alaskan Native, Asian, and Native Hawaiian/Pacific Islander. Therefore, analyses could not be performed for those groups.

The patient address and zip code on file may not always match the actual residence of the patient. Where zip codes were missing, the observation was deleted. Although imperfect, other variables, such as insurance type or the patient's residence, can and were used as proxies for other demographic variables.

Area Health Resource File (AHRF). The AHRF is a health information database containing more than 6,000 variables for each of the nation's counties. AHRF contains

information on health facilities, health professionals; measures of resource scarcity, health status, economic activity, health training programs, socioeconomic and environmental characteristics (Health Resources & Services Administration [HRSA], n.d.). AHRF was the source for measures of health status, resource scarcity, and socioeconomic and environmental characteristics.

Centers for Disease Control and Prevention (CDC). County-level data for diabetes risks were convenient and easily obtainable from the CDC. The web publication of the U.S. Diabetes Surveillance System provides resources documenting the public health burden of diabetes and its complications in the United States. The County Data application allows visitors to the site to view data and trends of diagnosed diabetes, obesity, and leisure-time physical inactivity at the national, state, and county levels (CDC, 2016). Indicators were selected and downloaded for this dissertation.

The high prevalence of multimorbidity has risk factors such as tobacco use, poor nutrition, and physical inactivity. Diabetes mellitus also increases the risk for heart disease along with high blood pressures and high cholesterol. The risk of death from heart disease for adults with diabetes is two to four times higher than adults who do not have diabetes (Centers for Disease Control and Prevention [CDC], 2015).

County Level Multiple Chronic Conditions (Multimorbidity) Prevalence, Medicare Utilization and Spending. The data used in the chronic condition reports were based upon CMS administrative enrollment and claims data for Medicare beneficiaries enrolled in the fee-for-service program from 2007 to 2015. These data are available from the CMS Chronic Condition Data Warehouse (CCW). The 19 chronic conditions were identified through Medicare administrative claims. A Medicare beneficiary is considered to have a chronic condition if the CMS administrative data have a claim indicating that the beneficiary received a service or treatment for the specific condition. Beneficiaries may have more than one of the chronic conditions listed. To classify multimorbidity for each Medicare beneficiary, these conditions were

counted and grouped into four categories: 0 to1, 2 to 3, 4 to 5, and 6 or more. Data include Medicare spending by all fee-for-service beneficiaries younger than 65, and 65 and older by number of conditions in 2010 by state and county. Nearly all studies examining the relationship between costs and outcomes observed a positive association of multimorbidity and use (costs) and many found that use significantly increased with each additional condition (Lehnert, Heider, Leicht, Heinrich, Corrieri, Luppa, ... & König, 2011).

The Racial Residential Segregation Measurement Project. The fourth and final data source for this dissertation was racial residential segregation measures from the Population Studies Center at The University of Michigan (UofM). UofM received funding for this initiative from the National Science Foundation, the Population Studies Center and the Inter University Consortium for Political and Social Research at the University of Michigan. In the early 2000s, several centers, researchers and groups were examining racial residential segregation. Other sources for this data were evaluated, such as data available by Brown University. The results from University of Michigan were found comparable to the data available by Brown University (Brown University, 2010).

FIPS. The Federal Information Processing Series (FIPS) is a unique two-digit numeric code that is assigned alphabetically by geographic name for states, counties; core based statistical areas, places, county subdivisions, consolidated cities and other areas. FIPS codes allow researchers to join the SID files with other data sets from the Census, AHRF, CMS and other non-federal sources (U.S. Census Bureau [Census] (2011). For example, the FIPS codes for North Carolina are 37, and for Mecklenburg County the code is 119.

The next section describes how a quantitative network approach was implemented using the SID followed by an overview of the statistical and spatial analysis performed for the analysis.

Institutional Review Board Approval. This dissertation was approved by the University of North Carolina Charlotte Institutional Review Board. After approval and the completion of a data user agreement, NC SID were obtained from HCUP.

Study Design

A cross sectional study design was used to explore the relationship between multimorbidity and the influence of various health indicators and risk factors. A cross sectional study is a type of observational study that analyzes data collected from a population, at a specific point in time. This methodology is often used to measure the prevalence of disease or other health factors necessary for planning and allocating health resources. The strengths and weaknesses of cross-sectional designs are listed below.

Strengths:

- Relatively quick and easy to conduct
- Data on all variables are collected for a point in time
- Prevalence measured for all factors under investigation
- Multiple outcomes and exposures can be studied
- Can target specific populations of interest
- Used as secondary data analysis
- Data used are collected by someone else (possibly for another purpose)
- Good for descriptive analyses and for generating hypotheses
- Sample sizes tend to be large
- May cover a large geographic area

Weaknesses:

- Difficult to determine whether the outcome followed exposure in time or exposure resulted from the outcome. Cannot infer causal relationships (only correlation)
- Not suitable for studying rare diseases or diseases with a long duration

- Measure prevalent rather than incident cases; data reflects variables related to survival as well as the cause of disease (Hennekens, Buring, & Mayrent, 1987)
- Unable to measure incidence (occurrence of new cases)
- Unable to assess the temporal relationship between risk factors and disease development
- Associations identified may be difficult to interpret

(Thisted, 2006; Carlson & Morrison, 2009; Health Knowledge, 2017).

Unit of analysis. The unit of analysis is the hospital discharge (i.e. the hospital stays), not a person or patient. This means that a person who is admitted to the hospital multiple times in one year is counted each time as a separate "discharge" from the hospital.

Operationalizing Multimorbidity – The Dependent Variable

Multimorbidity is defined as multiple, potentially interacting conditions. Taking each term one at a time, multiple means -two or more, potentially means capacity to happen, and interacting means -co-occurring, or the state of being connected. The assumption is that if two or more conditions are co-occurring at the same time, a pattern is made. Pattern refers to a form, configuration, or arrangement of the multiple conditions. However, the form may be generated or it may emerge. If emerged, this indicates that the conditions become apparent or prominent in some way because they are coming out of and into view. As the dependent variable, multimorbidity can change based on several factors. But how do we measure this fuzzy concept; the capacity for conditions to connect at the same time, forming patterns, and emergent structures? The network measure – average weighted degree, is used to empirically measure multimorbidity. Networks are a group of interconnected things and average weighted degree-measures how connected and how relevant things are (in a network).

The things in this case are the multiple conditions which were defined by diagnosis recorded in the SID. By using a cross sectional study design and SID, the burden of -- the capacity for conditions to connect at the same time, forming patterns and emergent structures, in North Carolina communities was quantitatively measured using network analysis. Average weighted degree was estimated for 5 subgroups: females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics.

Inclusion and other potential problems. All diagnoses were recorded and included in the study, whether primary or secondary diagnosis, to avoid selection bias. Selection bias occurs when data are selected in a way that is nonrandom and the sample is not representative of the population. Other problems may surface such as the same disease may be coded in different ways and therefore counted twice in the same patient (O'Malley, Cook, Price, Wildes, Hurdle, & Ashton, 2005). This problem can occur in either approach when using administrative or inpatient data. Another problem is that all conditions whether rare or long duration are included. This study design is not well suited for studying rare diseases or diseases with long duration because it may underestimate or overestimate the occurrence in the population. For example, this becomes problematic if the dissertation's aim was to determine if a clausal relationship exist between degree and various health indicators and risk factors. The goals of this dissertation are both exploratory and descriptive. The primary goal is to explore the application of quantitative network analysis to characterize multimorbidity and describe the burden in communities (counties) in North Carolina and geographic variations, and secondarily to assess the difference of multimorbidity and relationship with indicators and risk factors.

The SID contains useful core variables and requires little data collection. The NC SID were limited to areas within North Carolina and all patients admitted in the State were included. Data quality problems arise concerning the accuracy of some ICD-9-CM-coded diagnoses and procedures, including miscoding and omission of comorbidities. Regarding missing data

elements, the statewide discharge data include hospital charges but do not include the hospital's costs to provide the services, or may not include patient identifiers which would be useful for examining readmissions for some years. Data include some clinically related data elements such as ICD-9-CM-coded diagnoses and procedures, but they generally do not include detailed clinical data such as laboratory results. Most states do not have records for residents who use hospitals in another state (border crossing), which makes identification of "border crossing" difficult. Zip codes can be used to help identify those patients.

Limitations of hospital data affect their usefulness and accuracy for some analyses. As cited in Andrew (2015), the limitations fall into three types: (1) quality of data elements, (2) missing data elements, and (3) excluded populations (or selection bias). Delgado-Rodriguez and Llorca (2004) argue that selection bias occurs when the kind of patients gathered does not reflect cases in the population (external validity). For example, as the population ages, older and sicker people are admitted to hospitals, uninsured healthy groups use fewer services (and insured use more services), or uninsured groups tend to be more severely ill when diagnosed and receive less care (Hong, Holcomb, Bhandari, & Larkin, 2016; Hadley, 2003). Another issue occurs when clinical databases are regional or include areas with large referral centers (i.e. cancer centers), making findings less applicable to the general population (Delgado-Rodriguez &Llorca, 2004). Biases can be classified by the direction of the change they produce in a parameter (e.g., the odds ratio or regression coefficients). Bias toward the null or negative bias produces estimates closer to the null value (e.g., lower and closer OR to 1), whereas away from the null bias produces opposite, higher estimates than the true ones. The main limitation is that hospital discharges are not population-based, but rather discharges are identified from hospitals where they are diagnosed and/or treated, therefore limiting the generalization of study results to the larger patient population (Murphy, Alavi, & Maykel, 2013).

Network node selection

Each record consists of primary and secondary diagnoses. As many as 25 diagnoses can appear on a patient record and all are specified by ICD-9-CM codes. The diagnosis coding system used in the United States in 2010 was the International Classification of Diseases (ICD)-9-Clinical Modification (CM) (Cartwright, 2013). The first three digits specify the main disease category and the last two provide additional information about the disease. As of February 2010, ICD-9-CM had a total of 14,315 distinct diagnostic codes (CDC, 2015).

Principal diagnosis. The first listed condition on the patient record is considered the "primary" or "principal" diagnosis (Senathirajah, Owens, Mutter, & Nagamine, 2011). The primary diagnosis is established after clinical evaluation and predominantly responsible for the patient's admission to the hospital. Secondary diagnoses are concomitant conditions that coexist at the time of admission or that develop during the hospital stay. All listed diagnoses include the principal diagnosis plus additional secondary conditions.

Clinical Classifications Software (CCS). The CCS program was used to identify the CCS grouping assigned to each diagnosis. The program was developed at the Agency for Healthcare Research and Quality (AHRQ) and is a tool for grouping patient diagnoses and procedures into a manageable number of meaningful categories (Elixhauser, Steiner, & Palmer, 2015). The CCS tool offers researchers the ability to group conditions without having to sort through thousands of codes. CCS categorizes ICD-9-CM diagnoses and procedures into approximately 250 categories. This "clinical grouper" (HCUP, 2012) makes it easier to quickly understand patterns of diagnoses and procedures.

Edge selection

Edges represent the relationship between nodes and were defined by the presence of primary and secondary diagnosis on the patient discharge record. Multiple secondary diagnoses on the discharge record results in multiple edges from the primary to the secondary diagnosis (or

nodes). The direction is important because it indicates which diagnosis was listed first (or primary). The frequency with which specific primary and secondary diagnoses occur defines the line-weight of the edge. The line weight is the percentile of the pair. For example, if there are 100 pairs or edges in that county and 1 pair of diagnosis codes appears 10 times, then a line weight of 10% is assigned. Node and edge data were aggregated for all discharges that share the same FIPS. Location specific networks were constructed by creating node tables and edge tables of each group (e.g., females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics) for each county.

Building Adjacency Lists

Adjacency lists are the spreadsheets created to store diagnosis data collected from the SID. SAS version 9.4 was used to read the data from the SID and output the results to tables or text files. Attributes for diagnoses were used to create node lists and the frequency of the diagnoses pairs (edge weights) were used to create the edge lists. Node and edge lists were written in a specific format so that the text contained in the lists can be read into network software. Adjacency lists for nodes and edges were created for each group (race and gender) and all 100 counties in North Carolina using diagnoses from all discharge records contained in the SID. Because the objective of the dissertation is to determine if there is spatial variation, it is important to capture the node and edge information for subgroups in all counties. County FIPS is the spatial reference. The spatial differentiation of multimorbidity networks is vital to revealing potential location specific social determinants of health, health risk factors, and environmental factors. Table 6 represents a section of the node list for African Americans discharged from hospitals in Franklin County and Table 7 represents an edge list for females discharged from hospitals in Mecklenburg County in 2010.

Table 6. *Example of Node List.*

Node list contains information from discharge records of African American patients discharged from hospitals located in Franklin County in 2010. The Nodes column refers the CCS group code, the ID is the observation number and the label is the CCS group code.

Nodes	ID	Label
86	64	86
87	65	87
88	66	88
89	67	89
90	68	90
91	69	91
93	70	93
94	71	94
95	72	95
96	73	96
97	74	97
98	75	98
99	76	99
100	77	100
101	78	101
102	79	102
103	80	103
104	81	104

Table 7. *Example of Edge List*

Edge list contains information from discharge records of female patients discharged from hospitals located in Mecklenburg County in 2010. The source column refers to nodes listed first, the target column contains nodes listed second. The source and target columns represent direction, from the source to the target. The weight is defined as the percentage of diagnoses pairs listed in discharge records of female patients admitted to hospitals located in Mecklenburg County during 2010.

Source	Target	Type	ID	Label	Weight
1	1	Directed			1
2	1	Directed			1
5	1	Directed			3
8	1	Directed			1
10	1	Directed			1
14	1	Directed			1
19	1	Directed			3
37	1	Directed			1
47	1	Directed			3
52	1	Directed			1
56	1	Directed			1
77	1	Directed			1
94	1	Directed			1
95	1	Directed			2
108	1	Directed			2
113	1	Directed			2
114	1	Directed			2

Network Construction

The network was constructed based on the following rules: Each node was either the first listed diagnosis (primary reason for hospital admission) or secondary diagnoses which were concomitant conditions that coexisted at the time of admission or that developed during the hospital stay. Node data were generated using discharge information in the SID; and represented all discharges from all community hospitals in all counties throughout North Carolina. The edge weight was the percentage of diagnoses pairs in the population that each observation represents.

As long as the entities have a relationship of interest, potentially other possible networks can be constructed using the available data. For example, networks modeling cost, quality of health services, medical practice patterns, access to health care programs, and outcomes of treatments. The research problem selected for study defines the network and it is the analyst who determines how to apply the tools and interpret the results. The research questions place the topic into a context that defines the parameters of what is investigated. Table 8 shows the research question and how the questions were addressed by constructing a global multimorbidity network graph for demographic groups (females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics) and selected counties; by constructing an egocentric coronary heart disease network graphs for groups and selected counties, and assessing the structure and measuring topological characteristics.

Table 8. *Review of Research Question, Network Construction Steps and Analysis*

Research Question	**Network Construction and Analysis**
1. Can networks characterize multimorbidity? If so, what is the content and structure of multimorbidity networks?	Prepared network data (diagnosis nodes and edges), created adjacency lists and uploaded node and edge tables into Gephi. Visualized the network graph,

	selected layout (mini-programs to arrange the graph components) and computed network statistics/measurements to understand the structure or topological characteristics of multimorbidity networks for subgroups.
2. What does an egocentric network study of coronary heart disease reveal?	To probe content, built queries to filter graph using topology and degree range. Degree range function filtered and nodes sorted. In graph display, selected coronary heart disease node (label 101), selected a layout to observe connected diagnosis nodes.
3. What does centrality measures such as betweenness and closeness reveal about the relative importance of conditions?	The centrality of a node is an indication of its importance in the network. Closeness centrality indicates how long it takes for information from a given node to reach other nodes in the network. The smaller the value, the more central role the node plays in the network. The more central a node is the lower its total distance from all other nodes.
4. How does the network measure - average weighted degree change or vary geographically?	The weighted degree is similar to the simple degree measure. The number of edges a node has going to other nodes is summed. Weighted degree is the frequency of pairwise connections, summed, computed and ranked. Edges between nodes appeared thicker as frequency increases.
5. How does the average weighted degree of coronary heart disease networks change or vary geographically?	Created networks for each group and county and computed summary statistics (measures). Created table and joined to shapefile of North Carolina counties and created choropleth maps. A choropleth map is a thematic map in which areas are shaded in proportion using the measurement of the statistical variable being displayed, in this case the average

	weighted degree of each county.
8. Are there gender and racial and ethnic differences in coronary heart disease networks	To examine group differences, performed ANOVA and T-tests for global graph and ego-coronary heart disease network for groups.
9. What is the relationship between the underlying factors and the average weighted degree of heart disease networks?	To examine the relationship between the average weighted degree (dependent variable) and various health indicators and risk factors (independent variables), OLS regression performed. After performed analysis, the regression statistics were used to predict the dependent variable when the independent variables were known. Regression goes beyond correlation by adding prediction capabilities.

Network measurements

Network statistics are defined in this section. Betweenness and closeness centrality are the focal properties of the study. They determine the relative importance of concomitant conditions for groups and describe the topological characteristics of the egocentric coronary heart disease networks. Freeman (1979) argued that, centrality of an organization was predictable in part because of its own characteristics and from the properties of the network in which they were embedded. The next section describes the network measures selected for the analysis.

Definitions of network parameters (measures). The goal is to supplement the current understanding of multimorbidity with large-scale characteristics of multimorbidity networks. Basic network measures permit comparison and representation of various group networks. Let us assume that a diagnoses complex network G (V, E) is a connected and weighted graph with a set of nodes:

V={v1, v2 vN} and a set of links E={(vi, vj)| vi, vj ϵ V}. We defined a set of network parameters following definitions given in Gephi (Le, Uy, Dung, Binh, & Kwon, 2013).

Node degree – of a node vi is the number of edges connecting to vi.

Average Weighted Degree

We represent a network by a graph (N, g), which consists of a set of nodes N = {1, . . . , n} and n × n adjacency matrix g = [gij] i,jϵN. Formula adapted from Newman. (2001).

Adjacency matrix gijϵ {0, 1} represents the existence of an edge from node i to node j.

An edge gij=1 when an inpatient record has more than one (1) Clinical Classification Code, an arc is formed from the Clinical Classification Code associated with the primary diagnosis code i to a paired Clinical Classification Code associated with the a secondary diagnosis code j, the value is 0 otherwise.

For directed graphs:

Node i's in-degree is:

$$\sum_i g_{ij}$$

Node i's out-degree is:

$$\sum_j g_{ij}$$

Degree for node i is the sum of the in-degree and the out-degree:

$$\delta_i(g) = \sum_{ij} g_{ij}$$

The weighted degree for node i is:

$$\frac{\delta_i(g)}{n-1}$$

Average weighted degree for all Clinical Classification Codes in a county for a demographic cross section are averaged to produce a single country level value for that demographic cross section.

Network density – measures how close the network is to complete. A complete graph has all possible edges and density equal to 1.

Network diameter – is the average graph distance between all pairs of nodes. Connected nodes have graph distance 1. The diameter is the longest graph distance between any two nodes in the network (i.e. the distance between the two most distant nodes).

Average clustering coefficient of a node vi -- the ratio between the number of edges among the neighbors of vi and the maximum number of edges that could possibly exist between the neighbors of vi. This parameter measures degree to which nodes in a graph tend to cluster together and has a value in a range [0, 1].

Graph Density -- the measure of the level of connected edges within a network relative to the total possible value and has a value between 0 and 1.

Modularity - refers to community detection and the dividing of a network into communities of densely connected nodes. Modularity measures the intra-links within communities and reveals the complete hierarchical structure of a network (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Newman and Girvan (2004) define modularity as the overall structure of the network and connections taking place within and between communities. Modularity counts the number of edges within communities and compares it to the expected number of such links in an equivalent null model; or when there are more edges than expected by chance (Lambiotte, Delvenne, & Barahona, 2008).

Number of Communities - groups are viewed as communities. Community detection recognizes the inherent structure of networks, e.g., dividing a network into several communities that have high edge density within communities and low density between them. Community detection is linked to graph partition and traditional clustering (Zhou, Wang, & Wang, 2012).

Number of Components - refers to a set of nodes that are connected to each other by direct or indirect paths. In other words, a set of nodes in a graph is a connected component if

every node in the graph can be reached from every other node in the graph. Gephi detects strongly and weakly connected components. A set of nodes forms a strongly connected component (SCC) if there is a path from any node in the set to any other node. A set of nodes is weakly connected under a similar definition, except that the path can follow the paths in either a forward or backward direction. In this case, strongly connected components represent the most frequent or most prevalent diagnosis; we presume they contain chronic disease diagnoses. Weakly connected components represent nodes that can reach the SCC, but not vice versa. This component may consist of conditions or illnesses that point to diagnoses in the SCC, such as underlying comorbidities (e.g. neurologic disorders, drug and alcohol abuse, blood or fluid loss (Rubenstein & Josephson, 2002), pre-existing conditions that are not directly related to the principal diagnosis, infections as a secondary diagnosis (Elixhauser, & Jhung, 2008), and concomitant conditions. Secondary diagnoses are concomitant conditions that coexist at the time of admission or that develop during the stay (Russo & Steiner, 2007) and may include complications, side effects, or adverse events (disease, injury, or a symptom).

Average Path Length - the average network distance (shortest path length) between all pairs of nodes (Albert, Jeong & Barabási, 2000).

Analytical Strategies

To perform quantitative network analysis, data from the 2010 North Carolina SID were used. The unit of analysis in the SID was the discharge record and not individual patients (HCUP, 2014). If a person was admitted to the hospital multiple times during the course of a year, that person was counted each time as a separate discharge from the hospital. The discharge record contained up to 25 diagnosis variables. Hospital discharge diagnoses were coded using the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM). Clinical information was captured by the primary and secondary diagnoses coded using the ICD-9-CM system. This system contains over 14,000 codes and are often mapped into a smaller

number of diagnostic categories (e.g. congestive heart failure, myocardial infarction, renal disease) (Weingart, Iezzoni, Davis, Palmer, Cahalane, Hamel, Mukamal, Phillips, & Davies, Jr., 2000). ICD-9-CM codes were used to represent nodes and construct the networks. Edges represent the relationship between nodes and were defined by the presence of primary and secondary ICD-9-CM codes on the patient discharge record. Multiple secondary diagnoses (ICD-9-CM codes) on the discharge record resulted in multiple arcs from the primary to the secondary ICD-9-CM codes (or nodes). The frequency with which specific primary and secondary diagnoses occur defined the line-weight of the arc. Location specific networks were constructed using zip codes based on the patient's self-reported address. Multimorbidity networks were modelled by aggregating discharge networks for all discharges that share the same zip code (aggregated to counties). The spatial differentiation in the multimorbidity networks was vital to revealing potential location specific social determinants of health, geographic location, socioeconomic status, and environmental factors.

Quantitative Network Analysis

To test whether the network approach can be applied to the study of global multimorbidity networks, networks for each subgroup (females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics) and county were constructed. Below is an overview of the approach.

Multimorbidity network estimation. To estimate the co-occurrence of multiple conditions, network data (diagnoses nodes and edges) collected and adjacency lists (i.e. spreadsheets) were created. Node and edge files were uploaded into Gephi (version 9.1) open source network visualization software. Network graphs were visualized using a combination of various algorithms such as: Force Atlas, Fruchterman-Reingold, Open Ord, Force Atlas 2, and Noverlap (a Gephi plugin) (Gephi, 2017) and are shown in Figure 17.

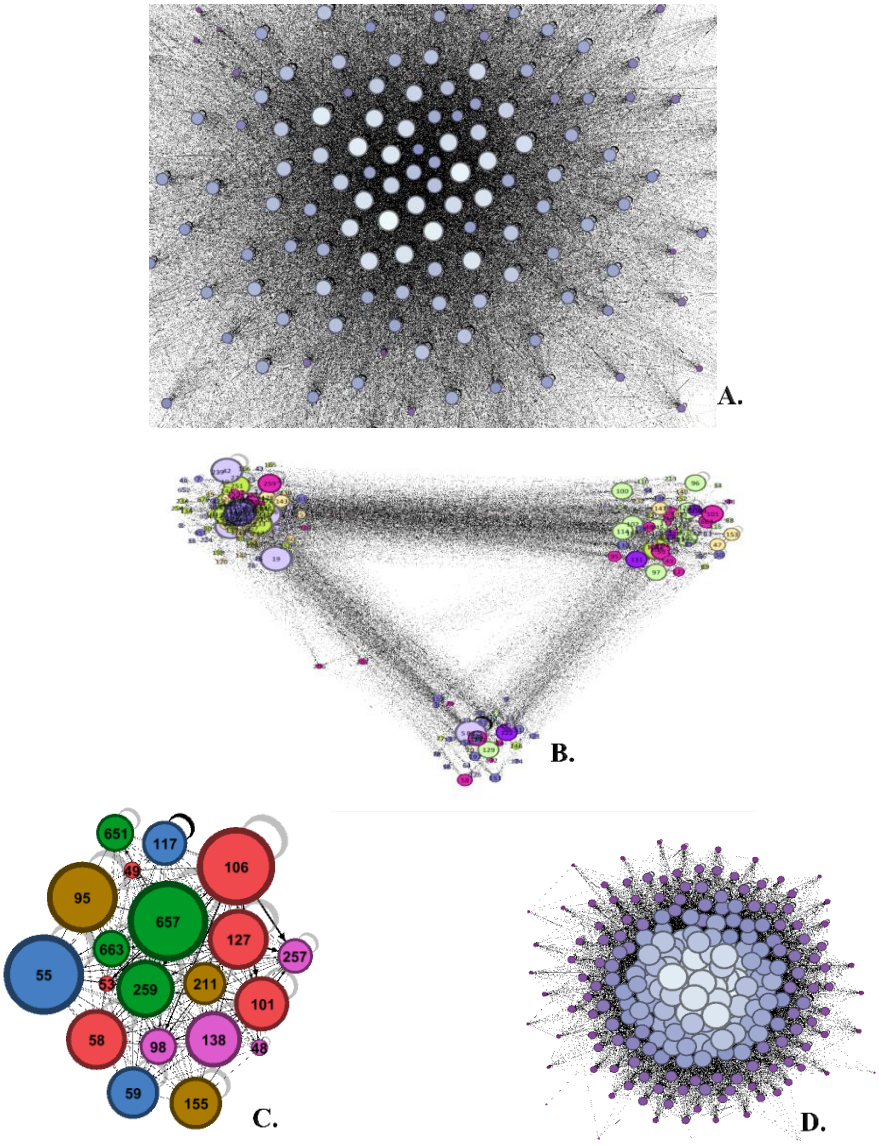


Figure 17. Network Graph Layouts: A. Force Atlas, B. Open Ord, C. Force Atlas 2, and Noverlap, D. Fruchterman-Reingold. Source: Farrow-Chestnut 2018.

The layout algorithms rendered a directed graph of the data and simplified the complex graph. Most network graphs are drawn in a two-dimensional "X-Y axis" space, where a node is drawn in the space is arbitrary – all the information about the network is contained in the node and edge lists. Gephi has built-in algorithms and optional plugins that can be downloaded. There are many, many ways to render a network graph, but the default tools in Gephi generate meaningful renderings and insights. Rendering settings were configured such as the size, color, and other properties of nodes, edges, and labels. Settings apply to the visualization in general but specific properties can be altered (e.g. the color of a particular node subset, the width of some edges, etc.) (Gephi, 2017). Shown in Figure 18 is a global multimorbidity network visualization. The multimorbidity network is large, composed of 234 nodes and 12,408 edges and rendering was time- and resource-intensive.

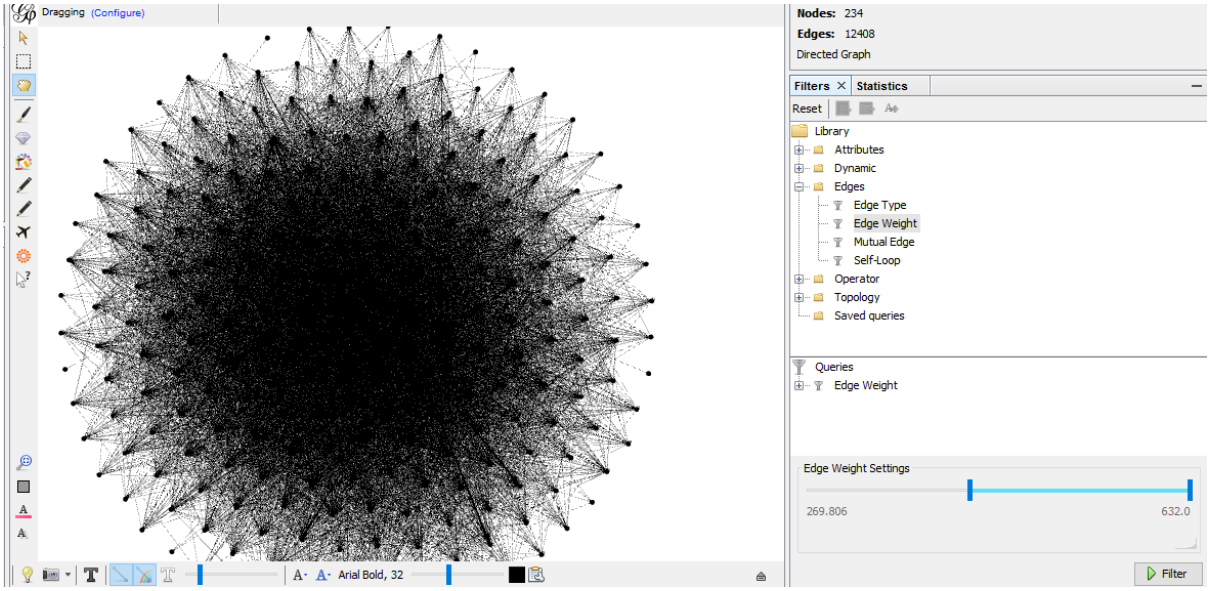


Figure 18. Initial Network Visualization. The multimorbidity network is large, composed of 234 nodes and 12,408 edges. Source: Farrow-Chestnut 2018.

To explore the topological characteristics of global multimorbidity networks, network statistics were computed in Gephi. As measures were computed in Gephi they were simultaneously recorded in Gephi's Data Laboratory application. Statistics were summarized for all groups for counties and presented as network summary measures. For example, computing closeness centrality resized nodes based on that attribute, and computing betweenness centrality recolored nodes based on that attribute. The larger nodes shaded a particular color were the most prominent nodes in the final visualization.

Coronary heart disease comorbidity (egocentric) network estimation. The same process was followed as described for multimorbidity network estimation with an additional step. The node representing the diagnosis of coronary heart disease was selected as the index condition by applying filters that sorted and selected the node labeled 101 from the multimorbidity network. As described earlier, the filtering process builds an egocentric network. Additional data collection was therefore unnecessary because all the primary and secondary diagnoses in the SID were collected, aggregated, and arranged into node and edge lists-spreadsheets and imported into Gephi. Diagnoses were grouped using the CCS categories (see data collection section). Nodes were all labeled. Per the CCS single level reference, 101 (see Appendix **G** reference list of CCS single level diagnosis codes) corresponds to "coronary atherosclerosis and other heart disease" (Elixhauser, Steiner, & Palmer, 2015) and is considered the *ego* – the focal node.

To probe the content, queries were built and the graph was filtered using topology and degree range functions. The degree range function filters out low degree nodes (nodes with few edges or connections). Networks for each subgroup and county were visualized and exported as a ping file. Gender-specific diagnoses for female patients (e.g., pregnancy) were excluded in network analysis of male patients and vice versa.

Outcome Measure (Dependent Variable)

The dependent variables were 1) average weighted degree of global multimorbidity and 2) average weighted degree of egocentric (comorbidity) coronary heart disease. The main outcome for multimorbidity and comorbidity coronary heart disease was operationalized as the average weighted degree of the respective networks for demographic groups and selected counties.

Primary Covariates (Independent Variables)

The main independent variables (primary covariates) were (RACE_X), ethnicity (HISPANIC_X), and sex (SEX=2 for female) as provided by the SID (HCUP Central Distributor [HCUP], 2008). Four race/ethnicity categories were created based on how the SID reported Latino or Hispanic descent and race (white, African America/black, American Indian/Alaskan Native, Asian, Native Hawaiian/Pacific Islander). A patient identifying as Hispanic was coded "Hispanic" irrespective of race. The resulting race/ethnicity categories were Race 3 for Hispanic (of any race), Race 1 for non-Hispanic white, Race 2 for non-Hispanic black, and Race 456 for all remaining race/ethnicities (combined because of small numbers represented in county patient groups). Research question #9 - *What is the relationship between the underlying factors and the average weighted degree of heart disease networks?* test whether centrality (relative importance) of conditions are predictable in part from counties in which they are embedded. The variable selection was guided by the theoretical frameworks described in the literature review and defined in multiple prior studies. Approximately 88 explanatory variables (potential underlying factors) that influence average weighted degree or disease burden in subgroups across counties in North Carolina were evaluated. A list of all variables is contained in Appendix J.

Controls included 2010 population, population density, and persons younger than 65. Health risk factors included the percentage of adults that were smokers, obese, engaged in no leisure time physical activity, diagnosed with diabetes, discharged from hospitals with heart

disease or hypertension. Social Determinants of Health (SDOH) were also considered. For example, a percentage of the population living below the poverty level and without a high school diploma; segregation (as a proxy for discrimination), income, unemployment, toxic sites, air pollution, without high school diploma, health insurance coverage (e.g. number of persons with or without health insurance, Medicaid eligible persons, Medicare and Medicaid dually eligible), access to health care (outpatient and emergency room visits), and the number of hospital beds and inpatient days (proxy for health care utilization). To account for county differences in healthcare expenditures (proxy for utilization of healthcare services), per capita Medicare spending by all fee-for-service beneficiaries, younger than 65, and 65 and older by number of conditions in 2010 were included in OLS regression model.

Variables were excluded from final models if they were highly collinear with the dependent variable (i.e. heart disease mortality) or other explanatory variables because collinearity and multicollinearity can seriously distort the interpretation of a model. If explanatory variables did not influence results (i.e. segregation – index of dissimilarity) they were also excluded from final models. In addition, because availability of physician supply for chronic conditions can influence clinical outcomes (Fisher & Wennberg, 2003), local access was accounted for by proxies for utilization at the county level.

Statistical Analysis

For both the global multimorbidity and egocentric coronary heart disease (comorbidity) approaches, structural analyses were performed as described earlier. Structural analyses of network graphs are equivalent to descriptive analysis. Descriptive statistics uses the data to provide descriptions of the population or universe of patient records, through numerical calculations, graphs, tables and network measures. Inferential statistics makes inferences and predictions about a population based on a sample of data taken from the population in question. Performing univariate (descriptive) network statistics is a standard first (and sometimes only) step

in statistical analysis for networks. The tools in Gephi permit exploration of centrality -- how well-connected nodes and edges are in a multimorbidity network. For both analyses, average weighted degree (and other network measures) was treated as a discrete variable. Newman and Clauset (2016) note that degrees are discrete variables, and their distribution is described by a discrete function (x-values are distinct, such as integers or whole numbers in this case). Average weighted degree was estimated for 5 demographic groups: females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics.

To estimate the associations between area factors and average weighted degree, Ordinary Least Squares (OLS) regression analysis was performed. The OLS model is shown below:

$$H = \alpha + Xt\beta + Et + \varepsilon t$$

(or $Y = a + b1\ X + b0$)

Where:

H measures multimorbidity operationalized by average weighted degree at time t (2010)

E indicates macroeconomic conditions

X is a vector of covariates (SDOH, risk factors, controls) –

ε is an error term (Ruhm, 2006)

The sample size was n=100 (counties). The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that the null hypothesis can be rejected, and that there is an association with underlying factors. A predictor (i.e. independent variable) that has a low p-value indicates that changes in the predictor's value are associated with changes in the dependent variable. A larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the dependent variable.

After confirming variables were normally distributed by performing univariate analysis, histograms and Q-Q plots, and five sets of analyses were performed to provide information on the individual and collective contribution of different underlying factors i.e. social determinant of health. Analysis 1) means and percentages for all variables were calculated. Analysis 2) Pearson's correlation was used to test the association among independent variables and average weighted degree for each subgroup. Analysis 3) series of bivariate linear regression models were used to assess the associations between multimorbidity and each of the independent variables. Analysis 4) a series of stepwise, AIC and RMSE regression models were computed for final model fit. Analysis 5), reiteration of above to obtain the final fully adjusted models, standardized betas for the variables to estimate the amount of variance in average weighted degree for each demographic group for a total of 5 models:

1. Average Weighted Degree of Coronary Heart Disease Networks for Female
2. Average Weighted Degree of Coronary Heart Disease Networks for Male
3. Average Weighted Degree of Coronary Heart Disease Networks for non-Hispanic whites
4. Average Weighted Degree of Coronary Heart Disease Networks for no-Hispanic blacks
5. Average Weighted Degree of Coronary Heart Disease Networks for Hispanics

Data preparation and statistical analysis were performed using SAS (Version 9.4).

Geographic Analysis

Geographical Information Systems (GIS) techniques were used to compare average weighted degree of subgroups across counties in North Carolina. GIS is a computer system designed to capture, store, manipulate, analyze, manage, and present all types of geographical data. GIS software and tools enable spatial analysis; permit the management of large datasets, and the display of information in a map/graphical form (Richards, Croner, Rushton, Brown & Fowler, 1999). To compare spatial patterns of average weighted degree of subgroups in counties, choropleth maps were developed. First, a geospatial data layer was created for modelling and

manipulation in a GIS. A data layer contains polygon (geometric shape) features representing the geography of North Carolina. All data, including the dependent variable statistics for groups and independent variables estimates were compiled into a spreadsheet and joined to the shapefile; a data storage format for storing the location, shape, and attributes of geographic of North Carolina counties. The GIS data for the North Carolina map was downloaded from the North Carolina Department. of Transportation website. A GIS layer (references data sets) representing county (and state) boundaries and the North Carolina shoreline (N.C. Department of Transportation, Connect NCDOT [NCDOT], 2017) was generated in GIS. Choropleth maps were developed in ArcGIS software program based on variables of interest outlined above to visualize descriptive statistics. Maps featured a quintile classification scheme (five breaks in the data as indicated by the map legend) and graduated color symbolization to depict average weighed degree by county in North Carolina. A choropleth map is a thematic map in which areas are shaded in proportion using the measurement of the dependent (and independent variables) displayed for each county. The values were evaluated to understand the variability and distribution of the data.

Multivariate associations are explored from a spatial perspective using parallel coordinate plots (PCP) linked with map views in GeoDa, an open source package for exploratory spatial data analysis (University of Chicago, Center for Spatial Data Science Computation Institute, 2017). Anselin, L. (2017) designed the parallel coordinate plot (PCP) as an approach to visually identifying clusters and patterns in multi-dimensional variable space. The author describes how each variable is represented as a (parallel) axis and each observation consists of a line that connects points on the axes. Clusters consist of groups of lines (i.e. observations) that follow a similar path. The PCP can be applied to a large number of variables. Outliers in a PCP are lines that show a very different pattern from the rest, similar to outliers in a scatterplot. Tools such as PCP provide additional insight into the data and the associations between the dependent and independent variables. Appendix G and H contain maps of parallel coordinate plots.

Multivariate regression analysis was performed in SAS and GeoDa by peparing the specification for a linear regression model, calculating ordinary least squares estimation (OLS), adding OLS predicted values and residuals to the data table; creating maps with predicted values and residuals. Dependent and independent variables were selected, as well as the spatial weights, based on a queen matrix rook. Spatial weights are central components of many areas of spatial analysis. In general terms, for a spatial data set composed of n locations (points, areal units, network edges, etc.), the spatial weights matrix expresses the potential for interaction between observations at each pair i, j of locations (Anselin, 1994). The starting point of any statistical test or model is the spatial weights matrix. According to Anselin, the spatial weights matrix conveys the spatial arrangement (topology, contiguity) of the data.

According to Anselin (2018), spatial weights are based on the idea of contiguity between polygons (or counties in this study). Spatial weights are a key component in any cross-sectional analysis of spatial dependence. They are an important part when computing spatial autocorrelation statistics. In its most simple form, the spatial weights matrix expresses the existence of a neighbor, either yes or no, represented with weights 1 and 0. Contiguity means that two spatial units share a common border. There are different types of weights such as a rook and a queen (yes, like in chess). The queen criterion defines neighbors as spatial units sharing a common edge. The queen contiguity weights were constructed for this study. According to the queen criterion, selected observations have six neighbors (rook has fewer neighbors).

Fit diagnostics, test of association and normality. All variables are represented in Appendix G. Histograms and normal Q-Q plots generated to estimate the probability distribution of all (continuous) variables and results show the relative contribution of all independent variables for each model (shown in Appendix K). To test the relationship between each dependent and all ~88 covariates, bivariate analyses were performed. No associations were observed (results are shown in Appendix R). To describe the relationship between the set of

dependent variables and independent variables, the OLS (Ordinary Least Squares) method was used to fit models. To shift through the large numbers of potential independent variables and determine the best subset of variables among all possible subsets, stepwise regressions were performed. To find the best linear model includes minimizing the RMSE and maximizing R2. Model diagnostics were computed for each model to help determine which model was "best". Model diagnostics include the root mean square error (RMSE) and the coefficient of determination (R2). Good linear models had low RMSE and a high R2 close to 1 (not shown). Interaction terms were computed, added, and skewed data transformed. Fit diagnostic performed for all models. Diagnostics for all other models displayed good fit and no non-linear patterns except for female and non-Hispanic black coronary heart disease models. Diagnostic results showed that the model fit the data poorly with non-linear patterns (shown in Appendix K and Appendix J). The Normal Q-Q plot showed that residuals were not normally distributed. Pearson correlation measured the linear correlation between all dependent and independent variables. For example, supply variables (and others) showed positive linear correlation for female and male average weighted degree and are shown in Appendix H (n=1300 obs).

Spatial autocorrelation and multicollinearity. Plots of student residuals indicated spatial error. Spatial error using OLS (Ordinary Least Squares) multiple regression, the assumption of uncorrelated error terms and independent observations were also violated. As a result, the estimates were inefficient. The summary of the output is located in Appendix L. A total of six test statistics were reported. Multicollinearity of the model was tested and the test statistic was > 20 (actual value 3737.744812). Jarque-Bera test was used to examine the normality of the distribution of the errors. This statistic tests the combined effects of both skewness and Kurtosis. The low probability of the Jarque-Bera test score (4) indicated the non-normal distribution of the error term. The low probabilities of the three tests pointed to the existence of heteroskedasticity. Six tests were performed to assess the spatial dependence of the

model. First, Moran's I showed the trend was not highly significant, indicating weak at best spatial autocorrelation of the residuals. Tests of the lag and error were not significant, indicating no presence of spatial dependence. The robust tests helps identify what type of spatial dependence may be at work if any. The robust measure for error was not significant and the robust lag test was not significant. Additional tests did not support the presence of spatial dependence after all. However to confirm, the model was re-estimated with the maximum likelihood approach while controlling for the spatial dependence. The new model included the new variable (LAMDA) for spatial lag and was not significant and the general model fit did not improve. After the skewed data was log transformed and interactions tested, general model fit improved.

Diagram of Work Flow

Figure 19 is a diagram summarizing all the steps described above.

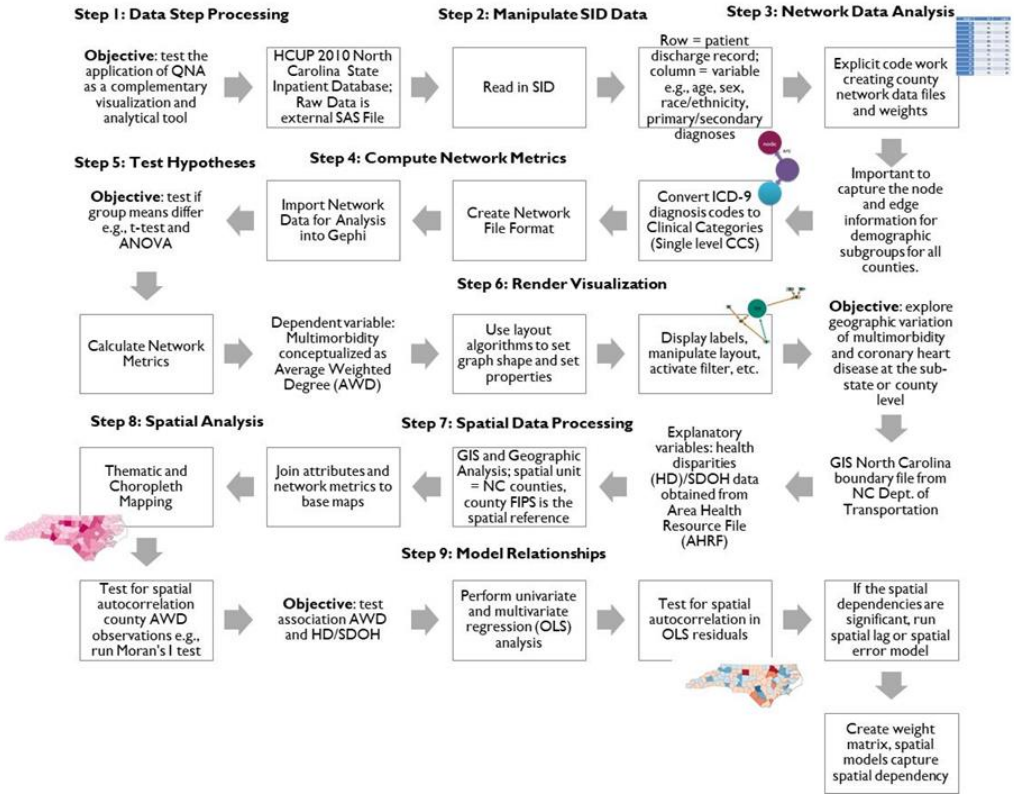


Figure 19. Diagram of Work Flow. Source: Farrow-Chestnut 2018.

CHAPTER 4: RESULTS

Patient Population

North Carolina 2010 population characteristics are shown in Figure 20. The total population was 9,535,483, 68.5% were non-Hispanic white, 21.5% non-Hispanic black and 4% Hispanic. Females represented 51.3% of the population. Compared to the hospital population of 1,129,367 discharges, 728,757 (67.4%) were non-Hispanic white, 258,360 (23.9%) non-Hispanic black, and 46,050 (4.3%) were Hispanic. The average age of patients was 48 years old, females represented 58% of discharges, and the average length of stay was approximately 5 days in 2010.

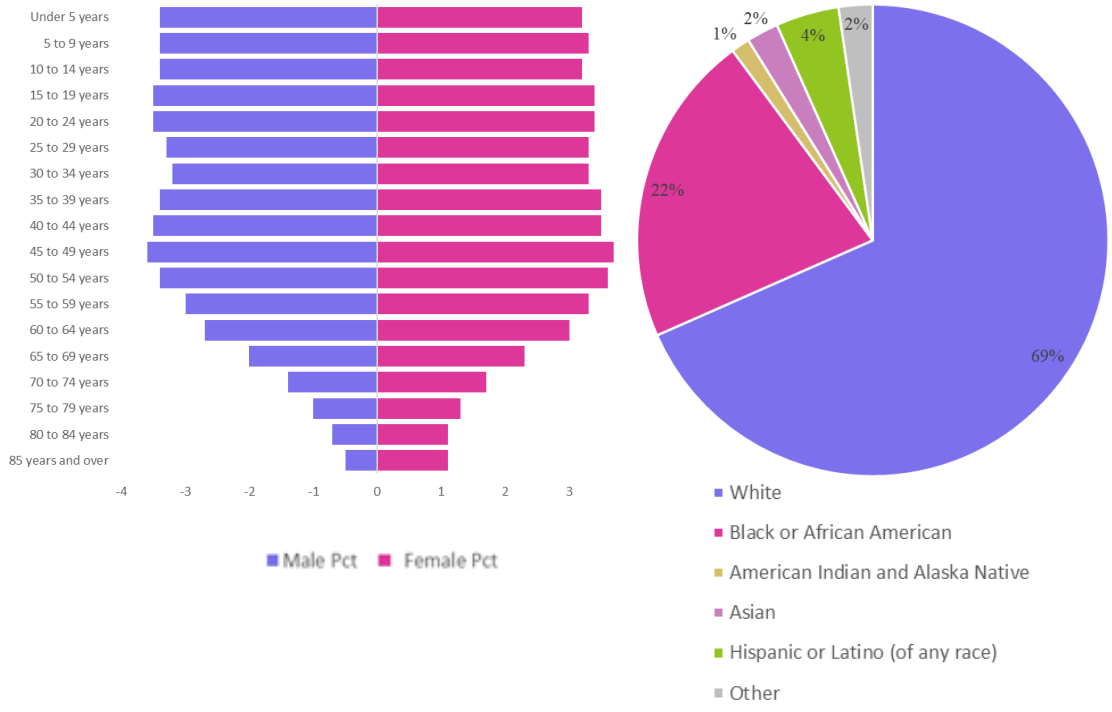


Figure 20. North Carolina Population by Age and Gender, Percent Race/Ethnicity, 2010. Source: 2010 Census Summary File 1: 2010, U.S. Census.

Network statistics for population sub-groups

Network statistics for multimorbidity networks are summarized for all groups for all counties and presented as aggregate network summary measures in Table 9. Descriptive network statistics are described in Table 9 and Table 10 for all counties and represent the structure of the global multimorbidity disease networks by groups (e.g., females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics). Refer to Appendix A for average weighted degree statistics for groups and all counties; Appendix T for all network statistics for all groups, and Appendix U for average weighted degree network statistics for all groups.

Table 9. *Descriptive Multimorbidity Network Statistics for male and female, North Carolina, 2010.*

	Nodes	*Edges*	*Average Weighted Degree*
Male			
N	100	100	100
Mean	207.6	5964.7	124.2
Median	213.0	5369.5	78.0
Standard Deviation	16.55	3537.59	145.90
Skewness	-2.19	1.04	3.21
Minimum	140	751	6.846
Maximum	223	18702	954.435
Coef of Variation	0.08	0.59	1.18
Female			
N	100	100	100
Mean	214.8	6623.8	145.0
Median	220.5	5804.0	82.0
Standard Deviation	16.75	3887.02	173.95
Skewness	-2.00	1.00	3.29
Minimum	151	776	7.212
Maximum	230	20546	1154.478

Coef of Variation	0.08	0.59	1.20

Nodes and Edges. Table 9 contains the descriptive network statistics, the number of nodes, edges and average weighted degree for male and female diagnosis networks in North Carolina for 2010. The resulting gender graphs comprise of 215 nodes, representing diagnoses appearing on discharge records when the patient is female and 208 nodes representing diagnoses appearing on discharge records when the patient is male. The gender graphs also comprise of 6,624 and 5,965 edges for females and males, respectively.

Gender. On average the number of primary diagnoses (nodes) and connections (edges) between concomitant diagnoses for all females discharged from North Carolina hospitals (215 nodes, 6624 edges) were greater than males (208 nodes, 5965 edges). Diagnoses data from patient records reveal that nodes for both females and males are negatively skewed (-2.00, -2.19 females and males, respectively) and have a long tail that extends to the left. Data from patient records reveal that edges for both females and males are positively skewed (1.0, 1.04 females and males, respectively) and have a long tail that extends to the right.

As a rule, data skewed to the left suggests that the mean is less than the median. In this case, left skewed diagnosis data suggest that the patient population contained many more patients with fewer diagnoses (nodes) which greatly affect the mean. The coefficient of variation (CV) measures the relative variability of the patient diagnoses data on a ratio scale. The CV results for females (0.08) and males (0.08) indicate that there is some variability in the diagnoses data compared to a data set with constant values (CV = 0). CV is useful because it is a dimensionless number and allows for comparison between population groups which may have different means. Values greater than 0 suggest skewness of a unimodal distribution to the left, with a long right tail, values less than 0 indicate skewness to the right with a longer tail to the left (skewness: where the id = $\alpha 3$).

Table 10. *Descriptive Multimorbidity Network Statistics for Race and Ethnicity, North Carolina, 2010.*

	Nodes	*Edges*	*Average Weighted Degree*
Non-Hispanic white			
N	100	100	100
Mean	222.9	7551.9	177.9
Median	228.5	6752.5	96.1
Standard Deviation	15.15	4335.15	199.15
Skewness	-2.23	0.70	2.51
Minimum	164	482	8
Maximum	236	20724	1101
Coef of Variation	0.07	0.57	1.12
Non-Hispanic black			
N	100	100	100
Mean	182.2	3739.9	63.7
Median	211.0	3454.0	38.7
Standard Deviation	59.34	3350.98	105.78
Skewness	-1.50	1.60	4.78
Minimum	4	3	1
Maximum	235	18579	827
Coef of Variation	0.33	0.90	1.66
Hispanic			
N	100	100	100
Mean	96.8	433.7	4.6
Median	100.5	231.5	2.8
Standard Deviation	56.12	678.58	6.50
Skewness	0.14	4.17	5.36
Minimum	3	0	0
Maximum	227	5011	54
Coef of Variation	0.58	1.56	1.42

Race/Ethnicity. Table 10 shows the descriptive network statistics for non-Hispanic white, non-Hispanic black and Hispanic diagnoses networks in North Carolina. On average the number of diagnoses and connections of Non-Hispanic white patients (223 nodes, 7552 edges) were greater than Non-Hispanic black patients (182 nodes, 3740 edges), and Hispanics (978 nodes, 434 edges). Diagnoses data for Non-Hispanic whites, and Non-Hispanic blacks were negatively skewed (-2.23 and -1.5 respectively). Data for edges followed the same pattern as gender with edges displaying a positive right skew (0.7 and 1.6 respectively). Both node and edge data for Hispanics are positively skewed (0.14 node, 4.2 edge). However, the edge data for Hispanics are considerably more skewed to the right with longer tails. Overall CV suggests there were racial and ethnic differences in the distribution of node and edge values. CV for Non-Hispanic whites (0.07 nodes, 0.57 edges) is the smallest, and CV for Hispanics (0.58 nodes, 1.56 edges) is the highest.

Average Weighted Degree. The edges have been assigned a weight or value characterizing each connection. In the case of the gender graphs, the weight of an edge linking i and j represents the number of occurrences or the total disease burden experienced by females and males. The average weighted degree also characterizes the heterogeneity of connection (weights characterizing edges) and provide alternative definitions of centrality, local cohesiveness, and affinity (Barthélemy, Barrat, Pastor-Satorras, & Vespignani, 2004).

Gender. The mean average degree for the female diagnoses network is 29.9 and the mean average degree for the male diagnoses network is 27.9, which means that a typical network has between 27 and 30 co-occurring diagnoses. The mean average weighted degree for the female and male diagnoses networks are 145 and 124.5 respectively.

Race/Ethnicity. The Non-Hispanic white patient diagnoses network has the highest mean average degree (66) and average weighted degree (178). This means that a typical number of

diagnoses of the Non-Hispanic white patient diagnosis network have between 66 and 178 co-occurring conditions.

Multimorbidity Networks for Selected Counties in North Carolina

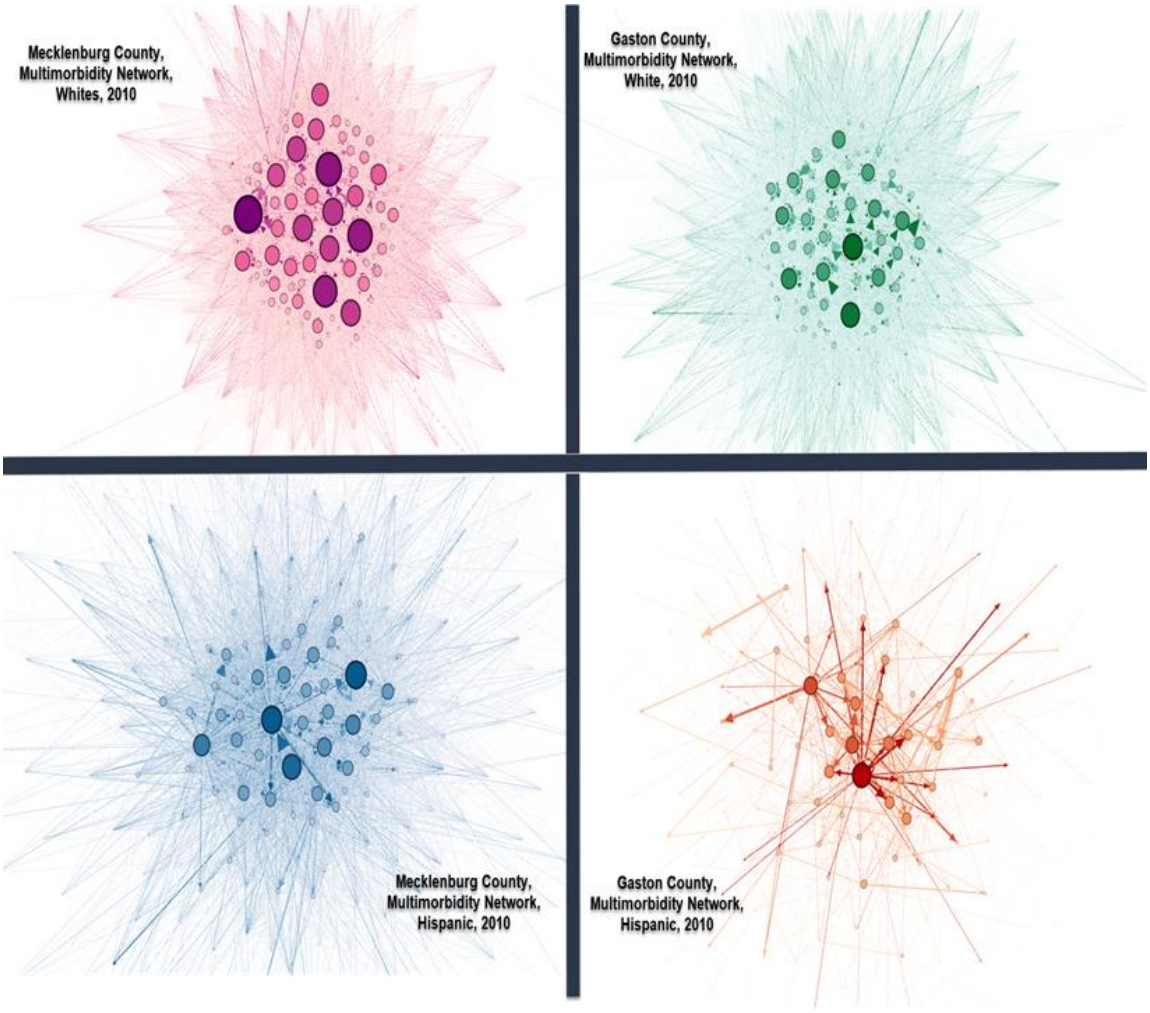


Figure 21. Multimorbidity Networks for non-Hispanic whites and Hispanics for Mecklenburg and Gaston Counties in North Carolina, 2010. Source: Farrow-Chestnut 2018.

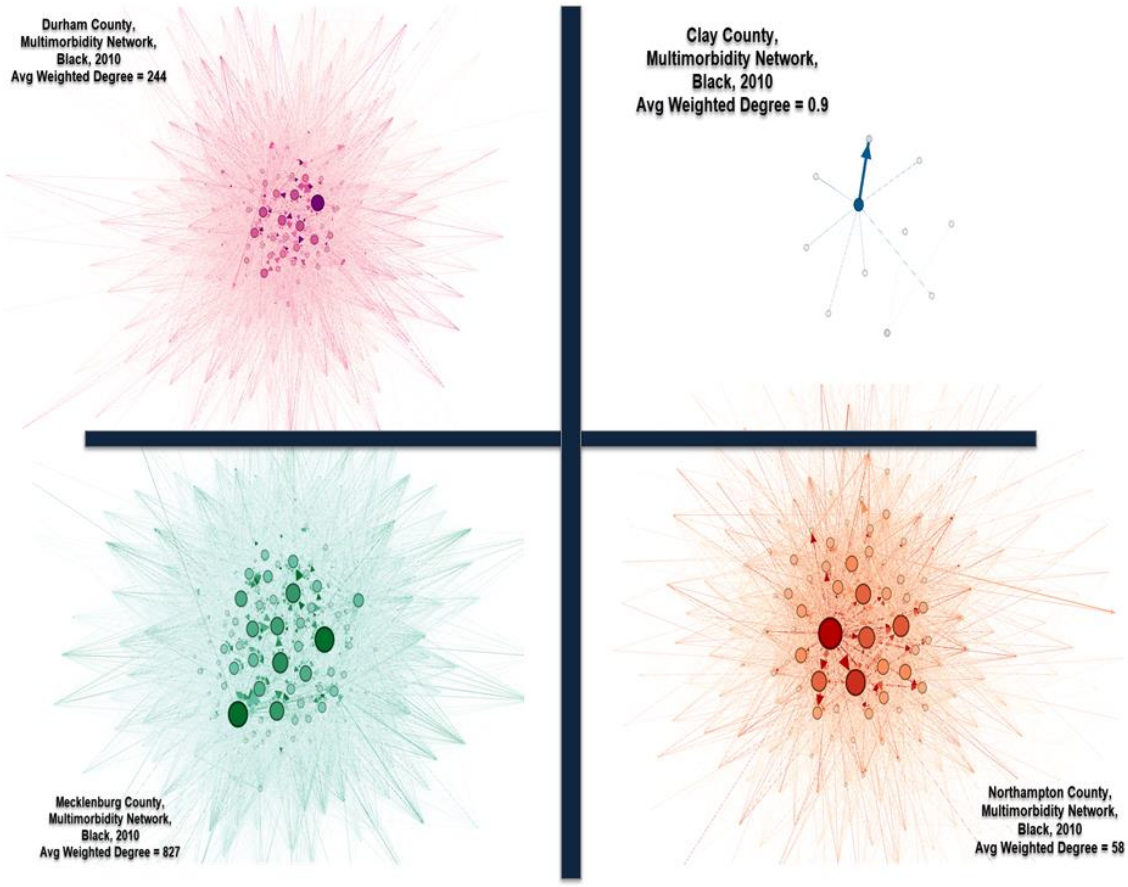


Figure 22. Multimorbidity Networks for Non-Hispanic Blacks in Durham, Clay, Mecklenburg and Northampton Counties, North Carolina, 2010. Source: Farrow-Chestnut 2018.

The main objective of the study was to employ quantitative network analysis as a novel way to characterize and help us understand multimorbidity patterns. The first task was to assess whether population level inpatient multimorbidity can be modeled as a network. The figures represent proof that population level inpatient multimorbidity was successfully modeled as a network. The county inpatient multimorbidity networks represent a "profile" of county multimorbidity for various demographic groups. This novel approach was applied to the study of global multimorbidity networks for each group and is shown in Figures 21 and 22. Networks represent multimorbidity of working age non-Hispanic whites, Hispanics and non-Hispanic blacks who resided in rural (Gaston and Clay) and urban (Mecklenburg) counties and were

admitted to community hospitals in 2010 (other subgroup networks are not shown for brevity). The nodes represent individual diagnosed diseases. The node stores the actual data for particular diagnoses and connects to another node. The larger nodes (darker shade) were the most prominent nodes in the final visualization. The actual nodes and edges can be observed visually in the smaller more rural county networks (Gaston and Clay Counties). Consider the very large multimorbidity network of Mecklenburg County; it is too dense to make any meaningful observations by eyeballing the graph. Therefore measures of overall network structure are necessary to make meaning out of the model. To explore the topological characteristics, such as nodes, edges and average weighted degree, properties were computed and presented in Tables 9 and 10.

To give a more complete picture of the number of diagnosed diseases (nodes), histograms of nodes where created to show the number of nodes in each group network model. The general idea behind a histogram is to divide the data set into ranges (or bins) of equal length which allows us to see the patterns in the data. Figure 23 shows the distribution of the number of nodes by gender. The ranges are on the horizontal axis and the frequency or incidence of each range is shown on the vertical axis. Although the distribution (curved line) looks similar, females had a higher frequency of between 220 – 230 nodes than males. All the histograms of node number for all demographic subgroups are contained in Appendix B.

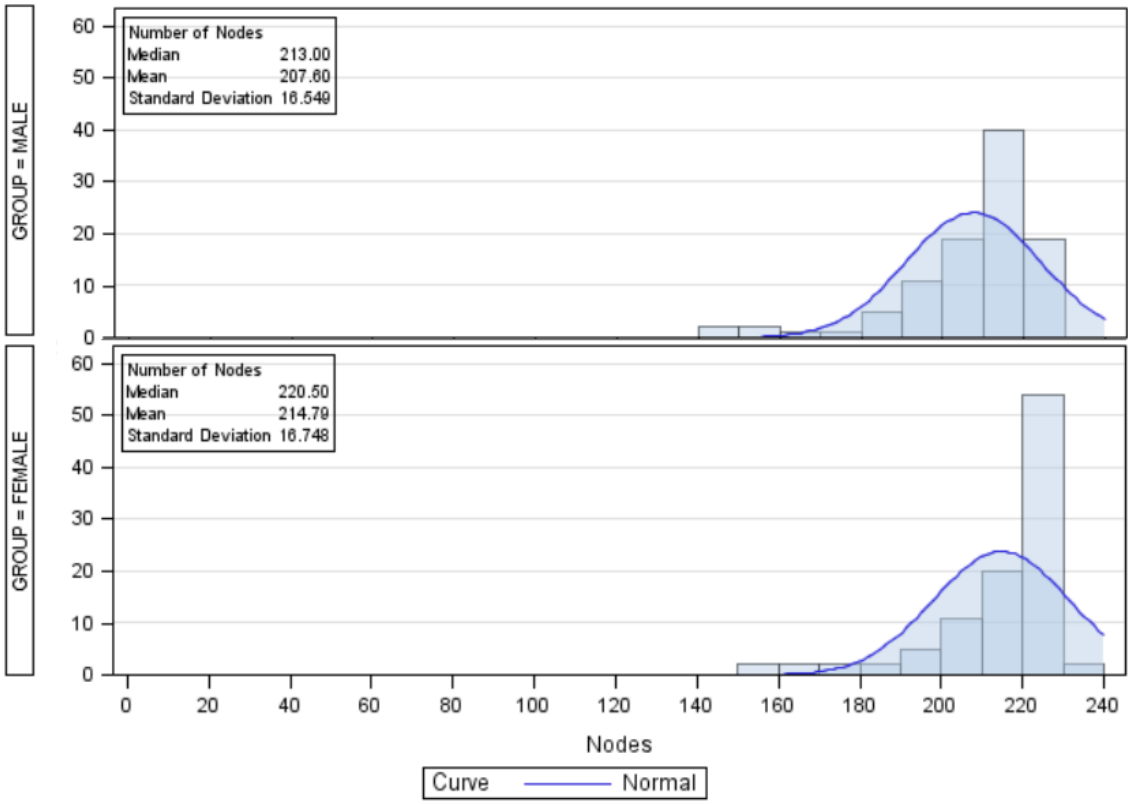


Figure 23. Comparative Histograms of the Number of Nodes for All Females and Males in 2010. Source: Farrow-Chestnut 2018.

Geographic pattern of Multimorbidity - Average Weighted Degree

Shown in Figures 24 and 25 are geographic patterns for female, male, race and ethnic group multimorbidity (average weighted degree) across counties in North Carolina. The general trend in North Carolina in 2010, was urban counties located in the center or piedmont region have higher average weighted degree (shaded darker) than more rural counties in the eastern part of the State and western mountains (shaded lighter) for sex, race and ethnicity. Additional maps of the geographic distribution of multimorbidity are contained in Appendix E.

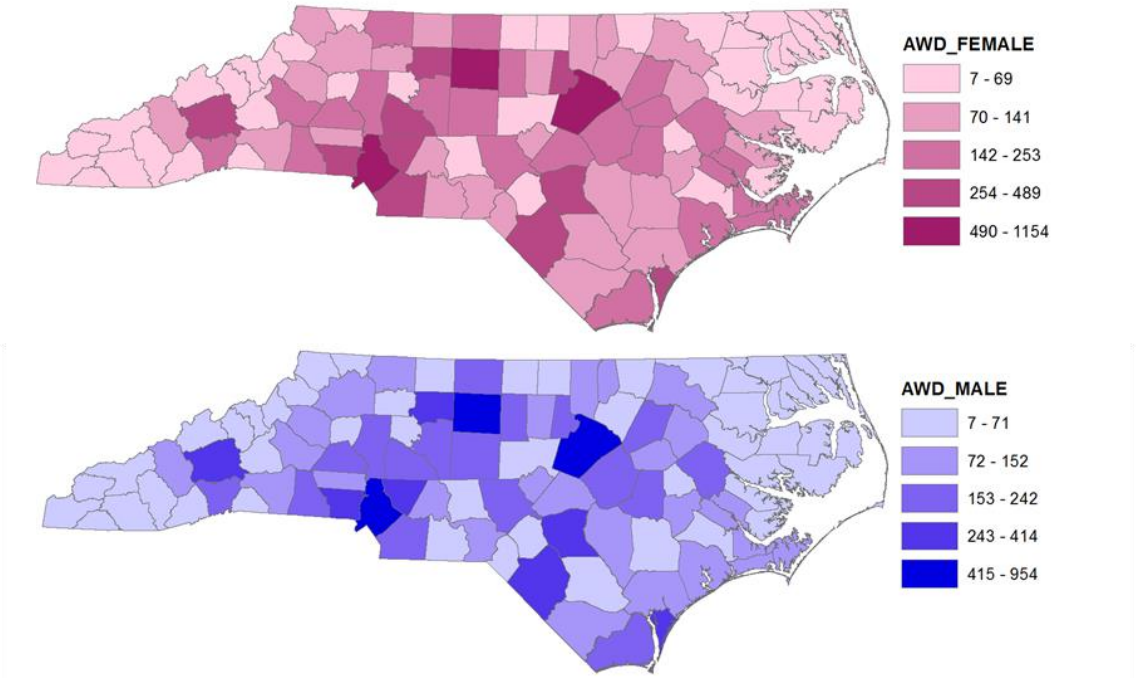


Figure 24. Spatial Distribution of Multimorbidity-Average Weighted Degree by Sex, North Carolina Counties in 2010. Source: Farrow-Chestnut, 2018.

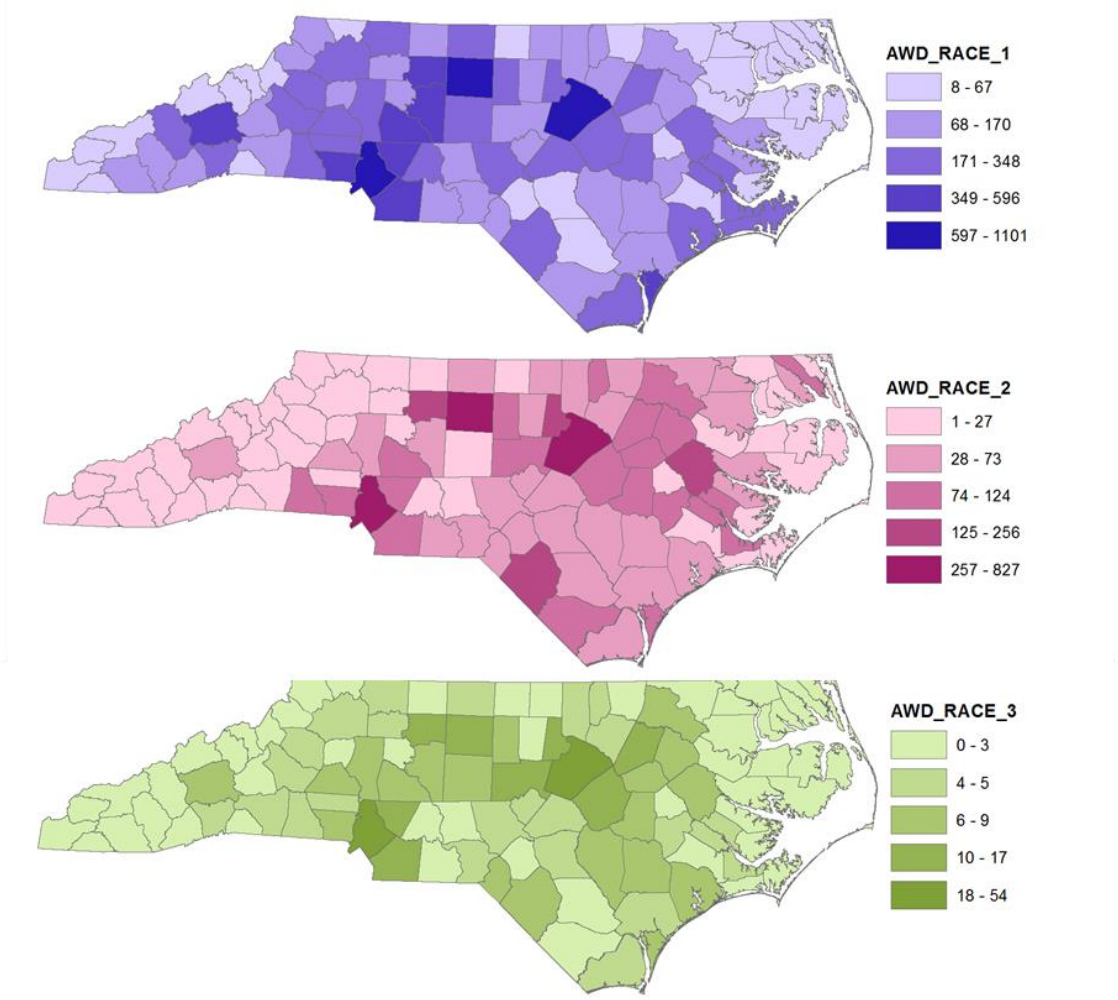


Figure 25. Spatial Distribution of Multimorbidity-Average Weighted Degree by Race/Ethnicity, North Carolina Counties, 2010. Source: Farrow-Chestnut, 2018.

Heart Disease Comorbidity Networks for Selected Counties

To test whether a quantitative network approach can be applied to the study of egocentric (comorbidity) networks for each subgroup (females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics), networks were constructed for rural (Martin, Yancey and Granville) and urban (Mecklenburg) counties and are shown in Figures 26 and 27. Coronary heart disease was selected as the index diagnosis (condition) and the multimorbidity network was filtered using node labeled 101 for coronary atherosclerosis. The attribute - closeness centrality was selected and nodes resized based on that attribute, and betweenness centrality was selected and nodes

recolored based on that attribute. The larger nodes are the most prominent and central nodes, having the highest number of edges (indicated by edge thickness). Node 98 - high blood pressure was the most prominent in both the female and male comorbidity networks. More nodes (conditions) were in the female comorbidity network (~13) as compared to the male comorbidity network (5). The dyad and triads were determined by the most prominent nodes and edge weight in the comorbidity network. The female network contained the dyad: high blood pressure/203 Osteoarthritis. The male network contained the triad: 98 high blood pressure/ 106 Cardiac dysrhythmias/108 Congestive heart failure; non-hypertensive.

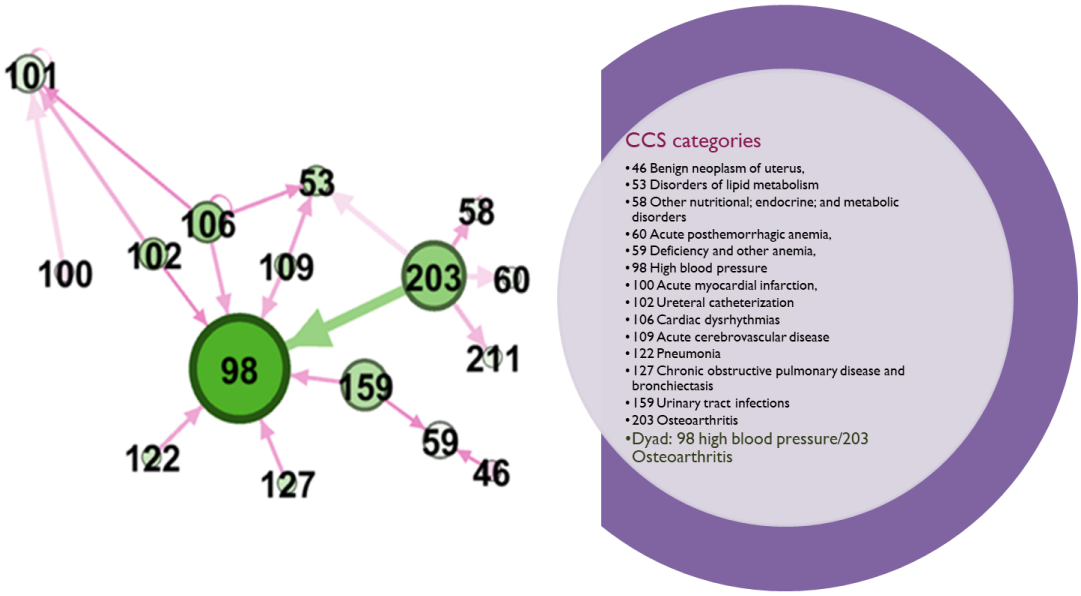


Figure 26. Coronary Heart Disease Comorbidity Networks for Females in Mecklenburg County, North Carolina, 2010. Source: Farrow-Chestnut, 2018.

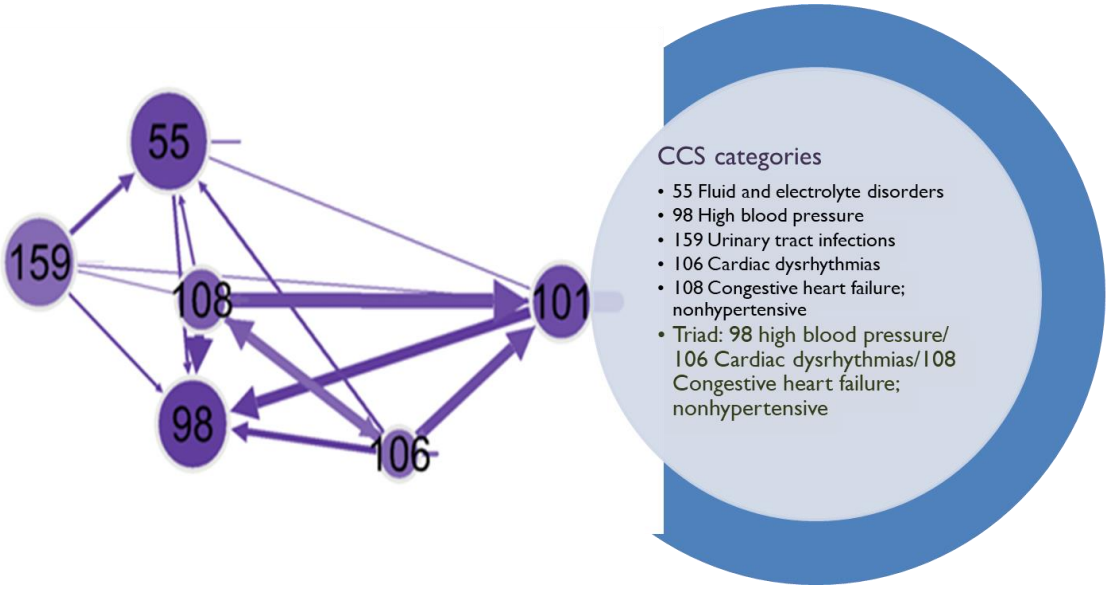


Figure 27. Coronary Heart Disease Comorbidity Networks for Males in Martin County, North Carolina, 2010. Source: Farrow-Chestnut, 2018.

To test whether a quantitative network approach can be applied to the study of egocentric (comorbidity) networks for non-Hispanic whites, non-Hispanic blacks and Hispanics, networks were constructed for rural (Yancey and Granville) and urban (Mecklenburg) counties and are shown in Figure 28. The same process for selecting the index condition and the most prominent nodes for gender was used for race and ethnicity. Node 657, 99 and 58 - were the most prominent nodes for non-Hispanic whites, non-Hispanic blacks and Hispanics comorbidity networks respectively. The comorbidity network for non-Hispanic blacks contained the highest number of nodes at 14. The dyad and triads were determined by the most prominent nodes and edge weight in the comorbidity network. The network for non-Hispanic whites contained the triad: 127 chronic obstructive pulmonary disease and bronchiectasis ~ 138 Esophageal disorders/ 657 Mood disorders/ 95 Other nervous system disorders. The network for non-Hispanic blacks contained the triad: 55 Fluid and electrolyte disorders/59 Deficiency and other anemia/99 Hypertension with complications and secondary hypertension. The network for Hispanics contained the triad: 50

Diabetes mellitus with complications/55 Fluid and electrolyte disorders/109 acute cerebrovascular disease. For the frequency of patients (n=), refer to Appendix V.

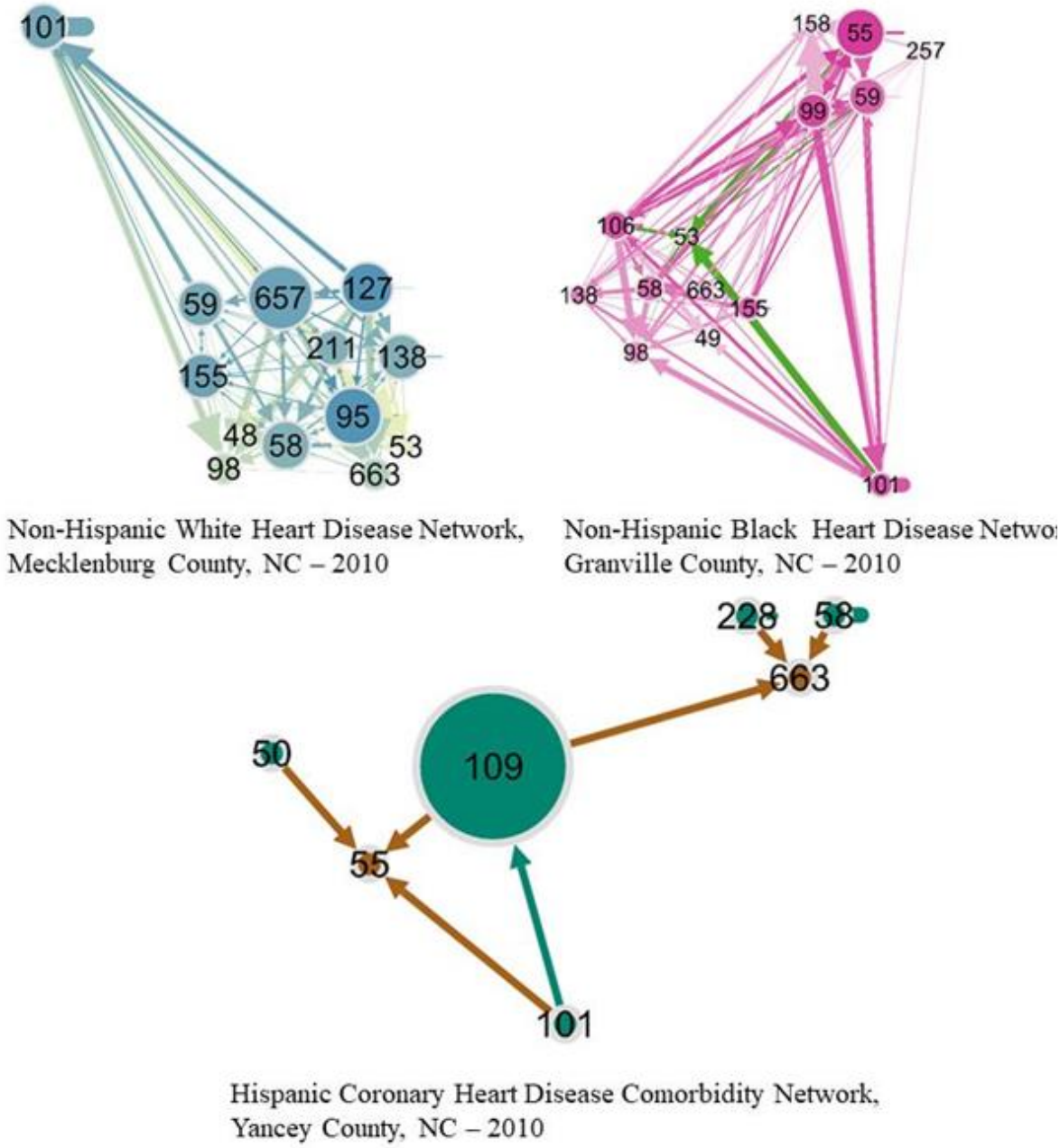


Figure 28. Coronary Heart Disease Comorbidity Networks for Non-Hispanic White, Non-Hispanic Black, And Hispanic for Selected Counties in North Carolina, 2010. Source: Farrow-Chestnut, 2018

The node labels and classifications are presented in Table 11 for race and ethnicity comorbidity networks.

Table 11. *Node Labels and Classifications for Race and Ethnicity Comorbidity Networks, Mecklenburg, Granville, and Yancey Counties, 2010.*

Non-Hispanic white coronary heart disease comorbidity network for Mecklenburg County:	
48 Thyroid disorders, 53 Disorders of lipid metabolism, 59 Deficiency and other anemia, 95 Other nervous system disorders, 127 Chronic obstructive pulmonary disease and bronchiectasis, 211 Other connective tissue disease, 138 Esophageal disorders, 155 Arthrocentesis, 211 Other connective tissue disease, 657 Mood disorders	*Triad*: 127 Chronic obstructive pulmonary disease and bronchiectasis ~ 138 Esophageal disorders/ 657 Mood disorders/ 95 Other nervous system disorders
Non-Hispanic black coronary heart disease comorbidity network for Granville County:	
49 Diabetes mellitus without complication, 53 Disorders of lipid metabolism, 55 Fluid and electrolyte disorders, 58 Other nutritional; endocrine; and metabolic disorders, 59 Deficiency and other anemia, 98 high blood pressure, 99 Hypertension with complications and secondary hypertension, 106 Cardiac dysrhythmias ,138 Esophageal disorders, 158 Chronic kidney disease, 663 Screening and history of mental health and substance abuse codes	*Triad*: 55 Fluid and electrolyte disorders/59 Deficiency and other anemia/99 Hypertension with complications and secondary hypertension
Hispanic coronary heart disease comorbidity network for Yancey County:	
50 Diabetes mellitus with complications, 55 Fluid and electrolyte disorders, 58 Other nutritional; endocrine; and metabolic disorders, 109 Acute cerebrovascular disease, 228 Skull and face fractures, 663 Screening and history of mental health and substance abuse codes	*Triad*: 50 Diabetes mellitus with complications/55 Fluid and electrolyte disorders/109 Acute cerebrovascular disease

Group Differences

The average weighted degree statistics for heart disease comorbidity networks by gender and racial/ethnic groups in 2010 were compared. T- tests determined whether the mean average weighted degree statistic for men differs significantly from the mean average weighted degree statistic for the women. The test statistics, associated degrees of freedom, and p-values are displayed in Table 11. The t-test results are highly significant. These values support the conclusion of a significant difference between male and female average weighted degree and differences between racial/ethnic average weighted degree.

Table 12. *T-test Results of Group Differences by Race and Gender*

Variables	*t-statistic*	*Degrees of Freedom (df)*	*p-value*	*Mean*
Non-Hispanic black & Non-Hispanic white	**-9.02****	98	<.0001	-2279.9
Hispanic & Non-Hispanic white	**-9.56****	72	<.0001	-3724.8
Hispanic & Non-Hispanic black	**-6.27****	72	<.0001	-798.8
Female & Male	**-8.8****	99	<.0001	-883.8

P < 0.05*, P < 0.001** statistical significance of the difference between gender, race and ethnicity multimorbidity (t-tests were performed for comparison of means).

Table 12 shows the results from the group test (ANOVA) performed to determine whether group means for the number of nodes and the average weighted degree differs significantly. There was a significant difference between the number nodes in male and female networks with female networks containing more nodes (215). There was a significant difference between the number of nodes in non-Hispanic white and non-Hispanic black networks with non-Hispanic white networks containing more nodes (223). No difference was found for the number of nodes in Hispanic networks compared to the networks of the other groups. There was

significant difference between Non-Hispanic white and Non-Hispanic black networks for average weighted degree with non-Hispanic whites having higher average weighted degree. There was no significant difference found between Hispanic networks and the other groups.

Table 13. *ANOVA Results of Group Differences by Race and Gender*

Network Measures	**Subgroups**				
	Male	*Female*	*Non-Hispanic white*	*Non-Hispanic black*	*Hispanic*
Nodes	**208***	**215***	**223***	**182***	112
Average Weighted Degree	124.2	145.0	**177.92***	**63.71***	4.57

P < 0.05*, P < 0.001** statistical significance of the difference between gender, race and ethnicity multimorbidity (ANOVA were performed for comparison of group means).

Geographic extreme values, hot spots and clustering. Shown in Figure 29 are percentile maps. A percentile map is a variant of a quantile map and is designed to highlight extreme values. Six ranges are created with the lowest 1% (shaded dark blue), 1-10%, 10-50%, 50-90%, 90-99% and the top 1% (shaded dark red). These maps are shown below for race and ethnic group multimorbidity (average weighted degree). The county with multimorbidity in the top 1% (shaded dark red) for all race and ethnic groups is Lee County, located in the central Piedmont region of the State. The county with multimorbidity in the lowest 1% for non-Hispanic whites is Hyde County, located on the coast, and for non-Hispanic blacks Madison County, located in the western-mountain region of the State. There was no county with multimorbidity in the lowest 1% for Hispanics. However Hispanics had the highest number of counties where multimorbidity in the 90-99% percent ranges (shaded medium-blue).

Based on discharge records in 2010, Mecklenburg, Guilford and Wake Counties had the highest average weighted degree for non-Hispanic white networks 595.59 – 1101.19 and for non-

Hispanic black networks 256.43 – 827.45 (shown in Appendix C). The significance map indicates that these two counties had significant local Moran statistics (LISA), for both non-Hispanic blacks and non-Hispanic whites. In other words the LISA maps show counties with ($p<.001$) high-high spatial clustering (hot spots or outliers) where values of average weighted degree were the highest.

The queen contiguity weights were constructed for this study. According to the queen criterion, selected observations have six neighbors. The values in Table 14 represent the actual correlation coefficients. The values are extremely low and not significant. This test does not reveal evidence of spatial autocorrelation—clustering. Additional LISA maps are shown in Appendix D.

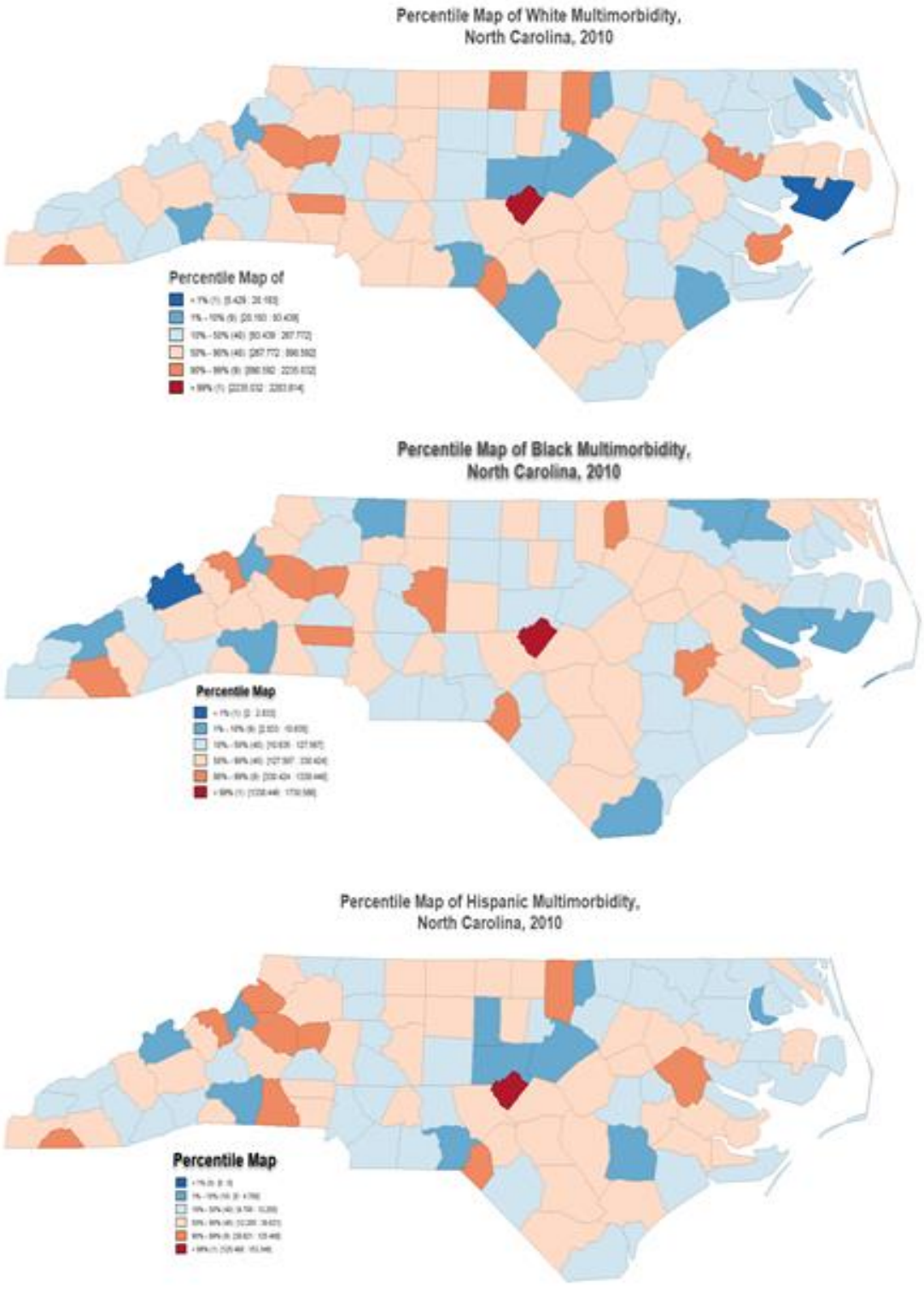


Figure 29. Percentage Maps of Multimorbidity by Race and County, North Carolina, 2010. Source: Farrow-Chestnut, 2018.

Table 14. *Spatial Autocorrelatioin, Contiguity Spatial Weights*

Global Moran's I			
	Queens Contiguity		
	δ-1	*δ-2*	*δ-3*
Gender			
Male	0.0158	0.0283	-0.0001
Female	-0.0056	0.0256	-0.0019
Race			
non-Hispanic white	0.0158	0.0311	-0.0036
non-Hispanic black	0.0098	0.0149	-0.0389
Hispanic	0.0768	0.0272	-0.0018
Other	-0.0461	-0.0233	-0.0182
Age			
Age 17-44	-0.0256	0.0349	0.0088
Age 45-64	0.0092	0.0141	-0.0095
Age 65+	-0.0001	0.0327	0.0013
Medical Coverage			
Private	0.0327	0.0356	-0.0081
Medicaid	-0.0075	0.0009	-0.0089
Medicare	-0.0147	0.0219	0.0017
Self-Pay	-0.0133	0.0309	-0.0076

Fit diagnostics, test of association and normality. All variables are represented in Appendix G. Histograms and normal Q-Q plots generated to estimate the probability distribution of all (continuous) variables and results show the relative contribution of all independent variables for each model (not shown). To test the relationship between each dependent and all ~88 covariates, bivariate analyses were performed. No associations were observed (results are shown in Appendix I). To describe the relationship between the set of dependent variables and independent variables, the OLS (Ordinary Least Squares) method was used to fit models. To shift through the large numbers of potential independent variables and determine the best subset

of variables among all possible subsets, stepwise regressions were performed. To find the best linear model includes minimizing the RMSE and maximizing R2. Model diagnostics were calculated for each model to help determine which model was "best". Model diagnostics include the root mean square error (RMSE) and the coefficient of determination (R2). Good linear models had low RMSE and a high R2 close to 1 (not shown). Interaction terms were computed, added, and skewed data transformed. Fit diagnostic performed for all models. Diagnostics for all other models displayed good fit and no non-linear patterns except for female and non-Hispanic black coronary heart disease models. Diagnostic results showed that the model fit the data poorly with non-linear patterns (shown in Appendix K and Appendix J). Normal Q-Q plot showed that residuals were not normally distributed. Pearson correlation measured the linear correlation between all dependent and independent variables. For example, supply variables (and others) showed positive linear correlation for female and male average weighted degree and are shown in Appendix H (n=1300 obs). All descriptive statistics, scatterplot output, Pearson Correlation coefficients, results of bivariate analysis, fit and outlier diagnostics are contained in Appendix K, L, M, N, O, P, Q. The results from the spatial regression are featured in Appendix S.

Coronary Heart Disease Comorbidity association with Risk Factors

Table 15. *Final Models of the Relationships between SDOH and Average Weighted Degree for Coronary Heart Disease Comorbidity Networks*

Significant factors - Independent Variables	*Dependent Variables*				
	Female AWD	Male AWD	Non-Hispanic white AWD	Non-Hispanic black AWD	Hispanic AWD
% HYPER_HOSP_DISC	22.23	---	---	---	---
% POVERTY	---	---	---	34.35	---
DIABETES_PREV	---	---	0.30	---	---
Hospital Beds 2010	---	---	---	---	-0.02
MCC _PCSpend_<65_2_3	-0.18	-0.24	---	---	---
MCC _PCSpend_All_>6	---	---	---	0.07	---
MCC _PCSpend_All_2_3	---	---	---	-0.35	---
OBESITY_PREV	0.058	0.09	---	---	---
OutpatVisitsGenHosp2010	---	---	---	---	-4.137E-05
Pers <65 with Health Insurance	---	---	---	---	0.00
TxcSite2012	215.16	364.39	657.01	---	---
Unemployed 2006-10	---	---	---	0.16	---
R^2	0.881	0.8975	0.7677	0.8424	0.8358

Note: The independent variables in the Hispanic Model are not statistically significant and have no influence on average weighted degree. Additional research required to model Hispanic CHD networks.

Final Models. Table 15 shows the results for the five multimorbidity (average weighted degree) models for the demographic groups. For the final model for females, the following independent variables were significant with average weighted degree: percentage of hospital discharges that were diagnosed with hypertension, actual per capita spending for Medicare beneficiaries less than 65 years old and have 2 to 3 multiple chronic conditions, the prevalence of obesity, number of toxic sites in 2012. The final model for males revealed that the following independent variables were significant with average weighted degree: actual per capita spending for Medicare beneficiaries less than 65 years old and have 2 to 3 multiple chronic conditions, the prevalence of obesity and toxic site locations in 2012. The final model for non-Hispanic whites revealed the prevalence of diabetes and toxic site locations in 2012 were significantly associated with average weighted degree. The model for non-Hispanic blacks showed that the percent of population in poverty, actual per capita spending for all Medicare beneficiaries with more than 6 multiple chronic conditions, 2 to 3 multiple chronic conditions, and the number of unemployed civilian labor force were significantly associated with the average weighted degree. Lastly, the model for Hispanic revealed that the number of hospital beds in 2010 was the only variable significantly associated with multimorbidity. Maps of the geographic distribution of significan variables in the final models are featured in Appendix F.

CHAPTER 5: DISCUSSION

Multimorbidity greatly increases the complexity of managing disease, suffering, expense and quality of life for the populations burdened with multiple chronic conditions and those that care for them. A better understanding of the interaction pattern of multimorbidity attributes and behavior may result in new insights. The goals of this dissertation were both exploratory and descriptive. To date, I am unaware of studies that employed quantitative network analysis and ESDA to study multimorbidity patterns. The aims were to supplement current understanding of multimorbidity with large-scale characteristics of multimorbidity networks and use ESDA to explore how multimorbidity varies at the sub-state or county level.

1. *Can networks characterize multimorbidity? If so, what is the content and structure of multimorbidity networks?*

Visualization of multimorbidity networks consisted of presenting network information in a graph format. This complex systems approach was implemented and multimorbidity networks were successfully rendered. Network analysis attempts to depict the entire burden of disease by collecting data on multiple occurring conditions within a defined population (Marsden, 1990). Borrowing from the field of epidemiology to explain the utility of graphs (Centers for Disease Control and Prevention [CDC], 2006), network graphs are an effective visualization tool to identify actual chronic conditions and their complex interconnections. Multiple chronic conditions were defined by diagnoses recorded in the SID and measure the capacity for conditions to connect at the same time, forming patterns and emergent structures. This construct was operationalized using the network property - average weighted degree.

Newman (2003) described how statistical methods such as degree distributions, describe what a huge network looks like since we can no longer just look at a big network and estimate its size. Consider the very large comorbidity network of Mecklenburg County; it is too dense to

make any meaningful observations by eyeballing the graph. Therefore measures of overall network structure are necessary to make meaning out of the model.

1. continued….If so, what is the content and structure of multimorbidity networks?

Network statistics are described in Tables 9 and 10 for all counties and represent the structure of the global multimorbidity disease networks by demographic groups (e.g., females, males, non-Hispanic whites, non-Hispanic blacks and Hispanics). On average the number of primary diagnoses (nodes) and connections (edges) between concomitant diagnoses for all females discharged from North Carolina hospitals were greater than males. On average the number of diagnoses and connections of Non-Hispanic white patients were greater than Non-Hispanic black patients, and Hispanic patients. These findings were consistent with the literature. Ward, Schiller, and Goodman (2014) and Gerteis, Izrael, Deitz, LeRoy, Ricciardi, Miller, and Basu (2014) observed that prevalence of multimorbidity varied by specific subpopulations. For example, the authors observed similar results in terms of gender prevalence: more women had more multiple chronic conditions compared with men, women were more likely than men to have 2, 3 or more conditions, women were nearly 2 times as likely to have arthritis or depression while men were less so. However, men were more likely to have ischemic heart disease (in the Medicare population). Among Medicare beneficiaries, the prevalence of multimorbidity was higher among non-Hispanic white adults. Among the noninstitutionalized, civilian US adult population, the prevalence of multimorbidity was higher among non-Hispanic white adults overall.

Jayasinghe, (2011) argues that systems within systems are interconnected, and their interactions are non-linear and lead to self-organizing and emergent properties. The author maintains that multiple levels of sub-systems or factors accumulate; from sub-cellular levels, individual, community, social group, country and global levels interact with exposure,

susceptibility and resistance. A complexity perspective views population health outcomes as an emergent property of dynamic interconnected systems.

2. What does an egocentric network study of cardiovascular/coronary heart disease reveal?

Coronary heart disease was selected as the index diagnosis (condition) and the multimorbidity network was filtered using the node labeled 101 for coronary atherosclerosis to generate the egocentric network for cardiovascular/coronary heart disease. Node 98 - high blood pressure was the most prominent in both the female and male comorbidity networks. More nodes (conditions) were in the female comorbidity network (~13) as compared to the male comorbidity network (5). The dyad and triads were determined by the most prominent nodes and edge weight in the comorbidity network. The female network contained the dyad: high blood pressure/203 Osteoarthritis. The male network contained the triad: 98 high blood pressure/ 106 Cardiac dysrhythmias/108 Congestive heart failure; non-hypertensive. These findings were consistent with those of Schäfer et al. (2010) who found that all patterns increase with the age of patients and that three patterns emerged: 1) cardiovascular/metabolic disorders, 2) anxiety/depression disorders and pain, and 3) neuropsychiatric disorders. The researchers concluded that about 50% of all persons belonged to at least one of those patterns, and gender differences are not always easily explained and might account for the different pattern compositions e.g., rheumatoid arthritis belongs exclusively to the female pattern.

The same process for selecting the index condition and the most prominent nodes for gender were similar to the most prominent for race and ethnicity. Nodes labeled 657, 99, and 58 were the most prominent nodes for non-Hispanic whites, non-Hispanic blacks and Hispanics comorbidity networks respectively. The comorbidity network for non-Hispanic blacks contained the highest number of nodes at 14. The network for non-Hispanic whites contained the triad: 127 chronic obstructive pulmonary disease and bronchiectasis ~ 138 Esophageal disorders/ 657 mood disorders/ 95 other nervous system disorders. The network for non-Hispanic blacks contained the

triad: 55 fluid and electrolyte disorders/59 deficiency and other anemia/99 hypertension with complications and secondary hypertension. The network for Hispanics contained the triad: 50 diabetes mellitus with complications/55 fluid and electrolyte disorders/109 acute cerebrovascular disease. Betancourt et al. found that members of minority groups suffered disproportionately from chronic conditions such as cardiovascular disease, diabetes, asthma, and cancer, among other conditions. The only group where diabetes appeared among the conditions listed as part of the comorbidity network was Hispanic. The NC CCDIHP examined North Carolina's inpatient hospitalization rates by race (Table 4) and found that non-Hispanic black hospitalization rates were higher than non-Hispanic whites (overall), for asthma, diabetes, kidney disease, and cardiovascular disease. This observation may be explained by the race and ethnicity composition of the county, proportion of the population that is insured or uninsured, age composition, and care for conditions such as diabetes. For example, if the proportion of African Americans is lower, there will be fewer African American patients admitted to the hospital than other groups resulting in an underestimation of utilization and chronic diseases diagnoses. The ethnic composition of the population of Granville County, NC is composed of nearly 60% non-Hispanic white, two times the proportion of non-Hispanic black residents (Deloitte, Datawheel, and Cesar Hidalgo, n.d.).

3. What do centrality measures such as betweenness reveal about the relative importance of conditions?

Node 98 - high blood pressure was the most prominent in both the female and male comorbidity networks. Node 657, 99 and 58 - were the most prominent nodes for non-Hispanic whites, non-Hispanic blacks and Hispanics comorbidity networks respectively. Node 657 are classified as mood disorders, 99 hypertension with complications and secondary hypertension, and 58 other nutritional; endocrine; and metabolic disorders. Results showing that nodes 98 and 99 are the most prominent are consistent with findings in the literature. Cardiovascular (CVD)

disease is the most common cause of mortality in developed countries. The Centers for Disease Control and Prevention [CDC] (2017a) estimates that nearly 610,000 people die of heart disease in the United States every year, representing 1 in every 4 deaths. Heart disease is the leading cause of death for both men and women. More than half of the deaths due to heart disease in 2009 occurred in men. Table 3 shows the percentages of all deaths caused by heart disease and by ethnicity in 2008. Table 2 displays the results of Ward and Schiller's review of the literature regarding the most prevalent chronic condition combinations. The authors found that for both women and men ages 45 to 64 years and 65 years and older, arthritis/hypertension and diabetes/hypertension were the most prevalent combinations followed by diabetes/hypertension,

In this study, degree and betweenness are the measures used to characterize multimorbidity and are the focal properties of this study. Degree is traditionally defined as the number of connections a node has and refers to the number of connections a condition has to other conditions. According to Boccaletti, Latora, Moreno, Chavez, and Hwang (2006), identifying which conditions are connected and which are central will enhance our ability to represent the complex interactions between and among conditions, complementing traditional analytical techniques and potentially discovering new insights. In this case, nodes 657 (mood disorders) was unexpected. However, after careful review, Lochner, Goodman, Posner, and Parekh (2013) included depression as part of the set of 15 conditions (the standard set promoted by HHS). Other chronic conditions included: Alzheimer's and related dementia, heart failure, hyperlipidemia, hypertension, ischemic heart disease, osteoporosis, and stroke to characterize whether Medicare beneficiaries had multimorbidity.

4. How does the network measure -average weighted degree of multimorbidity change or vary geographically?

The spatial differentiation in the multimorbidity networks is vital to revealing potential location specific social determinants of health, geographic variation, socioeconomic status, and

environmental risk factors. Figures 24 and 25 contain maps of the geographic patterns of multimorbidity (average weighted degree) for female, male, race and ethnicity groups across North Carolina counties. The general trend in North Carolina in 2010 was urban counties located in the center or piedmont region had higher average weighted degree (shaded darker) than more rural counties in the eastern part of the State and western mountains (shaded lighter) for sex, race and ethnicity. Mecklenburg, Guilford and Wake Counties had the highest average weighted degree for non-Hispanic white networks and for non-Hispanic black networks (shown in Appendix C). The LISA maps show (shown in Appendix D) values of average weighted degree were the highest for counties representing high-high spatial clustering (hot spots or outliers). The findings regarding the trend in North Carolina to have higher average weighted degree for counties located in the central Piedmont region of the State is consistent with findings of the NC CCDIHP which reported that chronic disease mortality patterns also differ geographically in North Carolina. The eastern regions of the State and the southern Piedmont regions (between the Atlantic Coastal Plain and the Appalachian Mountains) tend to consistently have the highest age-adjusted mortality rates. According the NC CCDIHP, these same counties (in the eastern part of North Carolina) often have high concentrations of poverty (as shown in Figure 8) and larger minority populations. Lochner et al. (2013) recognized that while studies have highlighted the important issue of multimorbidity for healthcare, characterizing geographic variations are effective for targeting service delivery, resource projections, and program planning.

5. How does average weighted degree of cardiovascular/coronary heart disease networks change or vary geographically?

Casper, Kramer, Quick, Schieb, Vaughan, and Greer, S. (2016) observed dramatic changes in the geographic patterns of heart disease mortality from 1973 to 1974, 2009 to 2010 for those aged 35 years and older. The authors detected that a substantial shift occurred in the concentration of high-rate counties from the Northeast to the Deep South. Although counties in

the South experienced a slow-decline, a nearly 2-fold increase in geographic inequality among counties was reported (as shown in Figure 7). Small-area surveillance of heart disease mortality is important because it can reveal patterns that are masked at the national level, and provide communities the historical context for understanding their current burden of heart disease (Casper et al., 2016).

Coronary heart disease (CHD) is the most common type of heart disease, killing over 370,000 people annually. Figure 6 shows the geographic variation by county. Counties such as Scotland, Pitt, Columbus and Bladen in North Carolina had the highest rates (per 100,000) of death for adults 65 years and older (indicated by dark red) (CDC, 2017a).

6. How might the structure of multimorbidity networks influence interventions and programs?

Grembowski, Schaefer, Johnson, Fischer, Moore, Tai-Seale, ... & LeRoy (2014) build on the AHRQ multimorbidity model and their version (shown in Figure 10). Contextual factors and their influence are represented with dashed line boxes and arrows. The authors described the size of the need-services gap as related to patient needs, system capacity, and the interaction between them. On the person and social support side (left side of Figure 10), the number, severity, and duration of a person's chronic conditions affect the level of need, as well as other conditions. The authors argued that characteristics such as age, gender, socioeconomic status, race, ethnicity, values, and preferences, impact the need even further. Often self-management is compromised for individuals with multimorbidity. Self-management is essential for optimal health outcomes and with inadequate social support, needs increase. The authors concluded that prevalence of multimorbidity is not distributed randomly but is instead concentrated in older individuals, families, and vulnerable communities (Grembowski et al., 2014).

The AHRQ multimorbidity conceptual model is an ecological model that emphasizes the interconnectedness of component elements. At the center, "complexity" is defined as the gap

between the major system components: an individual's needs and the capacity of healthcare services to support those needs. Because this model focuses on health care, this relationship is the heart of the conceptual model. However, health and healthcare are always influenced by the broader context, such as social determinants of health and healthcare policies that create economic incentives or disincentives. Part of the healthcare system's ongoing effort is to improve care for patients with multimorbidity through evidence-based research.

Multimorbidity creates a real challenge for research because of its complexity. The aging of the population and the stress involved in creating and adhering to multifaceted treatment programs, makes managing multimorbidity a complex problem for patients, their families as well as for clinicians and systems that serve them (Grembowski et al., 2014). However, guidelines and evidence-based disease management programs focus on single diseases. Therefore, research on multimorbidity requires a shift from a reductionist single-condition paradigm to one that accounts for the inherent complexity of multimorbidity (Grembowski, et al., 2014).

Information from measures such as average weighted degree and betweenness characterize multimorbidity and define the network structure, function, and are suitable inputs for health promotion strategies designed to build healthy public policy, create supportive environments for health, strengthen community action, develop personal skills, and re-direct health services (WHO, n.b.c). Focusing resources can alter the topology of multimorbidity network (e.g. feedback loop). In a complex system, a feedback loop is where change in a variable results in either increase (positive feedback) or a decrease (negative feedback) of that change (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, ... & Lai, 2012). For example, through past programs like the CDC's Healthy Communities Program, community-based solutions were essential to effectively preventing chronic disease and to maintaining the best possible health among persons living with chronic illnesses. In 2014, CDC awarded $49.3 million to 39 awardees representing designated geographic areas (CDC, 2014).

By focusing current resources on developing both community and individual capacity to address the unique needs of those with multimorbidity, intervention measures and programs can increase capacity resulting in improved self-management , and connections of individuals, family and friends to available resources (positive feedback). Therefore, measuring network structure and studying degree has implications for targeting intervention measures and programs, improving efficiency and effectiveness.

7. What directions might future research on multimorbidity networks and health in low income communities take?

Bell and Saraf (2016) found that the increasing prevalence of co-existing disease processes in the aging population adds to the complexity and challenges facing patients with CVD and the providers that care for them. The authors maintain to properly diagnose and manage CVD in older adults requires the following:

- a thorough understanding of the intersection between patient differences (heterogeneity)
- the accumulation and interactions of chronic and acute conditions

WHO (n.d.a) estimates that most cardiovascular diseases can be prevented by addressing behavioral risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol if population-wide prevention and interventions strategies are used. Additionally, HHS's framework seeks to "catalyze change" and usher in a "paradigm shift", while motivating researchers to discover the "constellations of conditions" (e.g., dyads and triads) (HHS, 2010, p.1). My aim was to build on earlier contributions by examining county level patterns using county level data (with less exclusion) and present a technique for observing constellations of multimorbidity conditions. As a result, a new framework was proposed -- *Multimorbidity Average Weighed Degree Conceptual Framework* (Farrow-Chestnut, 2018). The framework shows the relationship between patient gender, race and ethnicity, SDOH, rural and

urban geography, complexity and quality of care, and the patient's number of chronic conditions, and how factors increase multimorbidity average weighted degree. Disease combinations differ by age and gender.. Patient's age, gender, race and ethnicity interact with SDOH because members of minority communities tend to be more socioeconomically disadvantaged; have lower levels of education, which increases the likelihood that the only jobs available have higher rates of occupational hazard; and pushes vulnerable groups to live in areas with greater environmental hazards than members of the majority population. Differences in poverty, low SES, and lack of access to care, exists along gender, racial and ethnic lines adding yet another layer of complexity. Residential concentration of African Americans is associated with inequities in communities, socioeconomic circumstances; and medical care. SDOH shapes complexity and quality of care because the amount of money, power, and resources that people have, influences access to health services and the quality of those services. SDOH interacts with the quality of care and quality of care influences multimorbidity both negatively and positively.

The multimorbidity burden is not distributed equally among rural and urban counties, making geography associated with disease burden an indicator for selected health determinants (e.g., socioeconomics, personal behaviors, and environments) and the prevalence of chronic conditions. With an increase in number of conditions, there is an increased likelihood that one or more conditions occur more frequently (e.g., dyads and triads), which increases the complexity and generates quality of care challenges.

8. Are there gender and racial/ethnic differences in cardiovascular/coronary heart disease networks?

Differences were detected in gender and racial/ethnic networks. Table 12 shows the results from the group test (ANOVA) performed and there is a significant difference between the number of nodes in male and female networks, with female networks containing more nodes. There was a significant difference between the number of nodes in non-Hispanic white and non-

Hispanic black networks, with non-Hispanic white networks containing more nodes. No difference was found for the number of nodes in Hispanic networks compared to the networks of the other groups. There was significant difference between Non-Hispanic white and Non-Hispanic black networks for average weighted degree with non-Hispanic whites having higher average weighted degree. There was no significant difference found between Hispanic networks and the other groups. Some results were unexpected for example, no difference was found between Hispanic networks and the other groups. According to Ward, Schiller, and Goodman (2014), prevalence of multimorbidity varies by specific subpopulations. For example, the proportion of a population with multiple chronic conditions was higher among non-Hispanic white adults, non-Hispanic black adults, and non-Hispanic adults of other races than among non-Hispanic Asian adults and Hispanic adults. One possible explanation is the quality of the race variable in the 2010 SID and missing observations.

North Carolina resumed providing the race and ethnicity variable beginning in 2010. Beginning in fourth quarter 2010, the race and ethnicity data values changed. Although the group impacted the mot were patients who identified as American Indian/Alaskan Native, Asian, and Native Hawaiian/Pacific Islander, it is likely that this problem affected the accuracy of the SID for 2010 and results for Hispanics may be underestimated.

By focusing on the powerful role of social factors in shaping health across a wide range of health indicators, settings, and populations, this research has clearly exposed (HHS, 2010) gender and racial/ethnic differences in multimorbidity at the county level.

9. What is the relationship between the underlying factors and the average weighted degree of heart disease networks?

Relationships exist between underlying factors and the average weighted degree of heart disease networks. Table 13 shows the results for the five multimorbidity (average weighted degree) models for female, male, non-Hispanic white, non-Hispanic black and Hispanic.

Hypertension, spending for Medicare beneficiaries 65 and younger with 2 to 3 multiple chronic conditions is inversely associated, obesity, and number of toxic sites in 2012 are associated with average weighted degree of females. Spending for Medicare beneficiaries 65 and younger with 2 to 3 multiple chronic conditions inversely associated, obesity and toxic site locations significantly associated with average weighted degree of males. Diabetes and toxic site locations were the only risk factors found significantly associated with the average weighted degree of non-Hispanic whites. Poverty, spending for all Medicare beneficiaries with more than 6 multiple chronic conditions (is not inversely associated) and 2 to 3 multiple chronic conditions (is inversely associated); and unemployment are significantly associated with non-Hispanic blacks. Lastly, in the Hispanic model: the number of hospital beds in 2010 is the only variable significantly associated with the average weighted degree of Hispanics.

The NC CCDIHP examined North Carolina's inpatient hospitalization rates by race (Table 4). They found that non-Hispanic black hospitalization rates were higher than non-Hispanic whites (overall), for asthma, diabetes, kidney disease, and cardiovascular disease. While this may be one of several explanations for the results of the final average weighed degree egocentric (comorbidity) model for non-Hispanic blacks, the causes of disparities are multifactorial and perhaps the largest contributors are those related to social determinants of health. Williams (1999) found that members of minority communities tend to be more socioeconomically disadvantaged, have lower levels of education, which increases the likelihood that the only jobs available have higher rates of occupational hazard; live in areas with greater environmental hazards (such as air pollution and toxic waste sites) than members of the majority population. Figure 3 summarizes the SDOH conceptual model.

Health outcomes such as multimorbidity are shaped by the amount of money, power, and resources that people have, and ultimately influenced by policy (Healthy People.gov, n.d.). Additional factors that may explain the findings include:

- How a person develops during the first few years of life (early childhood development)
- How much education a person obtains - which is linked to unemployment with insurance, access, utilization, and poverty
- Having food or being able to get healthy food (food security) which is linked to obesity
- Having access to health services and the quality of those services – which is linked to the availability of hospital beds
- How much money a person earns
- Discrimination and social support (Healthy People.gov, n.d.)

According to Healthy People 2020 (Healthy People.gov, n.d..), health starts in our homes, schools, workplaces, neighborhoods, and communities and is also determined in part by access to social and economic opportunities; the resources and supports available in our homes, neighborhoods, and communities; the quality of our schooling; job tasks and workplace safety; the cleanliness of our water, food, and air; and the nature of our social interactions and relationships.

Differences in urban – rural counties

In 2010, North Carolina had the 17th-largest rural population in the nation (U.S. Census, n.d.), where 80 counties had population densities of 250 people per square mile or less. These counties were home to slightly more than 4 million people (45 percent of the state population). Regional cities or suburban counties consisted of 14 counties with population densities between 250 and 750 people per square mile. These counties accounted for approximately 2.4 million people (25 percent of the state population). Six counties were considered urban with population densities of more than 750 people per square miles and accounted for nearly 3.1 million people (33 percent of the state population).

There are several different ways to measure rurality and rural-urban comparisons using different definitions. Because the data used for this study were available at the county level and

sociodemographic, health factors, and SDOH variables were from the U.S. Census, CDC and Area Health Resource File, population density was used. Population density is a measure of average population per square mile (U.S. Census, n.d.). This independent variable was significant in the bivariate models (see Appendix O) but was not significant in the multivariate analysis after additional controls were included and was dropped from the final model. However, because health disparities and access to care in urban - rural analysis are central issues, an overview of urban rural differences is discussed.

According to Knopf (2018), hospitals and physicians are scarce in rural areas and residents have a more difficult time accessing healthcare. Most rural residents are older and poorer, more isolated, and have higher mortality. According to Holmes (2018), rural areas of North Carolina have higher rates of drug and alcohol use, suicide, years in productive life lost, injury, teen births, uninsured patients and preventable hospitalizations. These communities also have fewer places to exercise, such as parks, greenways and gyms. According to the interactive North Carolina Health Professions Data System, 20 counties did not have a pediatrician; 26 counties did not have an OB-GYN; and 32 were without a psychiatrist (Holmes, 2018). There were five rural hospital closures in North Carolina since 2010.

Clawar, Randolph, Thompson, Pink (2018) maintain that rural populations have more limited access to health care compared to urban areas. Generally, this disparity indicates a lack of access to primary care. Primary care typically serves as the initial contact with providers and includes services such as health promotion, health maintenance, disease prevention, counseling, patient education, and diagnosis and treatment of acute and chronic illnesses (Clawar et al., 2018). With access to primary care limited and fewer physicians available in rural communities, patients are more likely to receive less preventive care and have higher rates of illness and premature death.

Results show that urban counties had higher average weighted degree for female, male, race and ethnic groups than rural counties. Despite the physician shortage and hospital closures, results were in the direction expected given small numbers in rural locations and missing data at the zip code level. However, the possibility exists that the results exhibit bias (due to data accuracy) and therefore underestimate the occurrence of multimorbidity in rural hospital settings. In addition, the major teaching hospitals are located in urban counties such as Forsyth, Durham, Wake, Pitt and Mecklenburg Counties, and may overestimate multimorbidity (multiple chronic conditions diagnoses) given higher numbers of primary physicians and better quality of care compared to non-teaching hospitals in more rural counties (Allison, Kiefe, Weissman, Person, Rousculp, Canto,... & Centor, 2000).

Speculation on the Impact of the Affordable Care Act

The Affordable Care Act (ACA or the Act), President Obama's signature health care reform law was enacted into law in 2010. The Act emphasized disease prevention and many of the 10 major titles in the law, especially Title IV, Prevention of Chronic Diseases and Improving Public Health (Protection, P., & Act, A. C., 2010), supported a prevention theme through a wide variety of initiatives and funding efforts (Koh & Sebelius, 2010). Cross sectional studies such as this study are of limited use in describing longitudinal phenomena such as changes in health insurance status. While the ACA has no impact on the study results (e.g., the NC SID was collected in 2010 the year health care reform became law) and is not central to the hypotheses, the law the most impactful policy reform since Medicare and Medicaid and is worthwhile speculating on potential future impacts on multimorbidity of gender and racial and ethnic groups.

Health care access and insurance coverage were major factors that contributed to racial and ethnic disparities before the ACA implementation. According to Chen, Vargas-Bustamante, Mortensen and Ortega (2016) racial and ethnic disparities in access were reduced significantly during the initial years of the ACA implementation in 2014, which expanded access and

mandated that individuals obtain health insurance. According to Kennedy, Wood, and Frieden (2017), the ACA included multiple provisions that were intended to improve access and affordability for working-age adults, including those with disabilities. Specifically, with the creation of state and federal health insurance marketplaces and the expansion of Medicaid in participating states, coverage options were expected to improve for working-age adults. Preliminary studies confirmed that insurance coverage for select subgroups of adults with chronic conditions improved following full implementation of the ACA in 2014 (Kennedy, Wood, & Frieden, 2017) and gains were larger in expansion states (Griffith, Evans, & Bor, 2017). North Carolina was among 25 states that did not expand Medicaid. Garfield, Damico, Stephens, and Rouhani (2016) revealed that adults left in the "coverage gap"; because they had incomes above Medicaid eligibility limits but were still considered poor or working poor, were spread across states that did not expand their Medicaid programs and concentrated in states with the largest uninsured populations such as North Carolina - where nine percent (9%) of all people in the coverage gap resided.

Torres, Poorman, Tadepalli, Schoettler, Fung, Mushero, ...and McCormick (2017) found all outcomes varied considerably by state, and coverage increased more in states that expanded Medicaid. Although racial/ethnic minorities had greater improvements in some outcomes, approximately 1 in 5 African-Americans and 1 in 3 Hispanic persons with a chronic disease continued to lack coverage and access to care after ACA implementation.

Given these findings, it is unclear how the ACA would impact average weighted degree of racial and ethnic groups in North Carolina if the study were performed post implementation. The fact that the State has not expanded Medicaid as of the writing of this study makes it more likely that the average weighted degree results for African-American and Hispanics would be higher in urban and rural counties because persons with multiple chronic diseases would fall into the coverage gap and lack coverage and access to care.

In North Carolina, too many women are uninsured, especially in communities of color. Approximately 636,000 women, nearly 30% of North Carolina women, were uninsured in 2011. According to the National Women's Law Center (2012), the numbers were even higher for women of color. In North Carolina, 25.6% of African-American women and 51.5% of Hispanic women were uninsured compared to 15.3% of white women prior to the ACA implementation. Women who were able to buy health insurance on the individual market often paid more than men for the same coverage, a practice known as "gender rating", which accounted for 100% of the plans practiced in North Carolina. Individual market insurance plans often did not cover all of the services women needed and no individual market plans covered maternity care in North Carolina prior to implementation. According to Garfield and Damico (2017), even though women were more likely than men to qualify for Medicaid in states that did not expand their programs, women accounted for nearly the same share (48%) of adults in the coverage gap. This pattern occurs because women made up the majority of poor adults in states that did not expand their Medicaid programs including North Carolina.

Given these findings, it is unclear how the ACA would impact average weighted degree of women in North Carolina. Again, since the State has not expanded Medicaid women would continue to make up the majority of poor adults in North Carolina. If the study were performed today, it is more likely that the average weighted degree results of women, especially women of color, would be higher than men in urban and rural counties because women are more likely than men to qualify for Medicaid and account for nearly the same share of adults that fall into the coverage gap; in addition to the fact that uninsured rates for women of color have been higher than uninsured rates for white women historically.

Limitations

Variations are difficult to model. Interactions and connections are complex, and stochastic (showing randomness) models permit researchers to capture both the regularities in the

processes, generating network edges and recognize there is variability which is difficult to model with any detail. Different underlying processes may make similar qualitative predictions about network structures. Golbeck (2013) argued there are 2 levels of analysis – graph and node. To know more about the underlying process, researchers must focus the study at the node level, which may require qualitative investigations. Another network related limitation is the issue of inferring causality from the pattern layout of the interactions. Danks, Fancsali, Glymour, and Scheines (2010) argued that even simple associations cannot be used reliably to estimate causal relations; they ignore the assumption of conditional independent relations, generate measurement errors, confounding, and they give no direction to causal relations when they exist.

Modifiable area unit problem (MAUP) and ecologic fallacy. A serious limitation of the study is that the findings may vary with geography due to the "modifiable area unit problem (MAUP)" (Openshaw, 1989). Geographic units of analysis are problematic in the study of macro-social determinants because of the tendency toward aggregation bias (Kearney and Kiros 2009). Aggregation bias occurs when analyses are sensitive to changes in scale. MAUP is a potential source of error that can affect spatial studies which utilize aggregated data sources because the results are likely to vary with the level of aggregation (scale) and with the configuration of the zoning system (Fotheringham & Wong, 1991). The MAUP consists of both a scale and a zoning problem. The scale problem is relatively well known. It is the variation which can occur when data from one zoning system (state, county, city, census tract, etc.) is grouped into more or less areal units. Grouping data at various levels of spatial resolution will inevitably lead to variation in results which may lead to misinterpretation of the findings. For example, much of the variation in cities and towns are lost when the data are aggregated to the county level (Beale, Abellan, Hodgson, & Jarup, 2008).

Fotheringham and Wong (1991) argued that the modifiable areal unit problem produces unreliable results in the multivariate analysis of data drawn from areal units (e.g. in this study

county level data). The authors recommend reporting results at different levels of aggregation or avoid the use of aggregated data when possible but acknowledge that neither solution is viable (especially in health services research and health geography). Fotheringham, Charlton, and Brunsdon (1998) later showed that the statistical techniques such as geographically weighted regression (GWR) can be used both to account for and to examine the presence of spatial nonstationarity in relationships. The authors explain that in spatial analysis the data are drawn from geographical units and a linear regression equation is estimated. This analysis produces "average" or "global" parameter estimates which are assumed to apply equally over the whole area being studied. The relationships being measured are assumed to remain stationary over space and if not, exhibit spatial nonstationarity (where the "global" model cannot explain the relationships between variables). In other words, the nature of the model changes over space to reflect the structure or pattern inherent within the data (Brunsdon, Fotheringham & Charlton, 1996). This makes it difficult to interpret parameter estimates from a regression model.

Brunsdon, Fotheringham, and Charlton, (1996) successfully demonstrated GWR. The authors noted that all types of spatial analysis were subject to edge effects and GWR was no exception. GWR, or spatial statistics, is a local form of linear regression and is used to model spatially varying relationships. This spatial analysis technique takes non-stationary variables into consideration (e.g., social determinants of health, demographic factors; geographic location such as county) and models the local relationships between these predictors and an outcome of interest (e.g., average weighted degree). Spatial statistics was necessary in this study and was performed as part of the spatial regression analysis and a brief overview was provided in the Exploratory spatial data analysis (ESDA), Geographic Analysis, Spatial autocorrelation and multicollinearity sections.

Beale, Abellan, Hodgson, and Jarup (2008) recommend that results obtained from purely aggregate data (ecologic) should not be used to make assumptions about the nature of association

at the individual-level. Such assumptions may result in “ecologic fallacy”. Using small area data reduces some of the bias but does not completely eliminate bias since small area studies allow local effects. As a result, aggregated data may be more accurate because misclassification has less of an influence than misclassification in individual case studies (Beale, et al. 2008). Elliott and Wartenberg (2004) maintained that aggregation errors proliferate when researchers equate environmental exposure with biologic dose, current exposure with past exposure, and group exposure with individual exposure.

Data accuracy and exclusion. From a data perspective, the most important limitations of the study are related to hospital data accuracy and exclusion. As cited in Andrews (2015), the limitations fall into three types: (1) quality of data elements, (2) missing data elements, and (3) excluded populations (or selection bias). Delgado-Rodriguez and Llorca (2004) argue that selection bias occurs when the kind of patients gathered does not reflect cases in the population (external validity). For example, as the population ages, older and sicker people are admitted to hospitals, uninsured healthy groups use fewer services (and insured use more services), or uninsured groups are severely ill when diagnosed and receive less care (Hong, Holcomb, Bhandari, & Larkin, 2016; Hadley, 2003). Another issue occurs when clinical databases are regional or include areas with large referral centers (i.e. cancer centers), making findings less applicable to the general population (Delgado-Rodriguez &Llorca, 2004) such as Mecklenburg and Wake Counties where large trauma centers and or teaching hospitals are located.

Bias. Exclusion bias results from exclusion of particular groups from the sample, e.g. exclusion of subjects who have recently migrated into the study area (this may occur when newcomers are not available in a registry is used to identify the source population), or the changes that were made to the race and ethnicity variable in North Carolina beginning in 2010. Other forms of bias include Healthy user bias and Berkson's fallacy. Healthy user bias (Shrank,

Patrick, & Brookhart, 2011) occurs when the study population is likely healthier than the general population. For example, someone in poor health is unlikely to have a job as a manual laborer.

Final coronary heart disease model. An interesting finding by NC CCDIHP is that non-Hispanic black hospitalization rates were higher than non-Hispanic whites (overall) for asthma, diabetes, kidney disease, and cardiovascular disease. Berkson's fallacy (Sackett, 1979) states that the study population is selected from a hospital and therefore it is less healthy than the general population. This can result in a spurious negative correlation between diseases. For example, a hospital patient without diabetes is more likely to have a co-occurring disease, since they must have had some reason to enter the hospital in the first place. Either situation may explain the final model results for non-Hispanic blacks.

Finally, hospital discharges are not population-based, but rather discharges are identified from hospitals where they are diagnosed and/or treated, therefore limiting the generalization of study results to the larger patient population (Murphy, Alavi, & Maykel, 2013).

Future

Potential future research include expanding the research focus to all groups in all counties and nationwide, bridge symptoms, temporal evolution of multimorbidity networks, impacts of climate change, job tasks and workplace safety, and establishing a space metaphor for multimorbidity network and spatial analysis.

While Cramer et al.'s work flowed from the field of psychology and was itself a critique of the latent variable model (a statistical model that contains latent or unobserved variables), their discussion of "bridge" symptoms can be useful in explaining co-occurring disorders and may have application and is considered for future work. However, before expanding on the new framework -- Multimorbidity Average Weighed Degree Conceptual Framework, developing egocentric network models for all groups, all counties across the nation seem obvious but grinding. Additional software and programming are necessary to automate the computation of

networks. In addition to exploring spatial changes across the nation, an important direction is to explore the temporal evolution, and evaluate other structural properties of networks such as the number of communities and components. Lastly, develop a rationale for potential metaphors such as “disease space”, “diagnoses space”, or “multimorbidity space” to capture the essence of the research, without extraneous or irrelevant details.

In Conclusion - clear simple story about health disparities

The findings of this study reveal a story – a lack of access to care in rural counties, disability and health care (Medicare) spending depending on the number of conditions (when covered) and lack of insurance (if not covered), economic and environmental disadvantage leads to increased multimorbidity -- higher average weighted degree regardless of gender, race and ethnicity.

The study results show that urban counties had higher average weighted degree for female, male, race and ethnic groups than rural counties in North Carolina. With access to primary care limited and fewer physicians available in rural communities, patients were more likely to receive less preventive care and have higher average weighted degree because of higher rates of illness. The study also revealed that younger disabled Medicare beneficiaries, specifically non-Hispanic blacks with 2 to 3 chronic conditions, had lower average weighted degree when they spent more on care and services. When beneficiaries spent less they were more likely to have higher average weighted degree especially if those conditions were related to hypertension and obesity.

Toxic site locations were also associated with average weighted degree of all genders. This result suggests that North Carolinians living in socioeconomically disadvantaged communities with environmental hazards had more multimorbidity. These environmental conditions exist in both urban and rural communities.

Diabetes and toxic site locations were the only risk factors found significantly associated with the average weighted degree of non-Hispanic whites. Again these results suggest that residents living in socioeconomically disadvantaged communities with environmental hazards had more multimorbidity. While this may be the case for all genders and for non-Hispanic whites in particular, poverty and unemployment play more significant roles for non-Hispanic blacks. Poverty and unemployment were significantly associated with non-Hispanic blacks. For younger disabled Medicare beneficiaries and all Medicare beneficiaries with more than 6 multiple chronic conditions, spending was associated with higher average weighted degree of non-Hispanic blacks. Seventeen percent (17%) of this population live with more than six chronic conditions, and account for half of all spending among beneficiaries with chronic diseases (Gerteis Izrael, Deitz, LeRoy, Ricciardi, Miller, Basu (2014).

Lastly, in the Hispanic model - the number of hospital beds in 2010 was the only variable significantly associated with the average weighted degree of Hispanics. Delamater, Messina, Grady, WinklerPrins, and Shortridge (2013) found evidence for the effects of Roemer's Law, where variations in hospitalization rates were related to availability of hospital beds. Kirby and Kaneda (2010) found that non-Hispanic blacks were twice as likely to be uninsured and Hispanics were three times as likely to be uninsured compared to non-Hispanic whites. This phenomenon occurs when disproportionate rates of unemployment (and for the employed, disproportionate drop in employer-based health insurance coverage) for Hispanics and blacks exist. Consequently, Clancy, Munier, Brady J, et al. (2012) found that the uninsured are much less likely to have primary care providers than the insured; receive less preventive care, dental care, chronic disease management, and behavioral health counseling. Those without insurance were often diagnosed at later, less treatable disease stages than those with insurance and overall, had worse health outcomes, lower quality of life, higher mortality rates, and higher average weighted degree such as the case increasingly with Hispanics.

Network visualization is an old and at times imperfect technique because of the complexity of relationships, but it is a very useful exploratory tool. As an abstract of reality, networks have been used for decades to represent relationships, leading to useful discoveries (Knigge & Cope, (2006). ESDA and visualization using GIS and network software are approaches that are uniquely suited for the study of multimorbidity.

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APPENDIX A: NETWORK STATISTICS

FIPS	Nodes	Edges	Avg_Weighted_Degree	Group	COUNTY
37001	224	4709	59.96	AGE_17_44	ALAMANCE COUNTY
37001	224	4709	59.96	AGE_45_64	ALAMANCE COUNTY
37001	224	9714	222.594	AGE_65	ALAMANCE COUNTY
37001	227	10540	229.811	FEMALE	ALAMANCE COUNTY
37001	211	3404	34.569	INS_MEDICAID	ALAMANCE COUNTY
37001	231	10808	252.749	INS_MEDICARE	ALAMANCE COUNTY
37001	232	6311	84.276	INS_PRIVATE	ALAMANCE COUNTY
37001	215	3355	32.837	INS_SELFPAY	ALAMANCE COUNTY
37001	220	9487	199.205	MALE	ALAMANCE COUNTY
37001	233	12166	304.734	RACE_1	ALAMANCE COUNTY
37001	228	6737	96.566	RACE_2	ALAMANCE COUNTY
37001	159	775	6.755	RACE_3	ALAMANCE COUNTY
37001	180	1007	8.167	RACE_456	ALAMANCE COUNTY
37003	195	1621	15.277	AGE_17_44	ALEXANDER COUNTY
37003	216	3463	36.009	AGE_45_64	ALEXANDER COUNTY
37003	207	4077	50.932	AGE_65	ALEXANDER COUNTY
37003	207	4313	52.193	FEMALE	ALEXANDER COUNTY
37003	186	1287	10.634	INS_MEDICAID	ALEXANDER COUNTY
37003	213	4485	56.033	INS_MEDICARE	ALEXANDER COUNTY
37003	212	2953	28.33	INS_PRIVATE	ALEXANDER COUNTY
37003	130	495	5.238	INS_SELFPAY	ALEXANDER COUNTY
37003	212	4173	49.509	MALE	ALEXANDER COUNTY
37003	226	6181	86.049	RACE_1	ALEXANDER COUNTY
37003	149	861	8.671	RACE_2	ALEXANDER COUNTY
37003	69	94	1.464	RACE_3	ALEXANDER COUNTY
37003	44	55	1.364	RACE_456	ALEXANDER COUNTY
37005	144	503	4.417	AGE_17_44	ALLEGHANY COUNTY
37005	182	1389	11.159	AGE_45_64	ALLEGHANY COUNTY
37005	192	2592	24.99	AGE_65	ALLEGHANY COUNTY
37005	200	2411	20.925	FEMALE	ALLEGHANY COUNTY
37005	126	364	3.667	INS_MEDICAID	ALLEGHANY COUNTY
37005	202	2632	23.475	INS_MEDICARE	ALLEGHANY COUNTY
37005	182	1306	10.571	INS_PRIVATE	ALLEGHANY COUNTY
37005	89	189	2.438	INS_SELFPAY	ALLEGHANY COUNTY
37005	186	1990	17.634	MALE	ALLEGHANY COUNTY
37005	215	3144	28.158	RACE_1	ALLEGHANY COUNTY
37005	47	84	1.894	RACE_2	ALLEGHANY COUNTY
37005	59	91	1.712	RACE_3	ALLEGHANY COUNTY
37005	155	749	7.084	RACE_456	ALLEGHANY COUNTY
37007	190	1997	19.142	AGE_17_44	ANSON COUNTY
37007	214	4014	49.051	AGE_45_64	ANSON COUNTY
37007	208	4444	76.851	AGE_65	ANSON COUNTY
37007	210	4874	74.838	FEMALE	ANSON COUNTY
37007	183	1637	14.951	INS_MEDICAID	ANSON COUNTY

37007	216	5418	93.681	INS_MEDICARE	ANSON COUNTY
37007	204	2591	26.172	INS_PRIVATE	ANSON COUNTY
37007	153	852	8.49	INS_SELFPAY	ANSON COUNTY
37007	208	4678	69.245	MALE	ANSON COUNTY
37007	220	5046	75.191	RACE_1	ANSON COUNTY
37007	212	4462	62.033	RACE_2	ANSON COUNTY
37007	50	57	1.46	RACE_3	ANSON COUNTY
37007	80	138	2.175	RACE_456	ANSON COUNTY
37009	174	1175	10.931	AGE_17_44	ASHE COUNTY
37009	210	2669	23.871	AGE_45_64	ASHE COUNTY
37009	210	4441	58.195	AGE_65	ASHE COUNTY
37009	212	4874	74.132	FEMALE	ASHE COUNTY
37009	172	999	8.215	INS_MEDICAID	ASHE COUNTY
37009	216	4634	57.477	INS_MEDICARE	ASHE COUNTY
37009	201	2307	20.771	INS_PRIVATE	ASHE COUNTY
37009	152	588	4.987	INS_SELFPAY	ASHE COUNTY
37009	205	3705	43.293	MALE	ASHE COUNTY
37009	224	6146	82.527	RACE_1	ASHE COUNTY
37009	63	130	2.476	RACE_2	ASHE COUNTY
37009	94	172	2.16	RACE_3	ASHE COUNTY
37009	63	93	1.651	RACE_456	ASHE COUNTY
37011	158	720	6.532	AGE_17_44	AVERY COUNTY
37011	189	1922	16.91	AGE_45_64	AVERY COUNTY
37011	202	3218	35.876	AGE_65	AVERY COUNTY
37011	199	3057	32.417	FEMALE	AVERY COUNTY
37011	130	544	5.369	INS_MEDICAID	AVERY COUNTY
37011	206	3547	39.811	INS_MEDICARE	AVERY COUNTY
37011	183	1383	11.421	INS_PRIVATE	AVERY COUNTY
37011	108	224	2.537	INS_SELFPAY	AVERY COUNTY
37011	195	2575	25.764	MALE	AVERY COUNTY
37011	218	4460	50.477	RACE_1	AVERY COUNTY
37011	36	53	1.722	RACE_2	AVERY COUNTY
37011	37	48	1.378	RACE_3	AVERY COUNTY
37011	23	30	1.435	RACE_456	AVERY COUNTY
37013	199	2064	19.693	AGE_17_44	BEAUFORT COUNTY
37013	224	4644	53.799	AGE_45_64	BEAUFORT COUNTY
37013	221	5155	74.253	AGE_65	BEAUFORT COUNTY
37013	224	5758	76.924	FEMALE	BEAUFORT COUNTY
37013	195	1861	16.703	INS_MEDICAID	BEAUFORT COUNTY
37013	226	6021	89.226	INS_MEDICARE	BEAUFORT COUNTY
37013	218	3166	31.17	INS_PRIVATE	BEAUFORT COUNTY
37013	176	1022	9.006	INS_SELFPAY	BEAUFORT COUNTY
37013	217	5096	69.811	MALE	BEAUFORT COUNTY
37013	232	6492	93.172	RACE_1	BEAUFORT COUNTY
37013	217	3938	45.793	RACE_2	BEAUFORT COUNTY
37013	111	231	2.505	RACE_3	BEAUFORT COUNTY
37013	94	222	2.851	RACE_456	BEAUFORT COUNTY
37015	166	1017	10.151	AGE_17_44	BERTIE COUNTY
37015	209	2390	23.23	AGE_45_64	BERTIE COUNTY

37015	198	3258	41.318	AGE_65	BERTIE COUNTY
37015	205	3330	38.239	FEMALE	BERTIE COUNTY
37015	163	974	9.294	INS_MEDICAID	BERTIE COUNTY
37015	211	3795	48.943	INS_MEDICARE	BERTIE COUNTY
37015	180	1233	10.317	INS_PRIVATE	BERTIE COUNTY
37015	140	541	5.729	INS_SELFPAY	BERTIE COUNTY
37015	199	2997	34.583	MALE	BERTIE COUNTY
37015	203	2757	28.557	RACE_1	BERTIE COUNTY
37015	211	3444	40.626	RACE_2	BERTIE COUNTY
37015	35	50	1.829	RACE_3	BERTIE COUNTY
37015	77	191	3.026	RACE_456	BERTIE COUNTY
37017	189	1955	18.058	AGE_17_44	BLADEN COUNTY
37017	220	4137	48.391	AGE_45_64	BLADEN COUNTY
37017	200	4695	74.565	AGE_65	BLADEN COUNTY
37017	212	5433	78.09	FEMALE	BLADEN COUNTY
37017	190	1930	17.032	INS_MEDICAID	BLADEN COUNTY
37017	216	5553	87.833	INS_MEDICARE	BLADEN COUNTY
37017	208	2432	20.606	INS_PRIVATE	BLADEN COUNTY
37017	172	1161	10.541	INS_SELFPAY	BLADEN COUNTY
37017	206	4524	60.277	MALE	BLADEN COUNTY
37017	218	5103	66.94	RACE_1	BLADEN COUNTY
37017	208	3830	43.981	RACE_2	BLADEN COUNTY
37017	57	72	1.439	RACE_3	BLADEN COUNTY
37017	128	563	5.898	RACE_456	BLADEN COUNTY
37019	207	3384	35.744	AGE_17_44	BRUNSWICK COUNTY
37019	229	7097	109.991	AGE_45_64	BRUNSWICK COUNTY
37019	225	7692	181.551	AGE_65	BRUNSWICK COUNTY
37019	223	8481	166.269	FEMALE	BRUNSWICK COUNTY
37019	211	3296	34.265	INS_MEDICAID	BRUNSWICK COUNTY
37019	229	9044	207.996	INS_MEDICARE	BRUNSWICK COUNTY
37019	227	5056	59.026	INS_PRIVATE	BRUNSWICK COUNTY
37019	199	1899	17.191	INS_SELFPAY	BRUNSWICK COUNTY
37019	219	7903	166.018	MALE	BRUNSWICK COUNTY
37019	233	10787	266.785	RACE_1	BRUNSWICK COUNTY
37019	214	3962	45.636	RACE_2	BRUNSWICK COUNTY
37019	114	305	3.412	RACE_3	BRUNSWICK COUNTY
37019	127	436	4.173	RACE_456	BRUNSWICK COUNTY
37021	226	5601	83.327	AGE_17_44	BUNCOMBE COUNTY
37021	229	9455	183.502	AGE_45_64	BUNCOMBE COUNTY
37021	228	11153	312.487	AGE_65	BUNCOMBE COUNTY
37021	228	12076	325.947	FEMALE	BUNCOMBE COUNTY
37021	228	5754	74.412	INS_MEDICAID	BUNCOMBE COUNTY
37021	233	12619	368.592	INS_MEDICARE	BUNCOMBE COUNTY
37021	231	6598	97.294	INS_PRIVATE	BUNCOMBE COUNTY
37021	210	2350	23.024	INS_SELFPAY	BUNCOMBE COUNTY
37021	220	10701	262.659	MALE	BUNCOMBE COUNTY
37021	232	15012	510.97	RACE_1	BUNCOMBE COUNTY
37021	222	4561	50.631	RACE_2	BUNCOMBE COUNTY
37021	166	804	6.217	RACE_3	BUNCOMBE COUNTY

37021	141	584	5.206	RACE_456	BUNCOMBE COUNTY
37023	213	3272	42.009	AGE_17_44	BURKE COUNTY
37023	232	6582	100.017	AGE_45_64	BURKE COUNTY
37023	224	7462	166.353	AGE_65	BURKE COUNTY
37023	226	8318	173.115	FEMALE	BURKE COUNTY
37023	209	2851	32.067	INS_MEDICAID	BURKE COUNTY
37023	231	8223	179.571	INS_MEDICARE	BURKE COUNTY
37023	223	5142	66.058	INS_PRIVATE	BURKE COUNTY
37023	200	2138	23.56	INS_SELFPAY	BURKE COUNTY
37023	217	7122	139.59	MALE	BURKE COUNTY
37023	235	10494	267.881	RACE_1	BURKE COUNTY
37023	194	2333	23.304	RACE_2	BURKE COUNTY
37023	124	445	4.677	RACE_3	BURKE COUNTY
37023	140	576	6.557	RACE_456	BURKE COUNTY
37025	222	6019	83.18	AGE_17_44	CABARRUS COUNTY
37025	231	10062	206.771	AGE_45_64	CABARRUS COUNTY
37025	231	11683	377.442	AGE_65	CABARRUS COUNTY
37025	228	12830	378.785	FEMALE	CABARRUS COUNTY
37025	226	4603	50.027	INS_MEDICAID	CABARRUS COUNTY
37025	231	12430	405.641	INS_MEDICARE	CABARRUS COUNTY
37025	233	9380	165.489	INS_PRIVATE	CABARRUS COUNTY
37025	215	3593	36.819	INS_SELFPAY	CABARRUS COUNTY
37025	220	11214	304.8	MALE	CABARRUS COUNTY
37025	233	15121	545.107	RACE_1	CABARRUS COUNTY
37025	225	6929	103.644	RACE_2	CABARRUS COUNTY
37025	180	1288	10.389	RACE_3	CABARRUS COUNTY
37025	167	752	6.335	RACE_456	CABARRUS COUNTY
37027	216	3134	34.519	AGE_17_44	CALDWELL COUNTY
37027	227	5581	73.749	AGE_45_64	CALDWELL COUNTY
37027	225	6471	114.431	AGE_65	CALDWELL COUNTY
37027	226	7317	121.243	FEMALE	CALDWELL COUNTY
37027	205	2530	24.439	INS_MEDICAID	CALDWELL COUNTY
37027	229	6838	112.454	INS_MEDICARE	CALDWELL COUNTY
37027	229	5191	63.188	INS_PRIVATE	CALDWELL COUNTY
37027	170	1340	13.247	INS_SELFPAY	CALDWELL COUNTY
37027	216	6334	104.366	MALE	CALDWELL COUNTY
37027	233	9541	192.451	RACE_1	CALDWELL COUNTY
37027	176	1575	15.239	RACE_2	CALDWELL COUNTY
37027	120	422	4.883	RACE_3	CALDWELL COUNTY
37027	161	937	8.894	RACE_456	CALDWELL COUNTY
37029	94	223	3.032	AGE_17_44	CAMDEN COUNTY
37029	130	579	6.054	AGE_45_64	CAMDEN COUNTY
37029	136	820	9.316	AGE_65	CAMDEN COUNTY
37029	151	840	7.868	FEMALE	CAMDEN COUNTY
37029	86	200	2.779	INS_MEDICAID	CAMDEN COUNTY
37029	138	937	10.457	INS_MEDICARE	CAMDEN COUNTY
37029	118	341	3.508	INS_PRIVATE	CAMDEN COUNTY
37029	167	106	0.904	INS_SELFPAY	CAMDEN COUNTY
37029	140	781	8.221	MALE	CAMDEN COUNTY

37029	169	1199	10.982	RACE_1	CAMDEN COUNTY
37029	226	7499	123.735	RACE_2	CAMDEN COUNTY
37029	9	8	1	RACE_3	CAMDEN COUNTY
37029	10	8	1	RACE_456	CAMDEN COUNTY
37031	210	2898	29.61	AGE_17_44	CARTERET COUNTY
37031	226	6125	86.575	AGE_45_64	CARTERET COUNTY
37031	224	8591	185.897	AGE_65	CARTERET COUNTY
37031	226	8540	163.748	FEMALE	CARTERET COUNTY
37031	206	2589	24.655	INS_MEDICAID	CARTERET COUNTY
37031	230	9274	201.939	INS_MEDICARE	CARTERET COUNTY
37031	224	4314	44.987	INS_PRIVATE	CARTERET COUNTY
37031	194	1855	17.881	INS_SELFPAY	CARTERET COUNTY
37031	216	7617	140.824	MALE	CARTERET COUNTY
37031	231	11220	270.801	RACE_1	CARTERET COUNTY
37031	194	2177	21.01	RACE_2	CARTERET COUNTY
37031	86	149	1.93	RACE_3	CARTERET COUNTY
37031	118	330	3.449	RACE_456	CARTERET COUNTY
37033	151	671	6.609	AGE_17_44	CASWELL COUNTY
37033	197	1992	17.066	AGE_45_64	CASWELL COUNTY
37033	189	2219	20.661	AGE_65	CASWELL COUNTY
37033	200	2463	21.905	FEMALE	CASWELL COUNTY
37033	129	523	5.178	INS_MEDICAID	CASWELL COUNTY
37033	191	2396	21.963	INS_MEDICARE	CASWELL COUNTY
37033	191	1688	13.958	INS_PRIVATE	CASWELL COUNTY
37033	128	371	3.805	INS_SELFPAY	CASWELL COUNTY
37033	193	2192	20.124	MALE	CASWELL COUNTY
37033	211	2873	25.081	RACE_1	CASWELL COUNTY
37033	187	1713	15.053	RACE_2	CASWELL COUNTY
37033	34	38	1.324	RACE_3	CASWELL COUNTY
37033	38	40	1.184	RACE_456	CASWELL COUNTY
37035	224	4563	61.804	AGE_17_44	CATAWBA COUNTY
37035	231	7559	126.745	AGE_45_64	CATAWBA COUNTY
37035	225	8487	184.044	AGE_65	CATAWBA COUNTY
37035	227	9351	194.238	FEMALE	CATAWBA COUNTY
37035	222	3474	36.194	INS_MEDICAID	CATAWBA COUNTY
37035	230	8917	185.791	INS_MEDICARE	CATAWBA COUNTY
37035	230	7277	109.326	INS_PRIVATE	CATAWBA COUNTY
37035	201	1903	17.657	INS_SELFPAY	CATAWBA COUNTY
37035	219	8835	184.658	MALE	CATAWBA COUNTY
37035	234	12227	317.077	RACE_1	CATAWBA COUNTY
37035	208	3125	34.947	RACE_2	CATAWBA COUNTY
37035	165	751	6.388	RACE_3	CATAWBA COUNTY
37035	144	627	5.778	RACE_456	CATAWBA COUNTY
37037	191	1650	14.723	AGE_17_44	CHATHAM COUNTY
37037	219	3854	39.826	AGE_45_64	CHATHAM COUNTY
37037	214	5030	71.271	AGE_65	CHATHAM COUNTY
37037	218	5105	62.491	FEMALE	CHATHAM COUNTY
37037	180	1223	10.117	INS_MEDICAID	CHATHAM COUNTY
37037	220	5314	71.491	INS_MEDICARE	CHATHAM COUNTY

37037	214	3208	29.855	INS_PRIVATE	CHATHAM COUNTY
37037	183	1252	10.705	INS_SELFPAY	CHATHAM COUNTY
37037	215	4847	61.223	MALE	CHATHAM COUNTY
37037	223	5977	78.753	RACE_1	CHATHAM COUNTY
37037	223	5977	78.753	RACE_2	CHATHAM COUNTY
37037	165	1078	10.812	RACE_3	CHATHAM COUNTY
37037	168	823	6.827	RACE_456	CHATHAM COUNTY
37039	178	1184	10.601	AGE_17_44	CHEROKEE COUNTY
37039	207	2106	19.676	AGE_45_64	CHEROKEE COUNTY
37039	209	3575	44.823	AGE_65	CHEROKEE COUNTY
37039	210	3535	40.386	FEMALE	CHEROKEE COUNTY
37039	184	1127	9.842	INS_MEDICAID	CHEROKEE COUNTY
37039	221	4115	49.878	INS_MEDICARE	CHEROKEE COUNTY
37039	180	1081	8.95	INS_PRIVATE	CHEROKEE COUNTY
37039	132	469	4.674	INS_SELFPAY	CHEROKEE COUNTY
37039	204	3093	33.564	MALE	CHEROKEE COUNTY
37039	228	5105	64.338	RACE_1	CHEROKEE COUNTY
37039	87	270	3.759	RACE_2	CHEROKEE COUNTY
37039	37	54	1.73	RACE_3	CHEROKEE COUNTY
37039	43	69	1.767	RACE_456	CHEROKEE COUNTY
37041	145	554	5.566	AGE_17_44	CHOWAN COUNTY
37041	197	1793	14.503	AGE_45_64	CHOWAN COUNTY
37041	194	2661	28.907	AGE_65	CHOWAN COUNTY
37041	205	2619	25.259	FEMALE	CHOWAN COUNTY
37041	131	548	5.321	INS_MEDICAID	CHOWAN COUNTY
37041	205	3035	32.38	INS_MEDICARE	CHOWAN COUNTY
37041	184	1052	7.81	INS_PRIVATE	CHOWAN COUNTY
37041	109	324	4.073	INS_SELFPAY	CHOWAN COUNTY
37041	203	2290	20.167	MALE	CHOWAN COUNTY
37041	214	2825	27.495	RACE_1	CHOWAN COUNTY
37041	200	1972	16.125	RACE_2	CHOWAN COUNTY
37041	17	20	1.176	RACE_3	CHOWAN COUNTY
37041	59	98	1.746	RACE_456	CHOWAN COUNTY
37043	114	326	3.614	AGE_17_44	CLAY COUNTY
37043	161	869	7.888	AGE_45_64	CLAY COUNTY
37043	179	1643	17.52	AGE_65	CLAY COUNTY
37043	179	1470	14.296	FEMALE	CLAY COUNTY
37043	104	313	3.692	INS_MEDICAID	CLAY COUNTY
37043	190	1922	19.668	INS_MEDICARE	CLAY COUNTY
37043	127	375	3.575	INS_PRIVATE	CLAY COUNTY
37043	84	173	2.357	INS_SELFPAY	CLAY COUNTY
37043	176	1373	12.835	MALE	CLAY COUNTY
37043	203	2363	23.325	RACE_1	CLAY COUNTY
37043	11	9	0.909	RACE_2	CLAY COUNTY
37043	25	0	0	RACE_3	CLAY COUNTY
37043	10	8	1	RACE_456	CLAY COUNTY
37045	213	4333	60.934	AGE_17_44	CLEVELAND COUNTY
37045	231	7893	157.506	AGE_45_64	CLEVELAND COUNTY
37045	226	8997	246.805	AGE_65	CLEVELAND COUNTY

37045	226	9632	252.637	FEMALE	CLEVELAND COUNTY
37045	216	3974	49.269	INS_MEDICAID	CLEVELAND COUNTY
37045	233	10149	295.498	INS_MEDICARE	CLEVELAND COUNTY
37045	229	5935	82.664	INS_PRIVATE	CLEVELAND COUNTY
37045	198	2434	28.571	INS_SELFPAY	CLEVELAND COUNTY
37045	222	8812	216.419	MALE	CLEVELAND COUNTY
37045	234	11674	347.791	RACE_1	CLEVELAND COUNTY
37045	223	5919	101.691	RACE_2	CLEVELAND COUNTY
37045	84	223	3.095	RACE_3	CLEVELAND COUNTY
37045	122	352	3.852	RACE_456	CLEVELAND COUNTY
37047	209	3104	31.273	AGE_17_44	COLUMBUS COUNTY
37047	221	5601	80.837	AGE_45_64	COLUMBUS COUNTY
37047	221	6655	125.285	AGE_65	COLUMBUS COUNTY
37047	222	7273	130.239	FEMALE	COLUMBUS COUNTY
37047	213	3331	33.315	INS_MEDICAID	COLUMBUS COUNTY
37047	225	7645	153.178	INS_MEDICARE	COLUMBUS COUNTY
37047	217	3276	32.995	INS_PRIVATE	COLUMBUS COUNTY
37047	182	1459	13.599	INS_SELFPAY	COLUMBUS COUNTY
37047	215	6401	107.795	MALE	COLUMBUS COUNTY
37047	228	7922	143.096	RACE_1	COLUMBUS COUNTY
37047	219	5300	78.466	RACE_2	COLUMBUS COUNTY
37047	66	114	1.955	RACE_3	COLUMBUS COUNTY
37047	158	1107	10.228	RACE_456	COLUMBUS COUNTY
37049	219	3776	43.055	AGE_17_44	CRAVEN COUNTY
37049	225	6699	104.08	AGE_45_64	CRAVEN COUNTY
37049	223	8148	169.018	AGE_65	CRAVEN COUNTY
37049	226	8822	170.208	FEMALE	CRAVEN COUNTY
37049	209	2919	27.344	INS_MEDICAID	CRAVEN COUNTY
37049	230	9147	197.435	INS_MEDICARE	CRAVEN COUNTY
37049	228	4497	50.952	INS_PRIVATE	CRAVEN COUNTY
37049	190	2096	21.721	INS_SELFPAY	CRAVEN COUNTY
37049	216	7816	148.444	MALE	CRAVEN COUNTY
37049	232	10247	219.026	RACE_1	CRAVEN COUNTY
37049	225	5744	82.453	RACE_2	CRAVEN COUNTY
37049	119	318	3.134	RACE_3	CRAVEN COUNTY
37049	135	445	4.244	RACE_456	CRAVEN COUNTY
37051	228	7739	133.912	AGE_17_44	CUMBERLAND COUNTY
37051	230	10996	273.187	AGE_45_64	CUMBERLAND COUNTY
37051	226	10597	332.381	AGE_65	CUMBERLAND COUNTY
37051	227	13244	426.427	FEMALE	CUMBERLAND COUNTY
37051	231	6875	109.563	INS_MEDICAID	CUMBERLAND COUNTY
37051	232	12540	420.746	INS_MEDICARE	CUMBERLAND COUNTY
37051	227	7598	119.643	INS_PRIVATE	CUMBERLAND COUNTY
37051	220	4030	47.945	INS_SELFPAY	CUMBERLAND COUNTY
37051	220	11346	325.836	MALE	CUMBERLAND COUNTY
37051	231	5498	62.983	RACE_1	CUMBERLAND COUNTY
37051	225	3771	34.298	RACE_2	CUMBERLAND COUNTY
37051	116	271	2.948	RACE_3	CUMBERLAND COUNTY
37051	178	910	7.034	RACE_456	CUMBERLAND COUNTY

37053	126	374	4.032	AGE_17_44	CURRITUCK COUNTY
37053	163	922	7.773	AGE_45_64	CURRITUCK COUNTY
37053	164	1353	13.451	AGE_65	CURRITUCK COUNTY
37053	175	1392	11.469	FEMALE	CURRITUCK COUNTY
37053	99	244	3.202	INS_MEDICAID	CURRITUCK COUNTY
37053	170	1550	15.453	INS_MEDICARE	CURRITUCK COUNTY
37053	149	532	4.584	INS_PRIVATE	CURRITUCK COUNTY
37053	89	196	2.831	INS_SELFPAY	CURRITUCK COUNTY
37053	164	1169	12.037	MALE	CURRITUCK COUNTY
37053	195	2002	18.231	RACE_1	CURRITUCK COUNTY
37053	99	333	3.949	RACE_2	CURRITUCK COUNTY
37053	5	3	0.6	RACE_3	CURRITUCK COUNTY
37053	15	13	0.867	RACE_456	CURRITUCK COUNTY
37055	153	617	6.15	AGE_17_44	DARE COUNTY
37055	186	1405	12.097	AGE_45_64	DARE COUNTY
37055	193	2413	24.803	AGE_65	DARE COUNTY
37055	194	2180	21.696	FEMALE	DARE COUNTY
37055	108	405	4.833	INS_MEDICAID	DARE COUNTY
37055	203	2613	25.419	INS_MEDICARE	DARE COUNTY
37055	184	1097	8.815	INS_PRIVATE	DARE COUNTY
37055	106	351	5.113	INS_SELFPAY	DARE COUNTY
37055	197	2141	19.132	MALE	DARE COUNTY
37055	218	3448	34.372	RACE_1	DARE COUNTY
37055	105	243	3.19	RACE_2	DARE COUNTY
37055	34	44	1.382	RACE_3	DARE COUNTY
37055	38	48	1.368	RACE_456	DARE COUNTY
37057	224	4611	59.42	AGE_17_44	DAVIDSON COUNTY
37057	231	7964	142.19	AGE_45_64	DAVIDSON COUNTY
37057	225	9217	233.907	AGE_65	DAVIDSON COUNTY
37057	228	9824	232.846	FEMALE	DAVIDSON COUNTY
37057	220	3668	40.623	INS_MEDICAID	DAVIDSON COUNTY
37057	229	8408	174.424	INS_MEDICARE	DAVIDSON COUNTY
37057	230	9083	185.026	INS_PRIVATE	DAVIDSON COUNTY
37057	207	2700	26.986	INS_SELFPAY	DAVIDSON COUNTY
37057	218	9121	209.615	MALE	DAVIDSON COUNTY
37057	232	12520	375.996	RACE_1	DAVIDSON COUNTY
37057	215	4045	45.921	RACE_2	DAVIDSON COUNTY
37057	139	586	5.446	RACE_3	DAVIDSON COUNTY
37057	128	438	4.211	RACE_456	DAVIDSON COUNTY
37059	191	1568	14.309	AGE_17_44	DAVIE COUNTY
37059	213	3384	35.014	AGE_45_64	DAVIE COUNTY
37059	209	4951	68.789	AGE_65	DAVIE COUNTY
37059	214	4990	63.509	FEMALE	DAVIE COUNTY
37059	168	1106	10.298	INS_MEDICAID	DAVIE COUNTY
37059	213	4341	51.554	INS_MEDICARE	DAVIE COUNTY
37059	220	4364	47.4	INS_PRIVATE	DAVIE COUNTY
37059	147	630	5.857	INS_SELFPAY	DAVIE COUNTY
37059	207	4442	53.029	MALE	DAVIE COUNTY
37059	233	6847	95.966	RACE_1	DAVIE COUNTY

37059	161	1251	11.503	RACE_2	DAVIE COUNTY
37059	69	93	1.536	RACE_3	DAVIE COUNTY
37059	56	100	2.036	RACE_456	DAVIE COUNTY
37061	200	1898	18.235	AGE_17_44	DUPLIN COUNTY
37061	222	4130	48.865	AGE_45_64	DUPLIN COUNTY
37061	215	5386	86.121	AGE_65	DUPLIN COUNTY
37061	220	5560	81.35	FEMALE	DUPLIN COUNTY
37061	192	1618	14.896	INS_MEDICAID	DUPLIN COUNTY
37061	219	6039	99.726	INS_MEDICARE	DUPLIN COUNTY
37061	208	2855	28.332	INS_PRIVATE	DUPLIN COUNTY
37061	184	1140	9.592	INS_SELFPAY	DUPLIN COUNTY
37061	214	5069	70.626	MALE	DUPLIN COUNTY
37061	227	5912	85.581	RACE_1	DUPLIN COUNTY
37061	213	3971	46.977	RACE_2	DUPLIN COUNTY
37061	133	501	5.068	RACE_3	DUPLIN COUNTY
37061	96	164	1.917	RACE_456	DUPLIN COUNTY
37063	233	6331	86.116	AGE_17_44	DURHAM COUNTY
37063	230	4130	47.165	AGE_45_64	DURHAM COUNTY
37063	226	10138	245.885	AGE_65	DURHAM COUNTY
37063	229	12123	291.009	FEMALE	DURHAM COUNTY
37063	222	4527	49.968	INS_MEDICAID	DURHAM COUNTY
37063	232	11457	274.142	INS_MEDICARE	DURHAM COUNTY
37063	233	8896	142.296	INS_PRIVATE	DURHAM COUNTY
37063	220	4335	96.082	INS_SELFPAY	DURHAM COUNTY
37063	220	10815	242.323	MALE	DURHAM COUNTY
37063	234	11691	246.987	RACE_1	DURHAM COUNTY
37063	231	11024	243.853	RACE_2	DURHAM COUNTY
37063	192	1517	12.057	RACE_3	DURHAM COUNTY
37063	204	1689	12.554	RACE_456	DURHAM COUNTY
37065	208	3053	35.183	AGE_17_44	EDGECOMBE COUNTY
37065	223	5632	84.709	AGE_45_64	EDGECOMBE COUNTY
37065	215	5776	98.074	AGE_65	EDGECOMBE COUNTY
37065	225	6892	115.276	FEMALE	EDGECOMBE COUNTY
37065	218	3274	34.069	INS_MEDICAID	EDGECOMBE COUNTY
37065	224	6781	125.665	INS_MEDICARE	EDGECOMBE COUNTY
37065	216	3481	35.523	INS_PRIVATE	EDGECOMBE COUNTY
37065	170	1199	12.288	INS_SELFPAY	EDGECOMBE COUNTY
37065	214	5880	99.799	MALE	EDGECOMBE COUNTY
37065	226	5705	84.173	RACE_1	EDGECOMBE COUNTY
37065	226	6910	118.956	RACE_2	EDGECOMBE COUNTY
37065	124	525	6.306	RACE_3	EDGECOMBE COUNTY
37065	111	326	3.514	RACE_456	EDGECOMBE COUNTY
37067	230	7629	124.37	AGE_17_44	FORSYTH COUNTY
37067	234	12340	299.65	AGE_45_64	FORSYTH COUNTY
37067	233	13418	450.712	AGE_65	FORSYTH COUNTY
37067	229	14806	488.769	FEMALE	FORSYTH COUNTY
37067	229	6016	86.284	INS_MEDICAID	FORSYTH COUNTY
37067	232	12465	332.582	INS_MEDICARE	FORSYTH COUNTY
37067	235	14039	379.864	INS_PRIVATE	FORSYTH COUNTY

37067	220	4546	55.959	INS_SELFPAY	FORSYTH COUNTY
37067	222	13598	413.527	MALE	FORSYTH COUNTY
37067	234	16215	592.842	RACE_1	FORSYTH COUNTY
37067	232	11380	256.418	RACE_2	FORSYTH COUNTY
37067	201	2087	16.761	RACE_3	FORSYTH COUNTY
37067	184	1106	8.522	RACE_456	FORSYTH COUNTY
37069	209	2143	18.402	AGE_17_44	FRANKLIN COUNTY
37069	220	4428	52.918	AGE_45_64	FRANKLIN COUNTY
37069	211	5273	78.924	AGE_65	FRANKLIN COUNTY
37069	220	5689	78.15	FEMALE	FRANKLIN COUNTY
37069	196	1893	16.852	INS_MEDICAID	FRANKLIN COUNTY
37069	219	5783	84.9	INS_MEDICARE	FRANKLIN COUNTY
37069	225	3588	35.498	INS_PRIVATE	FRANKLIN COUNTY
37069	163	1074	9.613	INS_SELFPAY	FRANKLIN COUNTY
37069	215	5274	69.526	MALE	FRANKLIN COUNTY
37069	231	6608	89.853	RACE_1	FRANKLIN COUNTY
37069	218	4023	47.404	RACE_2	FRANKLIN COUNTY
37069	118	332	3.703	RACE_3	FRANKLIN COUNTY
37069	97	218	2.835	RACE_456	FRANKLIN COUNTY
37071	228	6366	104.618	AGE_17_44	GASTON COUNTY
37071	231	10605	263.55	AGE_45_64	GASTON COUNTY
37071	231	10891	354.009	AGE_65	GASTON COUNTY
37071	228	12564	403.754	FEMALE	GASTON COUNTY
37071	228	5844	88.719	INS_MEDICAID	GASTON COUNTY
37071	234	12091	392.132	INS_MEDICARE	GASTON COUNTY
37071	231	9218	184.104	INS_PRIVATE	GASTON COUNTY
37071	207	3201	38.937	INS_SELFPAY	GASTON COUNTY
37071	221	11251	336.891	MALE	GASTON COUNTY
37071	235	15113	595.583	RACE_1	GASTON COUNTY
37071	226	6533	104.124	RACE_2	GASTON COUNTY
37071	162	740	6.407	RACE_3	GASTON COUNTY
37071	169	1012	8.16	RACE_456	GASTON COUNTY
37073	94	236	3.649	AGE_17_44	GATES COUNTY
37073	137	711	7.022	AGE_45_64	GATES COUNTY
37073	163	1192	11.405	AGE_65	GATES COUNTY
37073	164	1081	9.86	FEMALE	GATES COUNTY
37073	113	340	4.133	INS_MEDICAID	GATES COUNTY
37073	167	1262	12.251	INS_MEDICARE	GATES COUNTY
37073	120	425	4.342	INS_PRIVATE	GATES COUNTY
37073	59	104	1.966	INS_SELFPAY	GATES COUNTY
37073	154	1019	10.045	MALE	GATES COUNTY
37073	170	1082	9.094	RACE_1	GATES COUNTY
37073	154	964	9.948	RACE_2	GATES COUNTY
37073	14	14	1.143	RACE_3	GATES COUNTY
37073	37	49	1.459	RACE_456	GATES COUNTY
37075	157	724	6.35	AGE_17_44	GRAHAM COUNTY
37075	175	1249	11.28	AGE_45_64	GRAHAM COUNTY
37075	171	1807	19.38	AGE_65	GRAHAM COUNTY
37075	189	1873	16.942	FEMALE	GRAHAM COUNTY

37075	147	635	6.129	INS_MEDICAID	GRAHAM COUNTY
37075	191	2096	19.838	INS_MEDICARE	GRAHAM COUNTY
37075	155	771	6.935	INS_PRIVATE	GRAHAM COUNTY
37075	98	292	3.612	INS_SELFPAY	GRAHAM COUNTY
37075	186	1796	16.575	MALE	GRAHAM COUNTY
37075	205	2895	28.917	RACE_1	GRAHAM COUNTY
37075	4	3	0.75	RACE_2	GRAHAM COUNTY
37075	5	4	0.8	RACE_3	GRAHAM COUNTY
37075	114	259	2.623	RACE_456	GRAHAM COUNTY
37077	209	2429	23.943	AGE_17_44	GRANVILLE COUNTY
37077	226	5145	59.46	AGE_45_64	GRANVILLE COUNTY
37077	212	5132	75.863	AGE_65	GRANVILLE COUNTY
37077	223	5749	80.928	FEMALE	GRANVILLE COUNTY
37077	211	2642	23.37	INS_MEDICAID	GRANVILLE COUNTY
37077	221	5870	86.534	INS_MEDICARE	GRANVILLE COUNTY
37077	216	3306	33.509	INS_PRIVATE	GRANVILLE COUNTY
37077	184	1240	10.728	INS_SELFPAY	GRANVILLE COUNTY
37077	215	5731	76.642	MALE	GRANVILLE COUNTY
37077	227	6113	84.991	RACE_1	GRANVILLE COUNTY
37077	222	5106	63.207	RACE_2	GRANVILLE COUNTY
37077	125	388	4.008	RACE_3	GRANVILLE COUNTY
37077	114	294	3.14	RACE_456	GRANVILLE COUNTY
37079	179	941	8.313	AGE_17_44	GREENE COUNTY
37079	211	2423	22.526	AGE_45_64	GREENE COUNTY
37079	198	2725	31.333	AGE_65	GREENE COUNTY
37079	205	3054	32.22	FEMALE	GREENE COUNTY
37079	140	551	5.536	INS_MEDICAID	GREENE COUNTY
37079	212	3288	37.165	INS_MEDICARE	GREENE COUNTY
37079	196	1722	14.485	INS_PRIVATE	GREENE COUNTY
37079	144	534	5.215	INS_SELFPAY	GREENE COUNTY
37079	205	2764	28.488	MALE	GREENE COUNTY
37079	215	3323	35.056	RACE_1	GREENE COUNTY
37079	204	2361	23.005	RACE_2	GREENE COUNTY
37079	71	124	2.099	RACE_3	GREENE COUNTY
37079	39	43	1.179	RACE_456	GREENE COUNTY
37081	230	9203	207.417	AGE_17_44	GUILFORD COUNTY
37081	234	14146	440.671	AGE_45_64	GUILFORD COUNTY
37081	231	15078	647.481	AGE_65	GUILFORD COUNTY
37081	229	16817	712.799	FEMALE	GUILFORD COUNTY
37081	232	7863	140.207	INS_MEDICAID	GUILFORD COUNTY
37081	233	14734	537.828	INS_MEDICARE	GUILFORD COUNTY
37081	235	15160	486.689	INS_PRIVATE	GUILFORD COUNTY
37081	222	5718	88.518	INS_SELFPAY	GUILFORD COUNTY
37081	221	15293	620.597	MALE	GUILFORD COUNTY
37081	234	17922	822.047	RACE_1	GUILFORD COUNTY
37081	234	13579	418.098	RACE_2	GUILFORD COUNTY
37081	195	1663	14.544	RACE_3	GUILFORD COUNTY
37081	209	3065	28.349	RACE_456	GUILFORD COUNTY
37083	202	2734	35.03	AGE_17_44	HALIFAX COUNTY

37083	228	5492	88.167	AGE_45_64	HALIFAX COUNTY
37083	223	6675	137.677	AGE_65	HALIFAX COUNTY
37083	225	7113	140.929	FEMALE	HALIFAX COUNTY
37083	210	2929	33.848	INS_MEDICAID	HALIFAX COUNTY
37083	229	7760	175.424	INS_MEDICARE	HALIFAX COUNTY
37083	220	3061	31.686	INS_PRIVATE	HALIFAX COUNTY
37083	175	1140	11.44	INS_SELFPAY	HALIFAX COUNTY
37083	212	6244	123.448	MALE	HALIFAX COUNTY
37083	229	6658	115.808	RACE_1	HALIFAX COUNTY
37083	225	6415	120.293	RACE_2	HALIFAX COUNTY
37083	117	383	5.308	RACE_3	HALIFAX COUNTY
37083	177	1598	17.356	RACE_456	HALIFAX COUNTY
37085	219	4095	44.329	AGE_17_44	HARNETT COUNTY
37085	230	7190	113.357	AGE_45_64	HARNETT COUNTY
37085	221	7883	164.95	AGE_65	HARNETT COUNTY
37085	223	8841	176.188	FEMALE	HARNETT COUNTY
37085	213	3536	37.033	INS_MEDICAID	HARNETT COUNTY
37085	228	9057	195.325	INS_MEDICARE	HARNETT COUNTY
37085	224	5058	58.366	INS_PRIVATE	HARNETT COUNTY
37085	199	2355	23.869	INS_SELFPAY	HARNETT COUNTY
37085	217	8170	151.816	MALE	HARNETT COUNTY
37085	230	10251	222.222	RACE_1	HARNETT COUNTY
37085	217	5301	73.47	RACE_2	HARNETT COUNTY
37085	128	430	4.078	RACE_3	HARNETT COUNTY
37085	154	589	5.078	RACE_456	HARNETT COUNTY
37087	205	2627	25.878	AGE_17_44	HAYWOOD COUNTY
37087	222	4863	57.333	AGE_45_64	HAYWOOD COUNTY
37087	222	6813	114.477	AGE_65	HAYWOOD COUNTY
37087	221	6923	112.312	FEMALE	HAYWOOD COUNTY
37087	200	2196	19.785	INS_MEDICAID	HAYWOOD COUNTY
37087	224	6962	110.406	INS_MEDICARE	HAYWOOD COUNTY
37087	220	4699	53.541	INS_PRIVATE	HAYWOOD COUNTY
37087	181	1408	12.895	INS_SELFPAY	HAYWOOD COUNTY
37087	213	6097	87.446	MALE	HAYWOOD COUNTY
37087	230	9495	184.235	RACE_1	HAYWOOD COUNTY
37087	119	424	4.429	RACE_2	HAYWOOD COUNTY
37087	72	107	1.722	RACE_3	HAYWOOD COUNTY
37087	73	129	2.178	RACE_456	HAYWOOD COUNTY
37089	210	3523	47.919	AGE_17_44	HENDERSON COUNTY
37089	225	6160	91.684	AGE_45_64	HENDERSON COUNTY
37089	224	9140	214.121	AGE_65	HENDERSON COUNTY
37089	226	8891	195.088	FEMALE	HENDERSON COUNTY
37089	202	2686	29.173	INS_MEDICAID	HENDERSON COUNTY
37089	229	9619	217.367	INS_MEDICARE	HENDERSON COUNTY
37089	229	5892	79.419	INS_PRIVATE	HENDERSON COUNTY
37089	196	1978	20.311	INS_SELFPAY	HENDERSON COUNTY
37089	218	8162	158.555	MALE	HENDERSON COUNTY
37089	231	11845	321.177	RACE_1	HENDERSON COUNTY
37089	185	1729	16.611	RACE_2	HENDERSON COUNTY

37089	157	532	4.446	RACE_3	HENDERSON COUNTY
37089	109	293	3.422	RACE_456	HENDERSON COUNTY
37091	179	1116	10.33	AGE_17_44	HERTFORD COUNTY
37091	201	2313	24.015	AGE_45_64	HERTFORD COUNTY
37091	201	3091	40.274	AGE_65	HERTFORD COUNTY
37091	212	3292	37.811	FEMALE	HERTFORD COUNTY
37091	182	1246	11.346	INS_MEDICAID	HERTFORD COUNTY
37091	213	3683	47.385	INS_MEDICARE	HERTFORD COUNTY
37091	181	1226	10.967	INS_PRIVATE	HERTFORD COUNTY
37091	112	368	4.536	INS_SELFPAY	HERTFORD COUNTY
37091	198	2861	34.086	MALE	HERTFORD COUNTY
37091	206	2592	25.835	RACE_1	HERTFORD COUNTY
37091	215	3464	42.753	RACE_2	HERTFORD COUNTY
37091	42	51	1.381	RACE_3	HERTFORD COUNTY
37091	74	156	2.527	RACE_456	HERTFORD COUNTY
37093	199	2198	21.131	AGE_17_44	HOKE COUNTY
37093	214	3837	45.762	AGE_45_64	HOKE COUNTY
37093	200	3691	55.195	AGE_65	HOKE COUNTY
37093	219	4519	61.361	FEMALE	HOKE COUNTY
37093	187	1576	14.075	INS_MEDICAID	HOKE COUNTY
37093	206	4240	65.845	INS_MEDICARE	HOKE COUNTY
37093	210	2865	27.824	INS_PRIVATE	HOKE COUNTY
37093	153	852	7.987	INS_SELFPAY	HOKE COUNTY
37093	206	4235	56.306	MALE	HOKE COUNTY
37093	210	3065	33.652	RACE_1	HOKE COUNTY
37093	211	3621	47.664	RACE_2	HOKE COUNTY
37093	62	97	1.839	RACE_3	HOKE COUNTY
37093	151	879	8.404	RACE_456	HOKE COUNTY
37095	83	143	2.229	AGE_17_44	HYDE COUNTY
37095	139	545	4.986	AGE_45_64	HYDE COUNTY
37095	157	1032	9.497	AGE_65	HYDE COUNTY
37095	162	973	8.296	FEMALE	HYDE COUNTY
37095	79	153	2.253	INS_MEDICAID	HYDE COUNTY
37095	158	1046	9.443	INS_MEDICARE	HYDE COUNTY
37095	128	427	4.07	INS_PRIVATE	HYDE COUNTY
37095	68	122	2.029	INS_SELFPAY	HYDE COUNTY
37095	145	751	7.069	MALE	HYDE COUNTY
37095	164	977	8.555	RACE_1	HYDE COUNTY
37095	144	714	6.542	RACE_2	HYDE COUNTY
37095	9	8	0.889	RACE_3	HYDE COUNTY
37095	4	2	0.5	RACE_456	HYDE COUNTY
37097	224	4869	55.683	AGE_17_44	IREDELL COUNTY
37097	231	7835	136.437	AGE_45_64	IREDELL COUNTY
37097	230	9728	231.5	AGE_65	IREDELL COUNTY
37097	227	10374	233.542	FEMALE	IREDELL COUNTY
37097	219	3312	32.498	INS_MEDICAID	IREDELL COUNTY
37097	233	10396	250.129	INS_MEDICARE	IREDELL COUNTY
37097	229	7668	119.576	INS_PRIVATE	IREDELL COUNTY
37097	195	1743	16.426	INS_SELFPAY	IREDELL COUNTY

37097	223	9294	198.3	MALE	IREDELL COUNTY
37097	232	12661	339.151	RACE_1	IREDELL COUNTY
37097	223	5216	69.982	RACE_2	IREDELL COUNTY
37097	154	682	5.481	RACE_3	IREDELL COUNTY
37097	131	542	5.099	RACE_456	IREDELL COUNTY
37099	186	1489	13.253	AGE_17_44	JACKSON COUNTY
37099	210	3329	31.762	AGE_45_64	JACKSON COUNTY
37099	210	4313	62.829	AGE_65	JACKSON COUNTY
37099	216	4616	56.19	FEMALE	JACKSON COUNTY
37099	184	1232	10.255	INS_MEDICAID	JACKSON COUNTY
37099	221	4876	65.95	INS_MEDICARE	JACKSON COUNTY
37099	208	2426	20.288	INS_PRIVATE	JACKSON COUNTY
37099	156	895	8.032	INS_SELFPAY	JACKSON COUNTY
37099	207	3969	49.237	MALE	JACKSON COUNTY
37099	229	6365	92.288	RACE_1	JACKSON COUNTY
37099	85	173	2.529	RACE_2	JACKSON COUNTY
37099	86	162	2.174	RACE_3	JACKSON COUNTY
37099	112	352	4	RACE_456	JACKSON COUNTY
37101	225	5118	65.622	AGE_17_44	JOHNSTON COUNTY
37101	232	8460	152.297	AGE_45_64	JOHNSTON COUNTY
37101	222	8809	201.104	AGE_65	JOHNSTON COUNTY
37101	227	10224	226.974	FEMALE	JOHNSTON COUNTY
37101	227	4340	48.189	INS_MEDICAID	JOHNSTON COUNTY
37101	229	10081	238.983	INS_MEDICARE	JOHNSTON COUNTY
37101	230	6823	94.37	INS_PRIVATE	JOHNSTON COUNTY
37101	209	2327	26.818	INS_SELFPAY	JOHNSTON COUNTY
37101	221	9269	195.566	MALE	JOHNSTON COUNTY
37101	234	12046	312.744	RACE_1	JOHNSTON COUNTY
37101	227	5731	78.238	RACE_2	JOHNSTON COUNTY
37101	185	1332	11.135	RACE_3	JOHNSTON COUNTY
37101	165	725	5.891	RACE_456	JOHNSTON COUNTY
37103	158	706	6.228	AGE_17_44	JONES COUNTY
37103	194	1879	17.371	AGE_45_64	JONES COUNTY
37103	193	2349	25.518	AGE_65	JONES COUNTY
37103	196	2342	23.286	FEMALE	JONES COUNTY
37103	139	628	6.165	INS_MEDICAID	JONES COUNTY
37103	198	2637	29.424	INS_MEDICARE	JONES COUNTY
37103	180	1190	9.461	INS_PRIVATE	JONES COUNTY
37103	133	448	4.774	INS_SELFPAY	JONES COUNTY
37103	194	2445	24.304	MALE	JONES COUNTY
37103	210	2805	27.262	RACE_1	JONES COUNTY
37103	186	1841	17.941	RACE_2	JONES COUNTY
37103	53	76	2.057	RACE_3	JONES COUNTY
37103	47	61	1.383	RACE_456	JONES COUNTY
37105	215	2836	26.591	AGE_17_44	LEE COUNTY
37105	223	5440	71.121	AGE_45_64	LEE COUNTY
37105	224	6275	107.696	AGE_65	LEE COUNTY
37105	226	7008	112.367	FEMALE	LEE COUNTY
37105	202	2154	19.698	INS_MEDICAID	LEE COUNTY

37105	229	7048	119.987	INS_MEDICARE	LEE COUNTY
37105	225	4260	45.884	INS_PRIVATE	LEE COUNTY
37105	184	1095	9.299	INS_SELFPAY	LEE COUNTY
37105	219	6210	92.721	MALE	LEE COUNTY
37105	230	8084	142.3	RACE_1	LEE COUNTY
37105	217	4166	47.908	RACE_2	LEE COUNTY
37105	136	462	4.537	RACE_3	LEE COUNTY
37105	156	609	5.282	RACE_456	LEE COUNTY
37107	211	2702	27.213	AGE_17_44	LENOIR COUNTY
37107	225	5756	81.502	AGE_45_64	LENOIR COUNTY
37107	220	6653	126.073	AGE_65	LENOIR COUNTY
37107	227	7262	123.427	FEMALE	LENOIR COUNTY
37107	209	2636	24.766	INS_MEDICAID	LENOIR COUNTY
37107	229	7789	151.659	INS_MEDICARE	LENOIR COUNTY
37107	221	3714	38.611	INS_PRIVATE	LENOIR COUNTY
37107	180	1466	15.594	INS_SELFPAY	LENOIR COUNTY
37107	213	6470	111.681	MALE	LENOIR COUNTY
37107	231	7436	128.576	RACE_1	LENOIR COUNTY
37107	217	6103	97.083	RACE_2	LENOIR COUNTY
37107	119	319	3.336	RACE_3	LENOIR COUNTY
37107	89	185	2.427	RACE_456	LENOIR COUNTY
37109	210	3005	32.143	AGE_17_44	LINCOLN COUNTY
37109	227	5877	87.921	AGE_45_64	LINCOLN COUNTY
37109	221	6769	129.606	AGE_65	LINCOLN COUNTY
37109	222	7295	132.676	FEMALE	LINCOLN COUNTY
37109	212	2603	27.198	INS_MEDICAID	LINCOLN COUNTY
37109	229	7395	142.397	INS_MEDICARE	LINCOLN COUNTY
37109	224	4838	58.152	INS_PRIVATE	LINCOLN COUNTY
37109	181	1461	14.028	INS_SELFPAY	LINCOLN COUNTY
37109	220	6652	117.714	MALE	LINCOLN COUNTY
37109	233	9639	215.017	RACE_1	LINCOLN COUNTY
37109	189	1945	20.058	RACE_2	LINCOLN COUNTY
37109	121	328	3.306	RACE_3	LINCOLN COUNTY
37109	137	463	4.131	RACE_456	LINCOLN COUNTY
37111	198	2220	22.99	AGE_17_44	MCDOWELL COUNTY
37111	219	3837	41.557	AGE_45_64	MCDOWELL COUNTY
37111	211	4764	64.033	AGE_65	MCDOWELL COUNTY
37111	220	5348	69.427	FEMALE	MCDOWELL COUNTY
37111	199	1967	18.07	INS_MEDICAID	MCDOWELL COUNTY
37111	220	5305	69.859	INS_MEDICARE	MCDOWELL COUNTY
37111	214	3069	28.855	INS_PRIVATE	MCDOWELL COUNTY
37111	151	773	7.609	INS_SELFPAY	MCDOWELL COUNTY
37111	208	4604	57.163	MALE	MCDOWELL COUNTY
37111	229	7228	111.179	RACE_1	MCDOWELL COUNTY
37111	144	762	7.486	RACE_2	MCDOWELL COUNTY
37111	64	91	1.688	RACE_3	MCDOWELL COUNTY
37111	70	124	1.957	RACE_456	MCDOWELL COUNTY
37113	161	943	9.28	AGE_17_44	MACON COUNTY
37113	212	2494	22.17	AGE_45_64	MACON COUNTY

37113	212	4630	59.014	AGE_65	MACON COUNTY
37113	213	4207	45.967	FEMALE	MACON COUNTY
37113	181	1985	8.541	INS_MEDICAID	MACON COUNTY
37113	218	4829	59.312	INS_MEDICARE	MACON COUNTY
37113	205	1782	14.463	INS_PRIVATE	MACON COUNTY
37113	153	670	5.797	INS_SELFPAY	MACON COUNTY
37113	209	3773	42.651	MALE	MACON COUNTY
37113	225	6063	80.689	RACE_1	MACON COUNTY
37113	93	170	2.075	RACE_2	MACON COUNTY
37113	60	60	1.1	RACE_3	MACON COUNTY
37113	26	22	0.885	RACE_456	MACON COUNTY
37115	174	827	6.879	AGE_17_44	MADISON COUNTY
37115	208	2094	17.755	AGE_45_64	MADISON COUNTY
37115	209	3087	34.167	AGE_65	MADISON COUNTY
37115	206	2994	29.563	FEMALE	MADISON COUNTY
37115	167	877	7.689	INS_MEDICAID	MADISON COUNTY
37115	218	3602	39.174	INS_MEDICARE	MADISON COUNTY
37115	190	1228	9.795	INS_PRIVATE	MADISON COUNTY
37115	84	151	2.226	INS_SELFPAY	MADISON COUNTY
37115	206	2908	28.84	MALE	MADISON COUNTY
37115	225	4636	52.964	RACE_1	MADISON COUNTY
37115	45	60	1.444	RACE_2	MADISON COUNTY
37115	19	16	1.105	RACE_3	MADISON COUNTY
37115	3	2	0.667	RACE_456	MADISON COUNTY
37117	186	1260	11.032	AGE_17_44	MARTIN COUNTY
37117	203	2829	30.005	AGE_45_64	MARTIN COUNTY
37117	205	4127	54.39	AGE_65	MARTIN COUNTY
37117	211	4079	49.791	FEMALE	MARTIN COUNTY
37117	175	1172	10.32	INS_MEDICAID	MARTIN COUNTY
37117	216	4691	61.042	INS_MEDICARE	MARTIN COUNTY
37117	194	1652	14.381	INS_PRIVATE	MARTIN COUNTY
37117	160	793	7.794	INS_SELFPAY	MARTIN COUNTY
37117	205	3745	42.683	MALE	MARTIN COUNTY
37117	213	3074	31.69	RACE_1	MARTIN COUNTY
37117	204	2284	21.255	RACE_2	MARTIN COUNTY
37117	54	97	2.259	RACE_3	MARTIN COUNTY
37117	195	3081	40.903	RACE_456	MARTIN COUNTY
37119	234	12408	336.855	AGE_17_44	MECKLENBURG COUNTY
37119	233	17988	746.901	AGE_45_64	MECKLENBURG COUNTY
37119	235	18057	959.647	AGE_65	MECKLENBURG COUNTY
37119	230	20546	1154.478	FEMALE	MECKLENBURG COUNTY
37119	234	11200	236.077	INS_MEDICAID	MECKLENBURG COUNTY
37119	234	19252	1020.838	INS_MEDICARE	MECKLENBURG COUNTY
37119	236	16644	569.881	INS_PRIVATE	MECKLENBURG COUNTY
37119	232	8535	159.901	INS_SELFPAY	MECKLENBURG COUNTY
37119	223	18702	954.435	MALE	MECKLENBURG COUNTY
37119	236	20583	1101.186	RACE_1	MECKLENBURG COUNTY
37119	234	18579	827.453	RACE_2	MECKLENBURG COUNTY
37119	227	5011	54.256	RACE_3	MECKLENBURG COUNTY

37119	228	4528	47.601	RACE_456	MECKLENBURG COUNTY
37121	160	897	8.431	AGE_17_44	MITCHELL COUNTY
37121	196	1903	16.148	AGE_45_64	MITCHELL COUNTY
37121	200	3050	33.265	AGE_65	MITCHELL COUNTY
37121	207	3039	29.744	FEMALE	MITCHELL COUNTY
37121	156	767	6.538	INS_MEDICAID	MITCHELL COUNTY
37121	205	3184	33.951	INS_MEDICARE	MITCHELL COUNTY
37121	200	1745	13.565	INS_PRIVATE	MITCHELL COUNTY
37121	63	96	1.841	INS_SELFPAY	MITCHELL COUNTY
37121	202	2641	24.802	MALE	MITCHELL COUNTY
37121	224	4484	48.567	RACE_1	MITCHELL COUNTY
37121	42	49	1.333	RACE_2	MITCHELL COUNTY
37121	22	20	0.955	RACE_3	MITCHELL COUNTY
37121	21	21	1.048	RACE_456	MITCHELL COUNTY
37123	177	1391	16.209	AGE_17_44	MONTGOMERY COUNTY
37123	211	3050	32.19	AGE_45_64	MONTGOMERY COUNTY
37123	210	4225	62.805	AGE_65	MONTGOMERY COUNTY
37123	214	4395	59.575	FEMALE	MONTGOMERY COUNTY
37123	170	1133	10.971	INS_MEDICAID	MONTGOMERY COUNTY
37123	223	4738	68.072	INS_MEDICARE	MONTGOMERY COUNTY
37123	200	2146	20.715	INS_PRIVATE	MONTGOMERY COUNTY
37123	154	765	7.338	INS_SELFPAY	MONTGOMERY COUNTY
37123	210	3768	48.1	MALE	MONTGOMERY COUNTY
37123	224	5467	77.987	RACE_1	MONTGOMERY COUNTY
37123	192	2165	25.12	RACE_2	MONTGOMERY COUNTY
37123	84	126	1.762	RACE_3	MONTGOMERY COUNTY
37123	116	299	3.19	RACE_456	MONTGOMERY COUNTY
37125	210	3051	35.724	AGE_17_44	MOORE COUNTY
37125	225	6281	100.378	AGE_45_64	MOORE COUNTY
37125	227	9700	264.687	AGE_65	MOORE COUNTY
37125	224	9195	211.241	FEMALE	MOORE COUNTY
37125	204	2536	26.162	INS_MEDICAID	MOORE COUNTY
37125	232	9877	259.216	INS_MEDICARE	MOORE COUNTY
37125	222	5826	81.928	INS_PRIVATE	MOORE COUNTY
37125	194	1842	17.062	INS_SELFPAY	MOORE COUNTY
37125	218	8511	196.573	MALE	MOORE COUNTY
37125	223	11340	312.82	RACE_1	MOORE COUNTY
37125	217	4751	71.152	RACE_2	MOORE COUNTY
37125	115	298	3.174	RACE_3	MOORE COUNTY
37125	168	754	6.488	RACE_456	MOORE COUNTY
37127	220	3785	45.495	AGE_17_44	NASH COUNTY
37127	228	7007	117.338	AGE_45_64	NASH COUNTY
37127	221	7860	168.457	AGE_65	NASH COUNTY
37127	227	8642	175.176	FEMALE	NASH COUNTY
37127	215	3695	44.981	INS_MEDICAID	NASH COUNTY
37127	228	9008	196.684	INS_MEDICARE	NASH COUNTY
37127	229	4803	55.642	INS_PRIVATE	NASH COUNTY
37127	185	1493	14.276	INS_SELFPAY	NASH COUNTY
37127	217	7926	157.724	MALE	NASH COUNTY

37127	234	9077	185.983	RACE_1	NASH COUNTY
37127	228	7050	119.728	RACE_2	NASH COUNTY
37127	148	862	9.615	RACE_3	NASH COUNTY
37127	149	635	5.47	RACE_456	NASH COUNTY
37129	222	5170	65.383	AGE_17_44	NEW HANOVER COUNTY
37129	228	9526	193.246	AGE_45_64	NEW HANOVER COUNTY
37129	229	10561	324.157	AGE_65	NEW HANOVER COUNTY
37129	228	11519	311.145	FEMALE	NEW HANOVER COUNTY
37129	214	4586	54.131	INS_MEDICAID	NEW HANOVER COUNTY
37129	230	12051	381.804	INS_MEDICARE	NEW HANOVER COUNTY
37129	231	6696	94.879	INS_PRIVATE	NEW HANOVER COUNTY
37129	215	3241	34.209	INS_SELFPAY	NEW HANOVER COUNTY
37129	219	10656	282.493	MALE	NEW HANOVER COUNTY
37129	233	13555	441.219	RACE_1	NEW HANOVER COUNTY
37129	226	7499	123.735	RACE_2	NEW HANOVER COUNTY
37129	156	711	5.795	RACE_3	NEW HANOVER COUNTY
37129	149	592	5.342	RACE_456	NEW HANOVER COUNTY
37131	177	1366	13.61	AGE_17_44	NORTHAMPTON COUNTY
37131	210	2946	31.471	AGE_45_64	NORTHAMPTON COUNTY
37131	213	3913	54.845	AGE_65	NORTHAMPTON COUNTY
37131	210	4145	54.162	FEMALE	NORTHAMPTON COUNTY
37131	175	1353	13.286	INS_MEDICAID	NORTHAMPTON COUNTY
37131	218	4588	67.61	INS_MEDICARE	NORTHAMPTON COUNTY
37131	191	1544	13.335	INS_PRIVATE	NORTHAMPTON COUNTY
37131	139	598	5.856	INS_SELFPAY	NORTHAMPTON COUNTY
37131	199	3741	46.864	MALE	NORTHAMPTON COUNTY
37131	213	3230	35.606	RACE_1	NORTHAMPTON COUNTY
37131	218	4287	58.335	RACE_2	NORTHAMPTON COUNTY
37131	67	119	2.134	RACE_3	NORTHAMPTON COUNTY
37131	41	38	1.146	RACE_456	NORTHAMPTON COUNTY
37133	220	4251	51.509	AGE_17_44	ONSLOW COUNTY
37133	226	7034	105.996	AGE_45_64	ONSLOW COUNTY
37133	224	7701	151.085	AGE_65	ONSLOW COUNTY
37133	226	8912	167.465	FEMALE	ONSLOW COUNTY
37133	217	2853	25.733	INS_MEDICAID	ONSLOW COUNTY
37133	231	8775	179.009	INS_MEDICARE	ONSLOW COUNTY
37133	224	4511	49.652	INS_PRIVATE	ONSLOW COUNTY
37133	202	2475	24.178	INS_SELFPAY	ONSLOW COUNTY
37133	216	7789	144.829	MALE	ONSLOW COUNTY
37133	233	10525	231.944	RACE_1	ONSLOW COUNTY
37133	221	4524	53.439	RACE_2	ONSLOW COUNTY
37133	172	888	6.942	RACE_3	ONSLOW COUNTY
37133	179	970	7.425	RACE_456	ONSLOW COUNTY
37135	212	3454	38.769	AGE_17_44	ORANGE COUNTY
37135	232	6114	76.022	AGE_45_64	ORANGE COUNTY
37135	225	7282	114.244	AGE_65	ORANGE COUNTY
37135	228	8193	125.583	FEMALE	ORANGE COUNTY
37135	196	2225	22.714	INS_MEDICAID	ORANGE COUNTY
37135	230	7969	125.474	INS_MEDICARE	ORANGE COUNTY

37135	230	4683	48.183	INS_PRIVATE	ORANGE COUNTY
37135	201	2239	22.149	INS_SELFPAY	ORANGE COUNTY
37135	221	7067	103.729	MALE	ORANGE COUNTY
37135	233	9435	156.438	RACE_1	ORANGE COUNTY
37135	220	4847	57.373	RACE_2	ORANGE COUNTY
37135	87	158	2.414	RACE_3	ORANGE COUNTY
37135	191	1216	9.215	RACE_456	ORANGE COUNTY
37137	138	628	6.601	AGE_17_44	PAMLICO COUNTY
37137	191	1876	16.67	AGE_45_64	PAMLICO COUNTY
37137	189	2328	24.714	AGE_65	PAMLICO COUNTY
37137	199	2404	21.899	FEMALE	PAMLICO COUNTY
37137	146	689	6.178	INS_MEDICAID	PAMLICO COUNTY
37137	205	2677	26.922	INS_MEDICARE	PAMLICO COUNTY
37137	167	970	8.713	INS_PRIVATE	PAMLICO COUNTY
37137	132	490	4.803	INS_SELFPAY	PAMLICO COUNTY
37137	199	2276	22.151	MALE	PAMLICO COUNTY
37137	213	3135	30.446	RACE_1	PAMLICO COUNTY
37137	175	1314	12.166	RACE_2	PAMLICO COUNTY
37137	51	73	1.784	RACE_3	PAMLICO COUNTY
37137	33	41	1.303	RACE_456	PAMLICO COUNTY
37139	175	1120	10.497	AGE_17_44	PASQUOTANK COUNTY
37139	206	2657	25.286	AGE_45_64	PASQUOTANK COUNTY
37139	201	3753	46.1	AGE_65	PASQUOTANK COUNTY
37139	214	3883	42.023	FEMALE	PASQUOTANK COUNTY
37139	160	903	8.444	INS_MEDICAID	PASQUOTANK COUNTY
37139	210	4246	51.224	INS_MEDICARE	PASQUOTANK COUNTY
37139	202	1740	14.446	INS_PRIVATE	PASQUOTANK COUNTY
37139	135	594	5.963	INS_SELFPAY	PASQUOTANK COUNTY
37139	197	3331	37.152	MALE	PASQUOTANK COUNTY
37139	217	4049	45.258	RACE_1	PASQUOTANK COUNTY
37139	199	3005	31.663	RACE_2	PASQUOTANK COUNTY
37139	68	88	1.353	RACE_3	PASQUOTANK COUNTY
37139	57	67	1.351	RACE_456	PASQUOTANK COUNTY
37141	202	2079	18.475	AGE_17_44	PENDER COUNTY
37141	215	4622	54.833	AGE_45_64	PENDER COUNTY
37141	216	5551	90.972	AGE_65	PENDER COUNTY
37141	222	5850	82.739	FEMALE	PENDER COUNTY
37141	190	1701	15.205	INS_MEDICAID	PENDER COUNTY
37141	220	6460	106.709	INS_MEDICARE	PENDER COUNTY
37141	210	2961	28.167	INS_PRIVATE	PENDER COUNTY
37141	173	1069	8.884	INS_SELFPAY	PENDER COUNTY
37141	212	5465	79.259	MALE	PENDER COUNTY
37141	228	7082	114.118	RACE_1	PENDER COUNTY
37141	207	3546	39.821	RACE_2	PENDER COUNTY
37141	110	368	4.418	RACE_3	PENDER COUNTY
37141	71	133	2.465	RACE_456	PENDER COUNTY
37143	132	467	5	AGE_17_44	PERQUIMANS COUNTY
37143	170	1250	11.4	AGE_45_64	PERQUIMANS COUNTY
37143	182	2158	22.247	AGE_65	PERQUIMANS COUNTY

37143	188	1909	17.426	FEMALE	PERQUIMANS COUNTY
37143	134	582	5.97	INS_MEDICAID	PERQUIMANS COUNTY
37143	188	2330	24.367	INS_MEDICARE	PERQUIMANS COUNTY
37143	145	668	6.359	INS_PRIVATE	PERQUIMANS COUNTY
37143	88	200	2.909	INS_SELFPAY	PERQUIMANS COUNTY
37143	181	1852	18.624	MALE	PERQUIMANS COUNTY
37143	197	2397	23.777	RACE_1	PERQUIMANS COUNTY
37143	167	1260	11.491	RACE_2	PERQUIMANS COUNTY
37143	8	8	1	RACE_3	PERQUIMANS COUNTY
37143	30	25	0.933	RACE_456	PERQUIMANS COUNTY
37145	189	1799	16.704	AGE_17_44	PERSON COUNTY
37145	216	3733	40.319	AGE_45_64	PERSON COUNTY
37145	215	4739	66.2	AGE_65	PERSON COUNTY
37145	222	4946	63.527	FEMALE	PERSON COUNTY
37145	194	1352	10.438	INS_MEDICAID	PERSON COUNTY
37145	225	4877	63.489	INS_MEDICARE	PERSON COUNTY
37145	213	3468	36.413	INS_PRIVATE	PERSON COUNTY
37145	168	1061	9.69	INS_SELFPAY	PERSON COUNTY
37145	209	4538	57.397	MALE	PERSON COUNTY
37145	227	5873	81.899	RACE_1	PERSON COUNTY
37145	214	3278	32.827	RACE_2	PERSON COUNTY
37145	37	43	1.297	RACE_3	PERSON COUNTY
37145	102	210	2.51	RACE_456	PERSON COUNTY
37147	226	5175	75.115	AGE_17_44	PITT COUNTY
37147	230	8261	149.213	AGE_45_64	PITT COUNTY
37147	224	8411	172.371	AGE_65	PITT COUNTY
37147	228	9895	210.268	FEMALE	PITT COUNTY
37147	219	4220	50.228	INS_MEDICAID	PITT COUNTY
37147	231	9955	222.97	INS_MEDICARE	PITT COUNTY
37147	231	6102	79.229	INS_PRIVATE	PITT COUNTY
37147	208	3060	37.764	INS_SELFPAY	PITT COUNTY
37147	219	9098	191.621	MALE	PITT COUNTY
37147	234	10082	208.017	RACE_1	PITT COUNTY
37147	230	8774	170.048	RACE_2	PITT COUNTY
37147	157	751	7.223	RACE_3	PITT COUNTY
37147	155	604	5.219	RACE_456	PITT COUNTY
37149	136	564	6.081	AGE_17_44	POLK COUNTY
37149	181	1382	12.867	AGE_45_64	POLK COUNTY
37149	196	2830	34.219	AGE_65	POLK COUNTY
37149	200	2541	27.95	FEMALE	POLK COUNTY
37149	127	441	4.472	INS_MEDICAID	POLK COUNTY
37149	203	3099	35.783	INS_MEDICARE	POLK COUNTY
37149	173	978	8.798	INS_PRIVATE	POLK COUNTY
37149	106	288	3.585	INS_SELFPAY	POLK COUNTY
37149	185	2235	23.097	MALE	POLK COUNTY
37149	213	3707	44.019	RACE_1	POLK COUNTY
37149	105	317	3.648	RACE_2	POLK COUNTY
37149	28	30	1.393	RACE_3	POLK COUNTY
37149	16	15	1	RACE_456	POLK COUNTY

37151	221	3897	48.385	AGE_17_44	RANDOLPH COUNTY
37151	228	7003	120	AGE_45_64	RANDOLPH COUNTY
37151	223	8023	199.126	AGE_65	RANDOLPH COUNTY
37151	229	8775	190.026	FEMALE	RANDOLPH COUNTY
37151	214	2967	32.939	INS_MEDICAID	RANDOLPH COUNTY
37151	231	7680	151.065	INS_MEDICARE	RANDOLPH COUNTY
37151	231	7779	147.701	INS_PRIVATE	RANDOLPH COUNTY
37151	204	2347	23.804	INS_SELFPAY	RANDOLPH COUNTY
37151	220	8155	177.009	MALE	RANDOLPH COUNTY
37151	234	11336	316.376	RACE_1	RANDOLPH COUNTY
37151	204	2612	27.196	RACE_2	RANDOLPH COUNTY
37151	165	931	8.564	RACE_3	RANDOLPH COUNTY
37151	157	713	6.261	RACE_456	RANDOLPH COUNTY
37153	205	2709	29.727	AGE_17_44	RICHMOND COUNTY
37153	224	5466	79.33	AGE_45_64	RICHMOND COUNTY
37153	220	6316	118.818	AGE_65	RICHMOND COUNTY
37153	220	6808	120.405	FEMALE	RICHMOND COUNTY
37153	205	2713	26.22	INS_MEDICAID	RICHMOND COUNTY
37153	228	7308	149.618	INS_MEDICARE	RICHMOND COUNTY
37153	216	3267	33.653	INS_PRIVATE	RICHMOND COUNTY
37153	176	1245	11.926	INS_SELFPAY	RICHMOND COUNTY
37153	214	6248	109.883	MALE	RICHMOND COUNTY
37153	229	7738	146.769	RACE_1	RICHMOND COUNTY
37153	217	4799	68.977	RACE_2	RICHMOND COUNTY
37153	102	252	2.814	RACE_3	RICHMOND COUNTY
37153	151	627	5.483	RACE_456	RICHMOND COUNTY
37155	229	6437	102.166	AGE_17_44	ROBESON COUNTY
37155	230	10286	264.174	AGE_45_64	ROBESON COUNTY
37155	229	10111	325.755	AGE_65	ROBESON COUNTY
37155	228	11812	378.346	FEMALE	ROBESON COUNTY
37155	228	6784	112.978	INS_MEDICAID	ROBESON COUNTY
37155	231	11850	422.723	INS_MEDICARE	ROBESON COUNTY
37155	229	6125	84.616	INS_PRIVATE	ROBESON COUNTY
37155	214	3732	51.131	INS_SELFPAY	ROBESON COUNTY
37155	221	10882	328.014	MALE	ROBESON COUNTY
37155	231	9652	229.801	RACE_1	ROBESON COUNTY
37155	227	7972	163.15	RACE_2	ROBESON COUNTY
37155	156	789	7.378	RACE_3	ROBESON COUNTY
37155	230	9862	241.852	RACE_456	ROBESON COUNTY
37157	222	3949	47.568	AGE_17_44	ROCKINGHAM COUNTY
37157	230	6779	111.965	AGE_45_64	ROCKINGHAM COUNTY
37157	226	7955	175.482	AGE_65	ROCKINGHAM COUNTY
37157	227	8733	183.357	FEMALE	ROCKINGHAM COUNTY
37157	215	3411	38.149	INS_MEDICAID	ROCKINGHAM COUNTY
37157	229	8131	172.38	INS_MEDICARE	ROCKINGHAM COUNTY
37157	229	6671	101.074	INS_PRIVATE	ROCKINGHAM COUNTY
37157	184	1794	18.777	INS_SELFPAY	ROCKINGHAM COUNTY
37157	218	7738	157.564	MALE	ROCKINGHAM COUNTY
37157	234	10343	252.124	RACE_1	ROCKINGHAM COUNTY

37157	219	5257	71.169	RACE_2	ROCKINGHAM COUNTY
37157	122	375	4.016	RACE_3	ROCKINGHAM COUNTY
37157	117	364	3.991	RACE_456	ROCKINGHAM COUNTY
37159	228	5187	70.842	AGE_17_44	ROWAN COUNTY
37159	232	8641	169.987	AGE_45_64	ROWAN COUNTY
37159	227	9820	266.493	AGE_65	ROWAN COUNTY
37159	227	10859	285.824	FEMALE	ROWAN COUNTY
37159	222	4070	50.347	INS_MEDICAID	ROWAN COUNTY
37159	232	9963	257.315	INS_MEDICARE	ROWAN COUNTY
37159	229	8573	157.624	INS_PRIVATE	ROWAN COUNTY
37159	212	2913	29.717	INS_SELFPAY	ROWAN COUNTY
37159	220	9671	232.732	MALE	ROWAN COUNTY
37159	233	13016	401.013	RACE_1	ROWAN COUNTY
37159	224	5791	90.513	RACE_2	ROWAN COUNTY
37159	146	667	5.897	RACE_3	ROWAN COUNTY
37159	149	607	5.503	RACE_456	ROWAN COUNTY
37161	203	2341	25.512	AGE_17_44	RUTHERFORD COUNTY
37161	225	5058	66.747	AGE_45_64	RUTHERFORD COUNTY
37161	216	6302	116.394	AGE_65	RUTHERFORD COUNTY
37161	222	6765	114.716	FEMALE	RUTHERFORD COUNTY
37161	207	2354	22.556	INS_MEDICAID	RUTHERFORD COUNTY
37161	222	7242	138.86	INS_MEDICARE	RUTHERFORD COUNTY
37161	224	3115	31.312	INS_PRIVATE	RUTHERFORD COUNTY
37161	180	1339	12.467	INS_SELFPAY	RUTHERFORD COUNTY
37161	217	5868	91.571	MALE	RUTHERFORD COUNTY
37161	233	8556	169.519	RACE_1	RUTHERFORD COUNTY
37161	200	2571	25.96	RACE_2	RUTHERFORD COUNTY
37161	105	232	2.848	RACE_3	RUTHERFORD COUNTY
37161	66	107	1.818	RACE_456	RUTHERFORD COUNTY
37163	210	2843	27.705	AGE_17_44	SAMPSON COUNTY
37163	220	5406	78.859	AGE_45_64	SAMPSON COUNTY
37163	219	6032	117.909	AGE_65	SAMPSON COUNTY
37163	220	6659	118.523	FEMALE	SAMPSON COUNTY
37163	208	2452	22.428	INS_MEDICAID	SAMPSON COUNTY
37163	224	6979	141.643	INS_MEDICARE	SAMPSON COUNTY
37163	212	3707	41.335	INS_PRIVATE	SAMPSON COUNTY
37163	189	1687	31.979	INS_SELFPAY	SAMPSON COUNTY
37163	212	6199	108.085	MALE	SAMPSON COUNTY
37163	227	6915	120.211	RACE_1	SAMPSON COUNTY
37163	214	4315	58.664	RACE_2	SAMPSON COUNTY
37163	133	568	6.774	RACE_3	SAMPSON COUNTY
37163	164	695	5.616	RACE_456	SAMPSON COUNTY
37165	203	2449	22.631	AGE_17_44	SCOTLAND COUNTY
37165	223	4368	54.578	AGE_45_64	SCOTLAND COUNTY
37165	213	4710	71.033	AGE_65	SCOTLAND COUNTY
37165	220	5590	79.573	FEMALE	SCOTLAND COUNTY
37165	206	2286	21.005	INS_MEDICAID	SCOTLAND COUNTY
37165	223	5652	88.587	INS_MEDICARE	SCOTLAND COUNTY
37165	213	2738	25.427	INS_PRIVATE	SCOTLAND COUNTY

37165	176	1114	10.233	INS_SELFPAY	SCOTLAND COUNTY
37165	211	4838	68.194	MALE	SCOTLAND COUNTY
37165	226	5690	78.447	RACE_1	SCOTLAND COUNTY
37165	218	4212	53.22	RACE_2	SCOTLAND COUNTY
37165	133	568	6.774	RACE_3	SCOTLAND COUNTY
37165	189	1261	10.217	RACE_456	SCOTLAND COUNTY
37167	202	2542	29.149	AGE_17_44	STANLY COUNTY
37167	224	5268	69.263	AGE_45_64	STANLY COUNTY
37167	220	6558	127.909	AGE_65	STANLY COUNTY
37167	219	6741	119.813	FEMALE	STANLY COUNTY
37167	194	2149	22.613	INS_MEDICAID	STANLY COUNTY
37167	225	6987	137.431	INS_MEDICARE	STANLY COUNTY
37167	222	4241	45.964	INS_PRIVATE	STANLY COUNTY
37167	187	1380	14.16	INS_SELFPAY	STANLY COUNTY
37167	215	6300	108.391	MALE	STANLY COUNTY
37167	230	8960	191.117	RACE_1	STANLY COUNTY
37167	166	1082	9.494	RACE_2	STANLY COUNTY
37167	81	144	2.111	RACE_3	STANLY COUNTY
37167	107	310	3.935	RACE_456	STANLY COUNTY
37169	187	1740	16.727	AGE_17_44	STOKES COUNTY
37169	215	4041	45.595	AGE_45_64	STOKES COUNTY
37169	217	5064	69.885	AGE_65	STOKES COUNTY
37169	216	5515	73.444	FEMALE	STOKES COUNTY
37169	180	1408	13.528	INS_MEDICAID	STOKES COUNTY
37169	216	4307	50.593	INS_MEDICARE	STOKES COUNTY
37169	221	4911	58.131	INS_PRIVATE	STOKES COUNTY
37169	156	858	8.032	INS_SELFPAY	STOKES COUNTY
37169	208	4578	58.808	MALE	STOKES COUNTY
37169	228	7348	115.083	RACE_1	STOKES COUNTY
37169	228	1082	6.912	RACE_2	STOKES COUNTY
37169	57	63	1.333	RACE_3	STOKES COUNTY
37169	53	87	1.755	RACE_456	STOKES COUNTY
37171	208	3181	35.639	AGE_17_44	SURRY COUNTY
37171	224	6169	90.518	AGE_45_64	SURRY COUNTY
37171	221	7756	172.683	AGE_65	SURRY COUNTY
37171	226	8067	164.535	FEMALE	SURRY COUNTY
37171	213	2758	25.263	INS_MEDICAID	SURRY COUNTY
37171	227	7506	143.868	INS_MEDICARE	SURRY COUNTY
37171	226	6466	102.031	INS_PRIVATE	SURRY COUNTY
37171	193	1930	18.87	INS_SELFPAY	SURRY COUNTY
37171	218	7288	131.5	MALE	SURRY COUNTY
37171	232	9766	220.491	RACE_1	SURRY COUNTY
37171	184	1621	13.647	RACE_2	SURRY COUNTY
37171	129	370	3.876	RACE_3	SURRY COUNTY
37171	210	3880	54.467	RACE_456	SURRY COUNTY
37173	192	1410	12.141	AGE_17_44	SWAIN COUNTY
37173	214	2693	24.57	AGE_45_64	SWAIN COUNTY
37173	200	3285	37.525	AGE_65	SWAIN COUNTY
37173	212	3586	39.047	FEMALE	SWAIN COUNTY

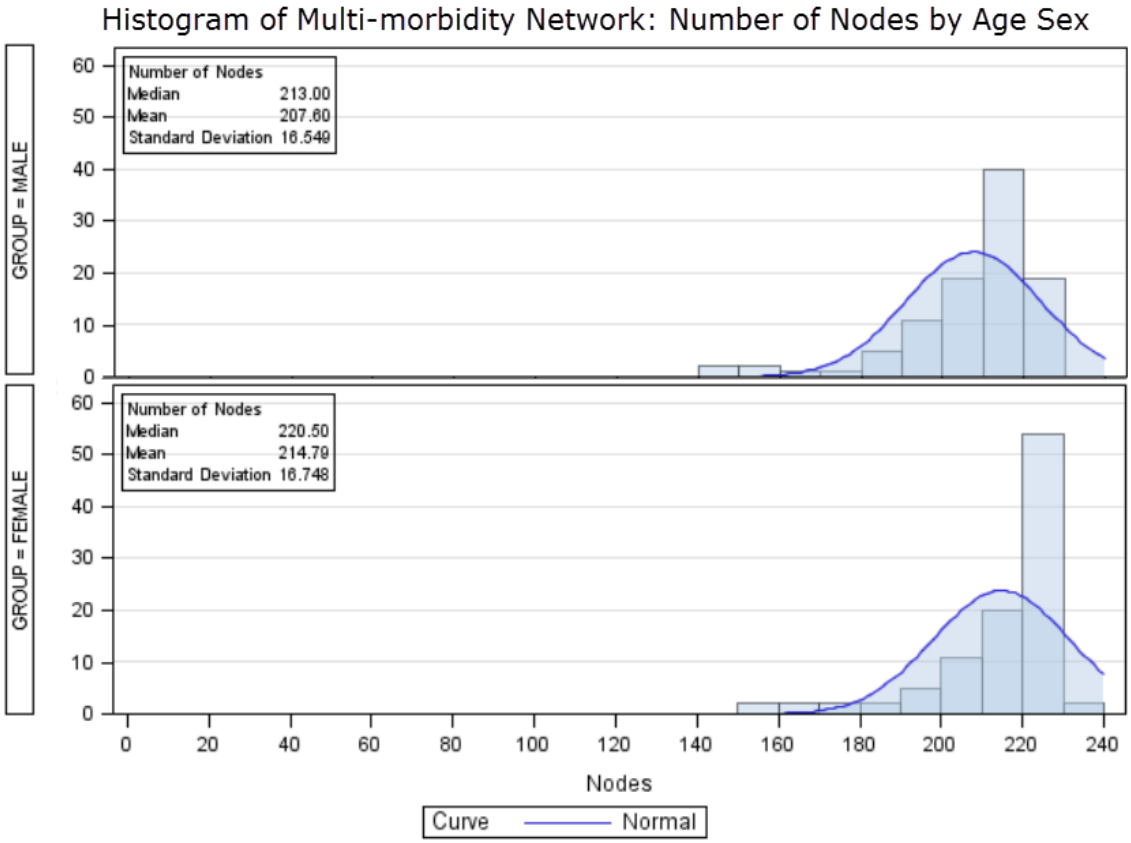
37173	186	1337	11	INS_MEDICAID	SWAIN COUNTY
37173	218	3676	40.95	INS_MEDICARE	SWAIN COUNTY
37173	200	1719	13.92	INS_PRIVATE	SWAIN COUNTY
37173	136	566	5.699	INS_SELFPAY	SWAIN COUNTY
37173	209	3250	32.612	MALE	SWAIN COUNTY
37173	224	482	50.326	RACE_1	SWAIN COUNTY
37173	33	41	1.394	RACE_2	SWAIN COUNTY
37173	59	106	2.068	RACE_3	SWAIN COUNTY
37173	198	1946	17.687	RACE_456	SWAIN COUNTY
37175	172	1123	12.099	AGE_17_44	TRANSYLVANIA COUNTY
37175	208	2504	26.952	AGE_45_64	TRANSYLVANIA COUNTY
37175	216	4603	61.907	AGE_65	TRANSYLVANIA COUNTY
37175	214	4240	53.033	FEMALE	TRANSYLVANIA COUNTY
37175	177	1086	10.91	INS_MEDICAID	TRANSYLVANIA COUNTY
37175	221	4821	63.561	INS_MEDICARE	TRANSYLVANIA COUNTY
37175	198	2016	19.444	INS_PRIVATE	TRANSYLVANIA COUNTY
37175	147	644	6.599	INS_SELFPAY	TRANSYLVANIA COUNTY
37175	207	3753	46.884	MALE	TRANSYLVANIA COUNTY
37175	227	5904	86.458	RACE_1	TRANSYLVANIA COUNTY
37175	138	605	6.681	RACE_2	TRANSYLVANIA COUNTY
37175	25	25	1.08	RACE_3	TRANSYLVANIA COUNTY
37175	35	25	0.771	RACE_456	TRANSYLVANIA COUNTY
37177	83	174	2.554	AGE_17_44	TYRRELL COUNTY
37177	136	552	5.404	AGE_45_64	TYRRELL COUNTY
37177	151	832	8.013	AGE_65	TYRRELL COUNTY
37177	151	776	7.212	FEMALE	TYRRELL COUNTY
37177	85	170	2.388	INS_MEDICAID	TYRRELL COUNTY
37177	157	979	9.65	INS_MEDICARE	TYRRELL COUNTY
37177	106	246	2.726	INS_PRIVATE	TYRRELL COUNTY
37177	64	98	1.656	INS_SELFPAY	TYRRELL COUNTY
37177	156	762	6.846	MALE	TYRRELL COUNTY
37177	167	959	8.287	RACE_1	TYRRELL COUNTY
37177	130	534	5.569	RACE_2	TYRRELL COUNTY
37177	3	3	1	RACE_3	TYRRELL COUNTY
37177	23	24	1.043	RACE_456	TYRRELL COUNTY
37179	219	4980	66.58	AGE_17_44	UNION COUNTY
37179	231	8855	175.649	AGE_45_64	UNION COUNTY
37179	231	10030	280.13	AGE_65	UNION COUNTY
37179	226	10992	293.704	FEMALE	UNION COUNTY
37179	220	3459	37.768	INS_MEDICAID	UNION COUNTY
37179	234	10917	305.423	INS_MEDICARE	UNION COUNTY
37179	232	7910	133.578	INS_PRIVATE	UNION COUNTY
37179	211	2888	31.526	INS_SELFPAY	UNION COUNTY
37179	221	9777	242.032	MALE	UNION COUNTY
37179	234	13351	420.325	RACE_1	UNION COUNTY
37179	225	5624	82.044	RACE_2	UNION COUNTY
37179	171	1099	9.754	RACE_3	UNION COUNTY
37179	155	729	6.49	RACE_456	UNION COUNTY
37181	195	2522	28.113	AGE_17_44	VANCE COUNTY

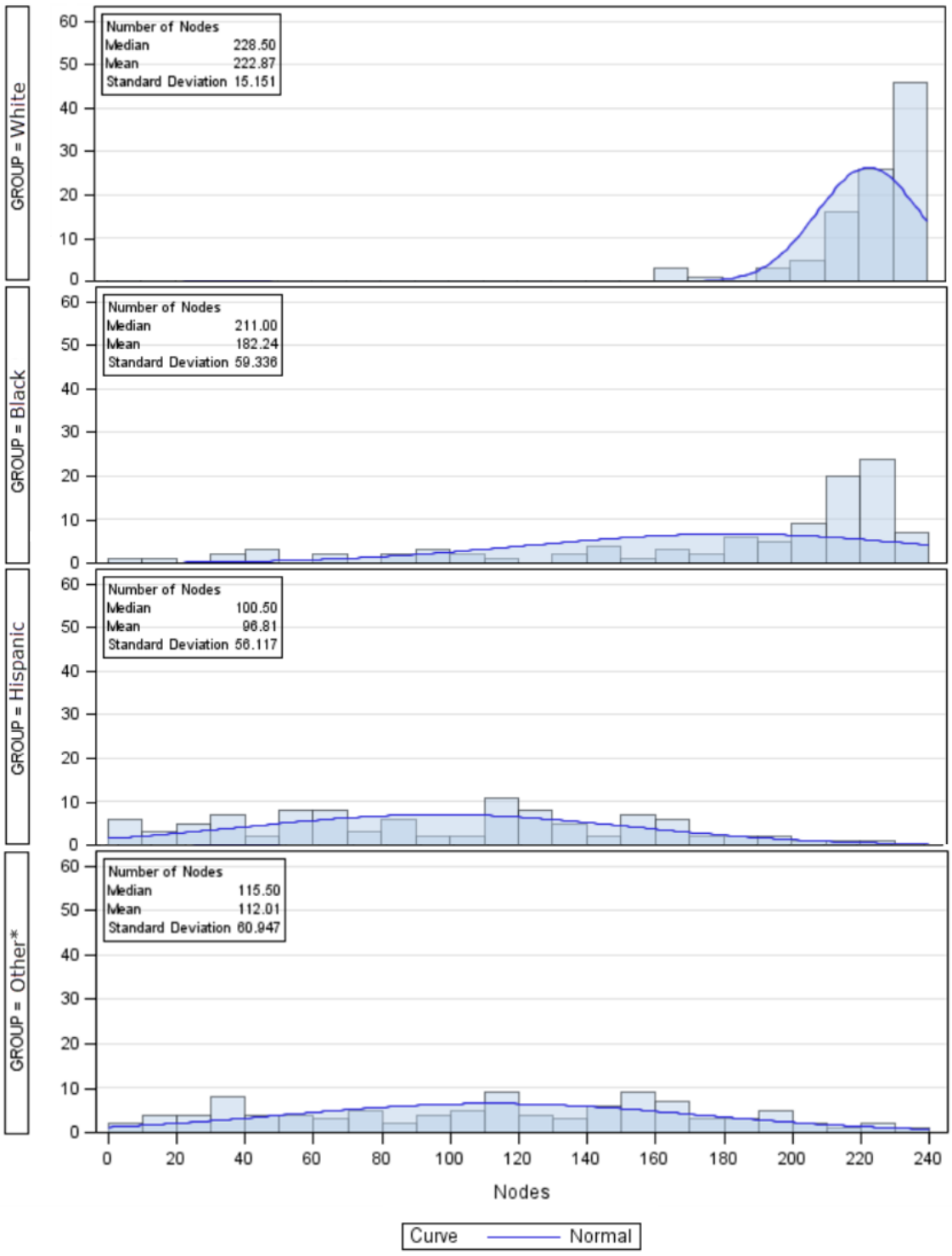
37181	220	4992	73.7	AGE_45_64	VANCE COUNTY
37181	212	5103	88.731	AGE_65	VANCE COUNTY
37181	219	6095	106.699	FEMALE	VANCE COUNTY
37181	200	2600	29.78	INS_MEDICAID	VANCE COUNTY
37181	214	5681	98.565	INS_MEDICARE	VANCE COUNTY
37181	215	3179	34.107	INS_PRIVATE	VANCE COUNTY
37181	170	1049	9.876	INS_SELFPAY	VANCE COUNTY
37181	208	5191	82.404	MALE	VANCE COUNTY
37181	218	5448	88.514	RACE_1	VANCE COUNTY
37181	222	5776	91.779	RACE_2	VANCE COUNTY
37181	99	236	3.03	RACE_3	VANCE COUNTY
37181	101	247	2.921	RACE_456	VANCE COUNTY
37183	234	1110	237.906	AGE_17_44	WAKE COUNTY
37183	234	15751	512.338	AGE_45_64	WAKE COUNTY
37183	231	17242	830.892	AGE_65	WAKE COUNTY
37183	230	18941	879.017	FEMALE	WAKE COUNTY
37183	232	7689	109.815	INS_MEDICAID	WAKE COUNTY
37183	233	18260	859.717	INS_MEDICARE	WAKE COUNTY
37183	235	15890	478.153	INS_PRIVATE	WAKE COUNTY
37183	228	6456	91.974	INS_SELFPAY	WAKE COUNTY
37183	222	17569	744.68	MALE	WAKE COUNTY
37183	235	20724	1054.332	RACE_1	WAKE COUNTY
37183	235	14558	431.277	RACE_2	WAKE COUNTY
37183	217	3274	30.447	RACE_3	WAKE COUNTY
37183	226	4531	43.044	RACE_456	WAKE COUNTY
37185	151	831	8.974	AGE_17_44	WARREN COUNTY
37185	189	2069	21.545	AGE_45_64	WARREN COUNTY
37185	194	3015	40	AGE_65	WARREN COUNTY
37185	200	2984	36.69	FEMALE	WARREN COUNTY
37185	153	955	10.444	INS_MEDICAID	WARREN COUNTY
37185	197	3156	40.858	INS_MEDICARE	WARREN COUNTY
37185	177	1205	10.819	INS_PRIVATE	WARREN COUNTY
37185	104	297	3.702	INS_SELFPAY	WARREN COUNTY
37185	188	2761	31.112	MALE	WARREN COUNTY
37185	200	2362	24.86	RACE_1	WARREN COUNTY
37185	202	3118	37.579	RACE_2	WARREN COUNTY
37185	43	55	1.442	RACE_3	WARREN COUNTY
37185	109	330	3.881	RACE_456	WARREN COUNTY
37187	150	651	5.68	AGE_17_44	WASHINGTON COUNTY
37187	187	1800	15.556	AGE_45_64	WASHINGTON COUNTY
37187	183	2225	25.295	AGE_65	WASHINGTON COUNTY
37187	195	2376	22.851	FEMALE	WASHINGTON COUNTY
37187	154	732	6.143	INS_MEDICAID	WASHINGTON COUNTY
37187	192	2613	28.896	INS_MEDICARE	WASHINGTON COUNTY
37187	178	952	7.685	INS_PRIVATE	WASHINGTON COUNTY
37187	125	390	3.784	INS_SELFPAY	WASHINGTON COUNTY
37187	193	2132	20.544	MALE	WASHINGTON COUNTY
37187	192	2207	22.156	RACE_1	WASHINGTON COUNTY
37187	191	2049	18.665	RACE_2	WASHINGTON COUNTY

37187	33	37	1.303	RACE_3	WASHINGTON COUNTY
37187	92	190	2.37	RACE_456	WASHINGTON COUNTY
37189	178	1233	10.865	AGE_17_44	WATAUGA COUNTY
37189	219	3072	27.324	AGE_45_64	WATAUGA COUNTY
37189	219	5297	69.534	AGE_65	WATAUGA COUNTY
37189	222	4962	55.856	FEMALE	WATAUGA COUNTY
37189	162	907	7.735	INS_MEDICAID	WATAUGA COUNTY
37189	226	5518	70.265	INS_MEDICARE	WATAUGA COUNTY
37189	215	2684	22.688	INS_PRIVATE	WATAUGA COUNTY
37189	143	633	6.252	INS_SELFPAY	WATAUGA COUNTY
37189	211	4301	50.929	MALE	WATAUGA COUNTY
37189	232	7023	96.328	RACE_1	WATAUGA COUNTY
37189	93	254	3.419	RACE_2	WATAUGA COUNTY
37189	73	127	2.288	RACE_3	WATAUGA COUNTY
37189	62	114	1.919	RACE_456	WATAUGA COUNTY
37191	222	4525	52.806	AGE_17_44	WAYNE COUNTY
37191	225	7809	139.56	AGE_45_64	WAYNE COUNTY
37191	223	8482	179.229	AGE_65	WAYNE COUNTY
37191	227	9494	195.797	FEMALE	WAYNE COUNTY
37191	191	1377	11.921	INS_MEDICAID	WAYNE COUNTY
37191	229	9663	213.057	INS_MEDICARE	WAYNE COUNTY
37191	232	7008	100.655	INS_PRIVATE	WAYNE COUNTY
37191	200	2400	25.68	INS_SELFPAY	WAYNE COUNTY
37191	218	8823	177.275	MALE	WAYNE COUNTY
37191	230	10432	225.465	RACE_1	WAYNE COUNTY
37191	230	7443	123.87	RACE_2	WAYNE COUNTY
37191	163	913	7.693	RACE_3	WAYNE COUNTY
37191	115	284	2.93	RACE_456	WAYNE COUNTY
37193	210	3285	35.762	AGE_17_44	WILKES COUNTY
37193	225	5997	84.271	AGE_45_64	WILKES COUNTY
37193	222	7366	141.122	AGE_65	WILKES COUNTY
37193	224	7739	139.281	FEMALE	WILKES COUNTY
37193	205	2715	25.585	INS_MEDICAID	WILKES COUNTY
37193	230	7775	145.078	INS_MEDICARE	WILKES COUNTY
37193	225	5300	65.618	INS_PRIVATE	WILKES COUNTY
37193	191	1808	17.141	INS_SELFPAY	WILKES COUNTY
37193	215	7176	123.726	MALE	WILKES COUNTY
37193	231	9899	210.584	RACE_1	WILKES COUNTY
37193	184	1609	13.891	RACE_2	WILKES COUNTY
37193	115	336	3.635	RACE_3	WILKES COUNTY
37193	193	2614	30.658	RACE_456	WILKES COUNTY
37195	218	3397	36.674	AGE_17_44	WILSON COUNTY
37195	228	6368	96.583	AGE_45_64	WILSON COUNTY
37195	224	7164	141.259	AGE_65	WILSON COUNTY
37195	224	7847	150.397	FEMALE	WILSON COUNTY
37195	214	3059	30.864	INS_MEDICAID	WILSON COUNTY
37195	228	8280	171.596	INS_MEDICARE	WILSON COUNTY
37195	222	4248	49.455	INS_PRIVATE	WILSON COUNTY
37195	194	1927	18.83	INS_SELFPAY	WILSON COUNTY

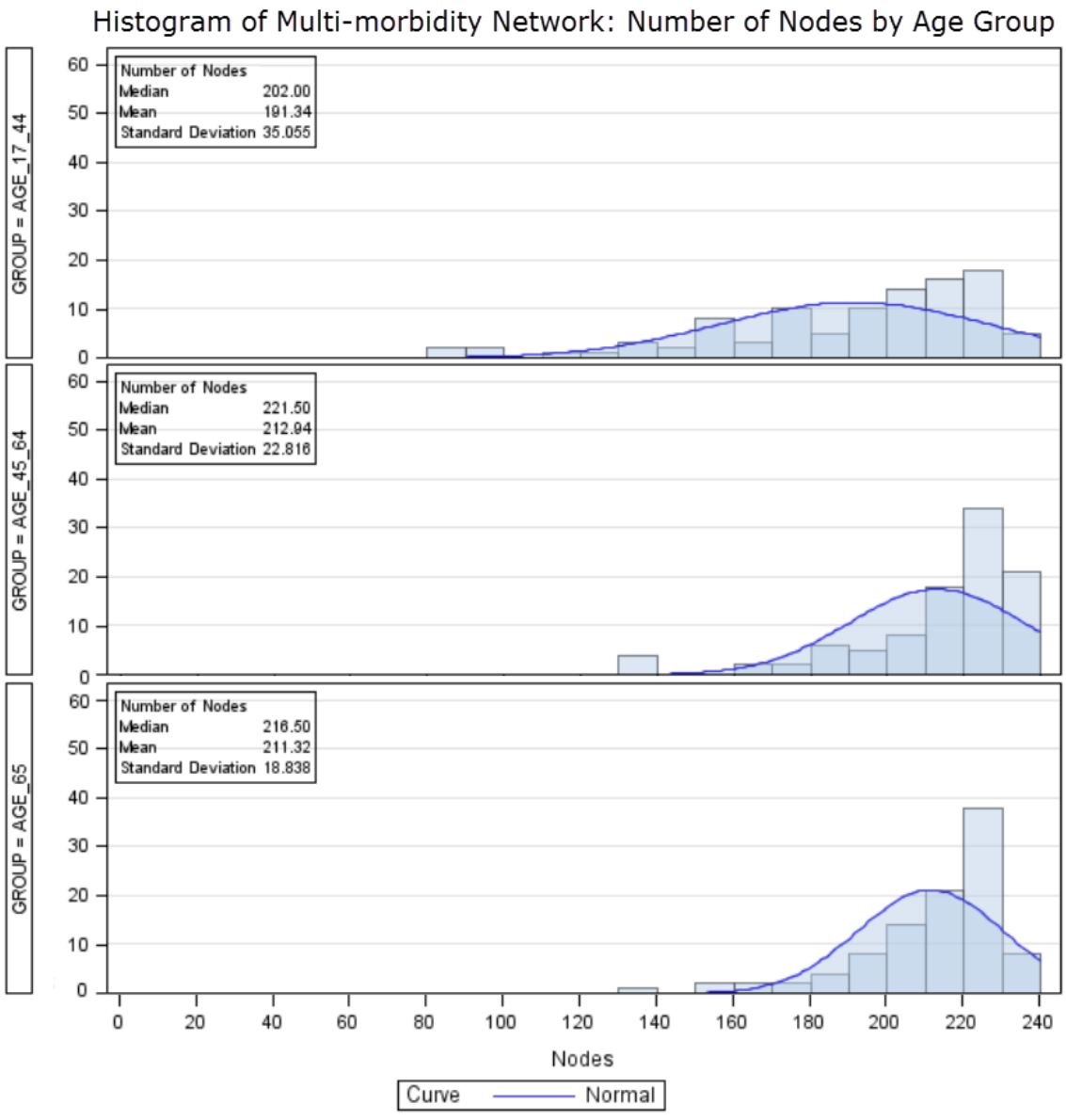
37195	216	7236	129.486	MALE	WILSON COUNTY
37195	232	8121	151.75	RACE_1	WILSON COUNTY
37195	223	6770	109.691	RACE_2	WILSON COUNTY
37195	153	639	5.634	RACE_3	WILSON COUNTY
37195	118	430	4.78	RACE_456	WILSON COUNTY
37197	194	1900	17.49	AGE_17_44	YADKIN COUNTY
37197	215	3855	41.447	AGE_45_64	YADKIN COUNTY
37197	219	5144	69.342	AGE_65	YADKIN COUNTY
37197	215	5428	71.409	FEMALE	YADKIN COUNTY
37197	186	1323	11.78	INS_MEDICAID	YADKIN COUNTY
37197	218	4461	52.275	INS_MEDICARE	YADKIN COUNTY
37197	224	4739	52.835	INS_PRIVATE	YADKIN COUNTY
37197	162	887	7.735	INS_SELFPAY	YADKIN COUNTY
37197	212	4705	57.25	MALE	YADKIN COUNTY
37197	228	6478	86.605	RACE_1	YADKIN COUNTY
37197	142	724	6.725	RACE_2	YADKIN COUNTY
37197	111	246	2.703	RACE_3	YADKIN COUNTY
37197	197	2791	32.462	RACE_456	YADKIN COUNTY
37199	153	881	8.987	AGE_17_44	YANCEY COUNTY
37199	200	2029	17.54	AGE_45_64	YANCEY COUNTY
37199	206	3026	31.903	AGE_65	YANCEY COUNTY
37199	204	3180	32.936	FEMALE	YANCEY COUNTY
37199	161	695	5.957	INS_MEDICAID	YANCEY COUNTY
37199	213	3421	35.817	INS_MEDICARE	YANCEY COUNTY
37199	191	1539	12.508	INS_PRIVATE	YANCEY COUNTY
37199	85	177	2.482	INS_SELFPAY	YANCEY COUNTY
37199	197	2549	24.041	MALE	YANCEY COUNTY
37199	218	4562	51.312	RACE_1	YANCEY COUNTY
37199	60	103	1.867	RACE_2	YANCEY COUNTY
37199	27	30	1.259	RACE_3	YANCEY COUNTY
37199	31	34	1.387	RACE_456	YANCEY COUNTY

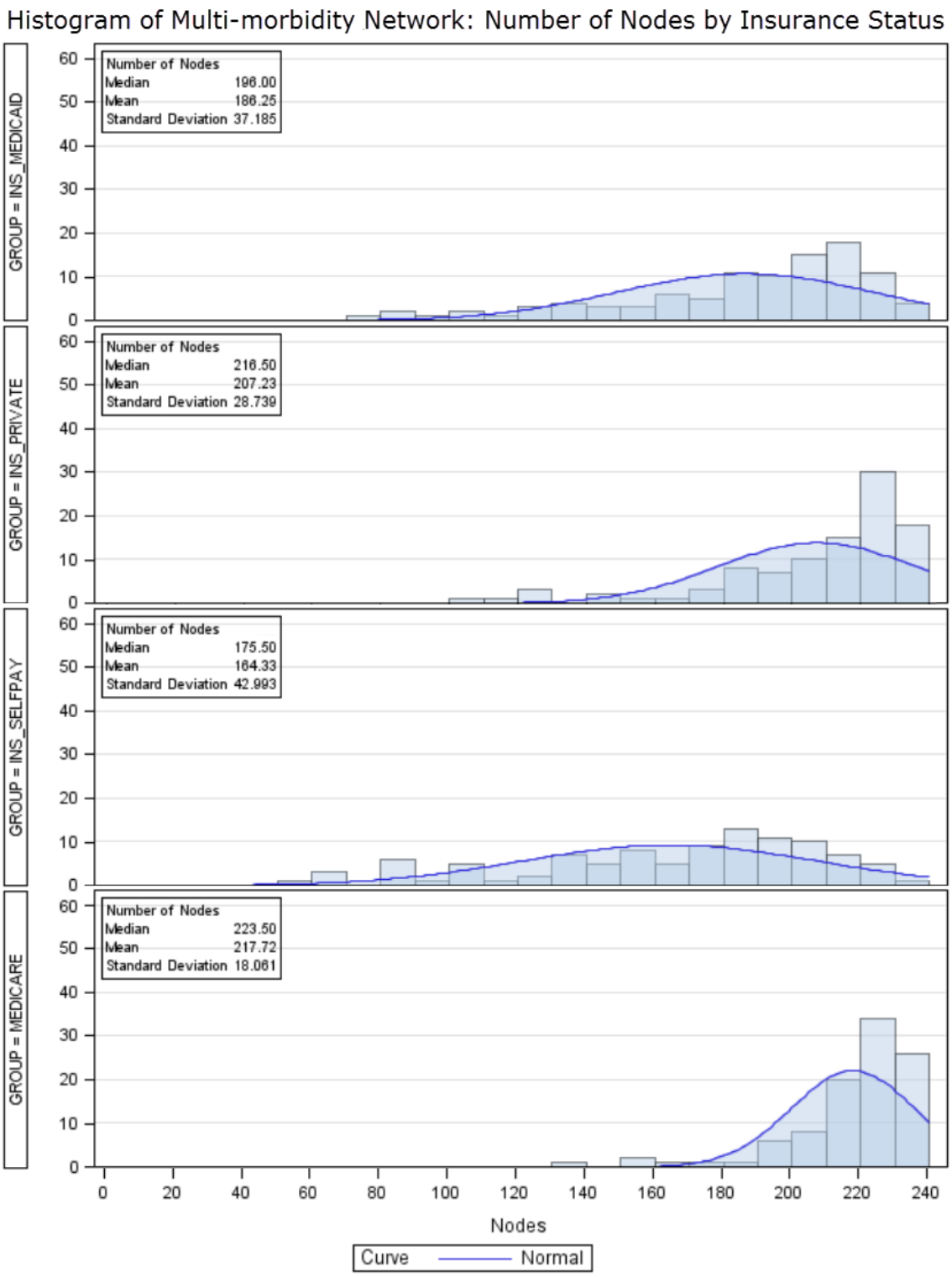
APPENDIX B: HISTOGRAMS MULTIMORBIDITY NETWORK





* Other race category= Asian, Pacific Islander, Native American and Other as defined by HCUP raw data files.

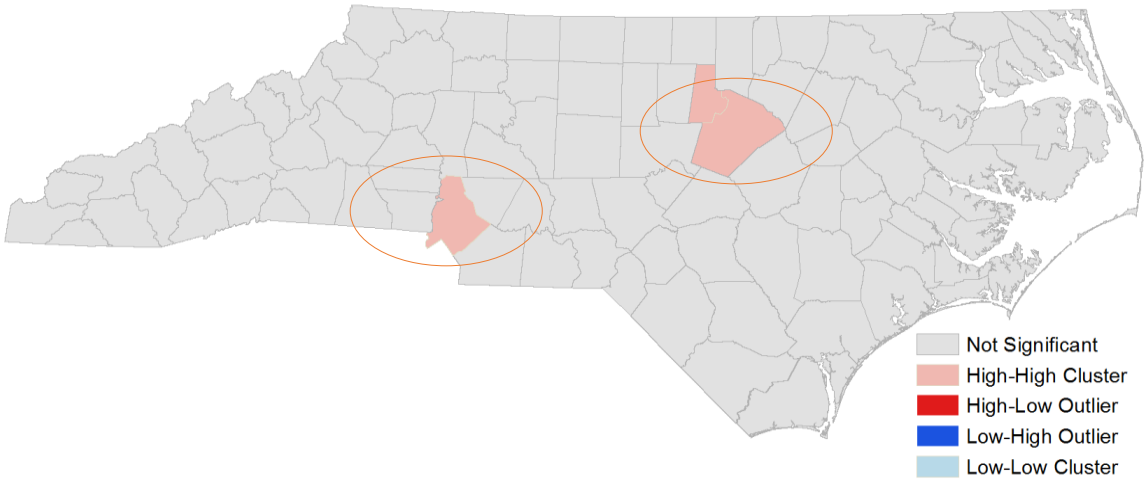

Histogram of Multi-morbidity Network: Number of Nodes by Age Group
GROUP = AGE_17_44
Number of Nodes
Median 202.00
Mean 191.34
Standard Deviation 35.055
GROUP = AGE_45_64
Number of Nodes
Median 221.50
Mean 212.94
Standard Deviation 22.816
GROUP = AGE_65
Number of Nodes
Median 216.50
Mean 211.32
Standard Deviation 18.838
0 10 20 30 40 50 60
0 20 40 60 80 100 120 140 160 180 200 220 240
Nodes
Curve Normal


Histogram of Multi-morbidity Network: Number of Nodes by Insurance Status
GROUP = INS_MEDICAID
Number of Nodes
Median 196.00
Mean 186.25
Standard Deviation 37.185
GROUP = INS_PRIVATE
Number of Nodes
Median 216.50
Mean 207.23
Standard Deviation 28.739
GROUP = INS_SELFPAY
Number of Nodes
Median 175.50
Mean 164.33
Standard Deviation 42.993
GROUP = MEDICARE
Number of Nodes
Median 223.50
Mean 217.72
Standard Deviation 18.061
0 10 20 30 40 50 60
0 20 40 60 80 100 120 140 160 180 200 220 240
Nodes
Curve Normal

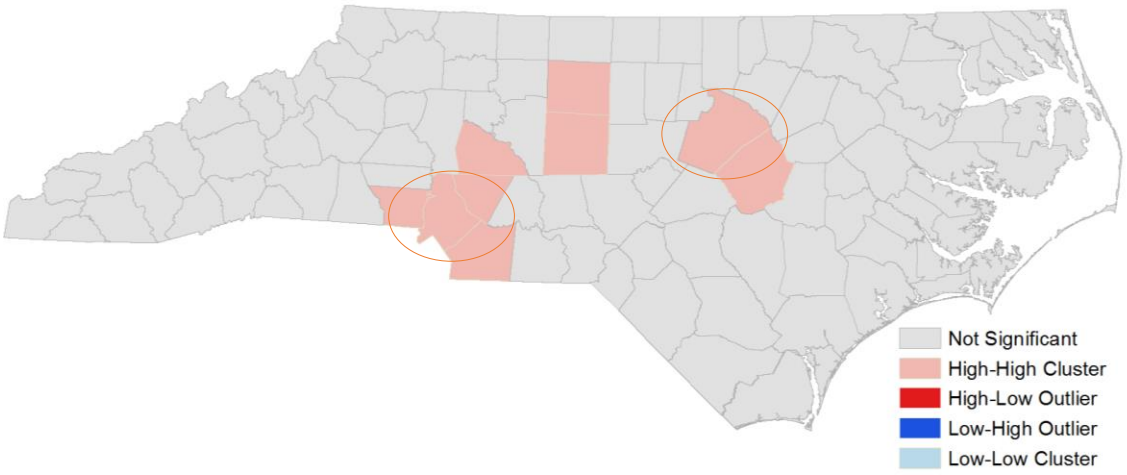
APPENDIX C: AREA CHART - AVERAGE WEIGHTED DEGREE

Average Weighted Degree by Gender and County – Actual values. Source: Farrow-Chestnut, 2017.

APPENDIX D: SPATIAL AUTOCORRELATION - LISA MAPS

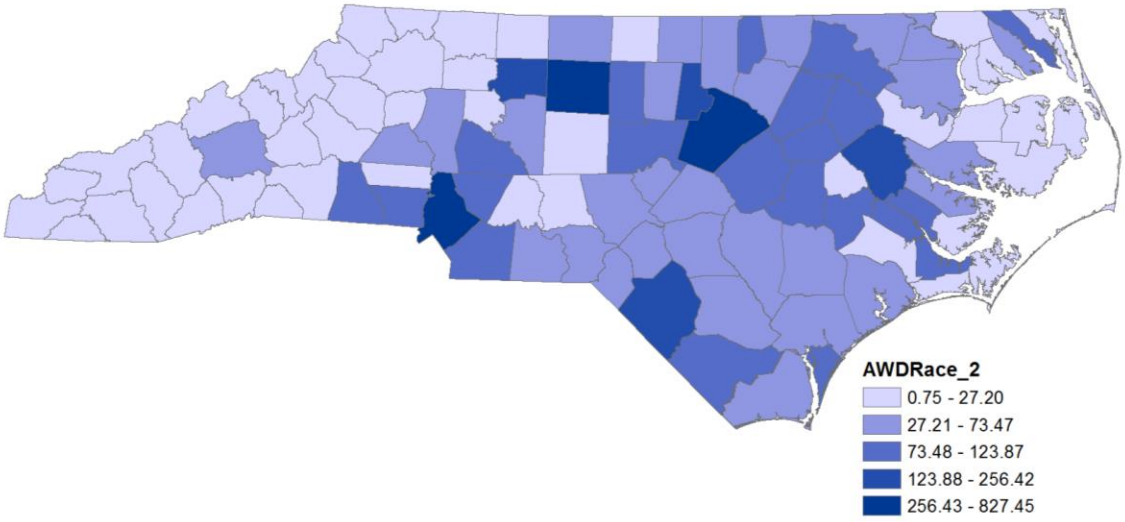


Avg Wtd Degree, Race_2 (non-Hisp black) Moran's I – Mecklenburg (37119) & Wake (37183) circled. Source: Farrow-Chestnut, 2017.

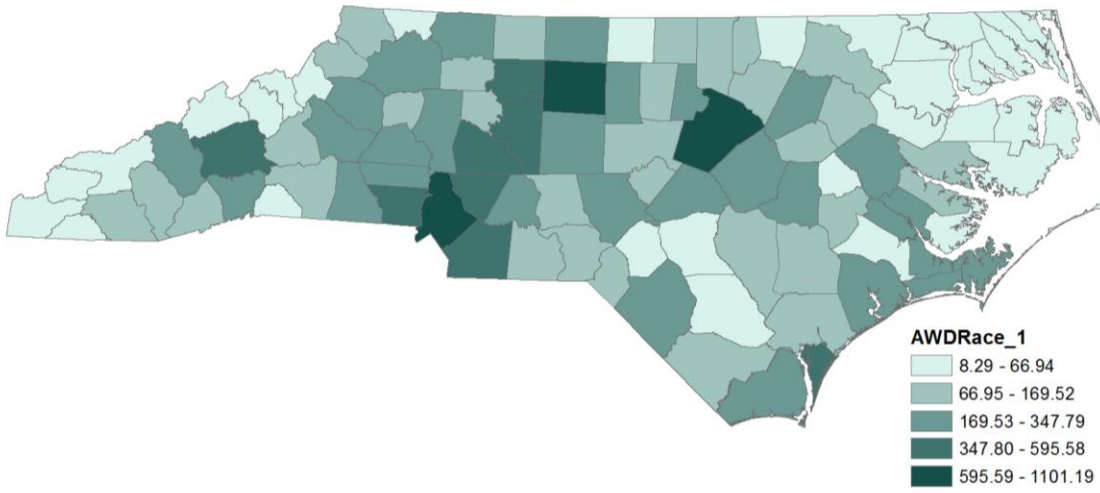


Avg Wtd Degree, Race_1 (non-Hisp white) Moran's I - Mecklenburg (37119) & Wake (37183) circled. Source: Farrow-Chestnut, 2017.

APPENDIX E: GEOGRAPHIC DISTRIBUTION - AVG WTD DEGREE

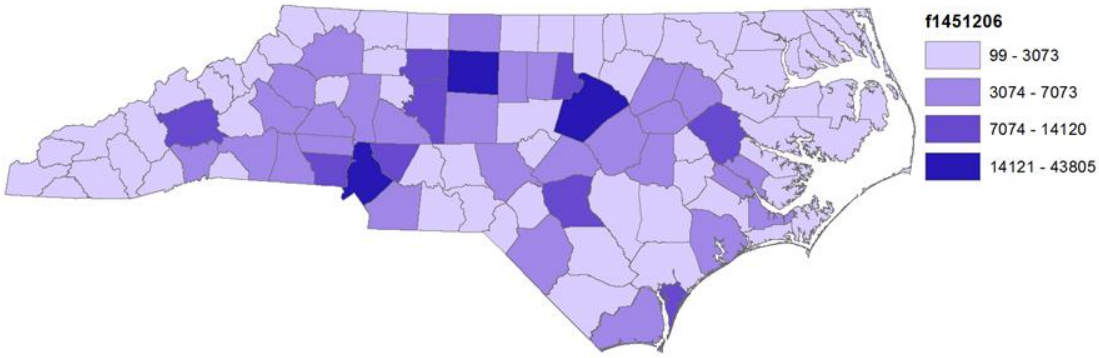


Avg Wtd Degree, Race_2. Source: Farrow-Chestnut, 2017.

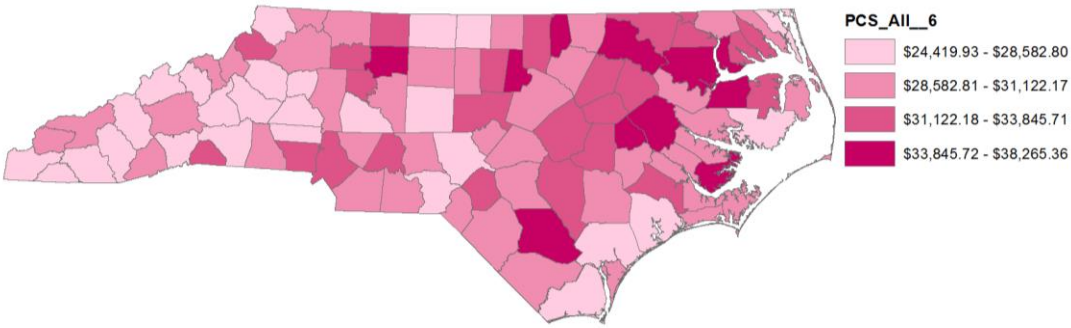


Avg Wtd Degree, Race_1. Source: Farrow-Chestnut, 2017.

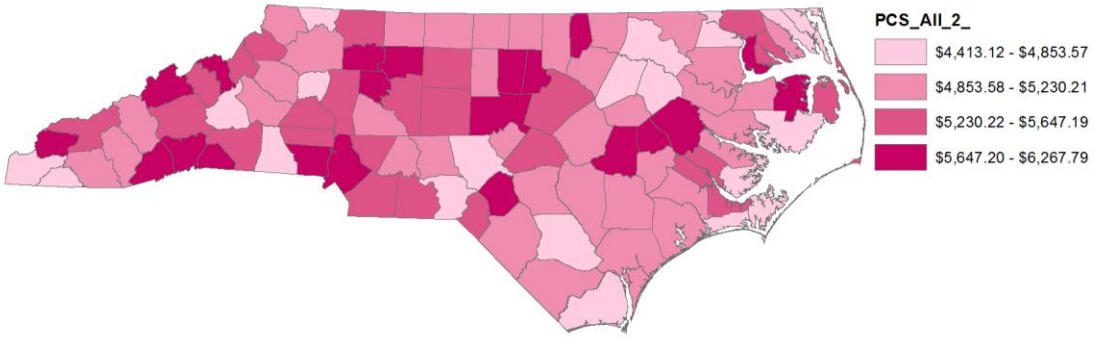
APPENDIX F: GEOGRAPHIC DISTRIBUTION - SIG. IND. VARIABLES



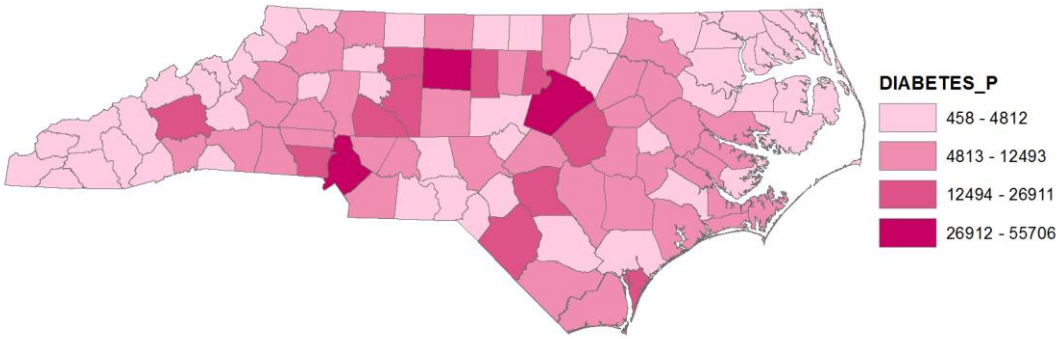
Prepared by: T. Farrow-Chestnut. (2017). Unemployed. Data Source: Area Resource File (AHRF) 2011/12.



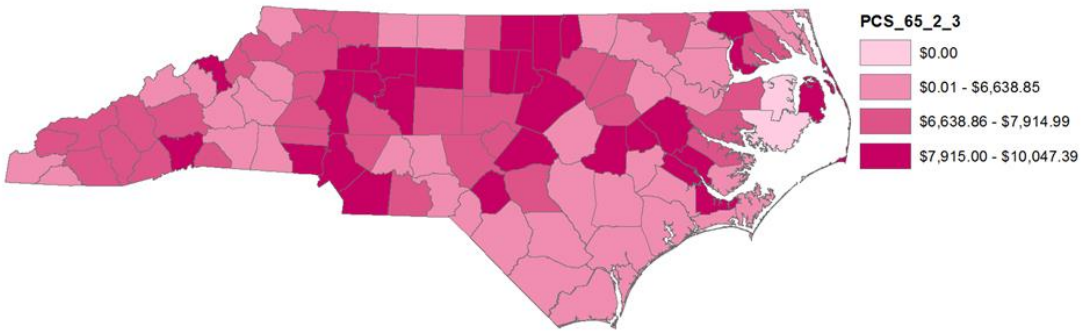
Prepared by: T. Farrow-Chestnut, (2017). Medicare Spending Per Beneficiary Age > 65 All conditions . Data Source: CMS Chronic Condition Data Warehouse (CCW), www.ccwdata.org. County Level Multiple Chronic Conditions (multimorbidity) Table: Prevalence, Medicare Utilization and Spending.



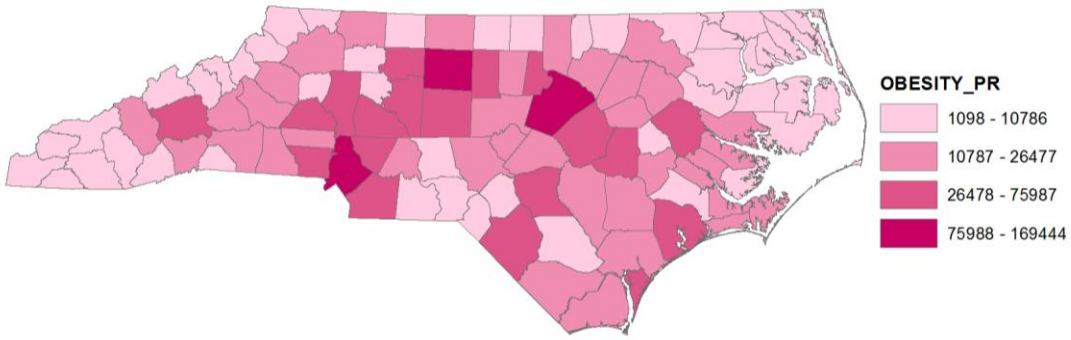
Prepared by: T. Farrow-Chestnut. (2017). Medicare Spending Per Beneficiary All Ages 2 to 3 conditions . Data Source: CMS Chronic Condition Data Warehouse (CCW), www.ccwdata.org. County Level Multiple Chronic Conditions (MULTIMORBIDITY) Table: Prevalence, Medicare Utilization and Spending.



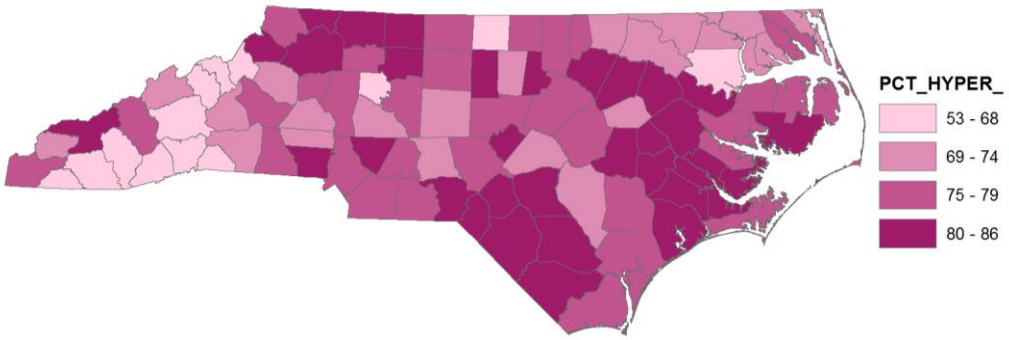
Prepared by: T. Farrow-Chestnut. (2017). Diabetes Prevalence. Data Source: Area Resource File (AHRF) 2011/12.



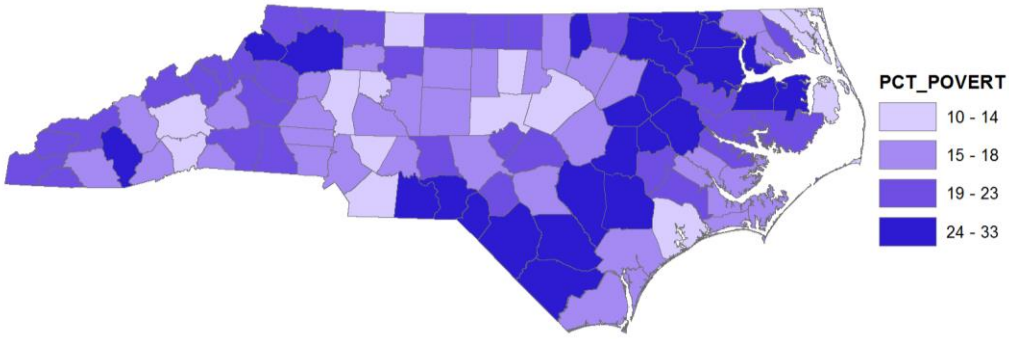
Prepared by: T. Farrow-Chestnut. (2017). Medicare Spending Per Beneficiary Age < 65 with 2 to 3 conditions . Data Source: CMS Chronic Condition Data Warehouse (CCW), www.ccwdata.org. County Level Multiple Chronic Conditions (MULTIMORBIDITY) Table: Prevalence, Medicare Utilization and Spending.



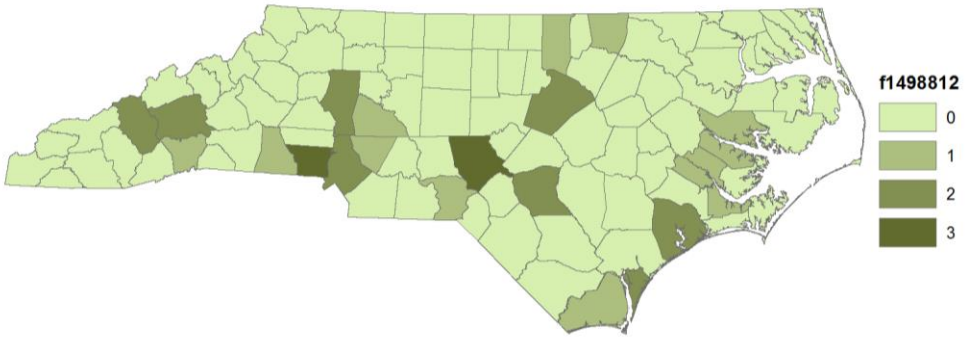
Prepared by: T. Farrow-Chestnut. (2017). Obesity Prevalence. Data Source: Area Resource File (AHRF) 2011/12.



Prepared by: T. Farrow-Chestnut. (2017). Percent of the Population with Hypertension. Data Source: Area Resource File (AHRF) 2011/12.

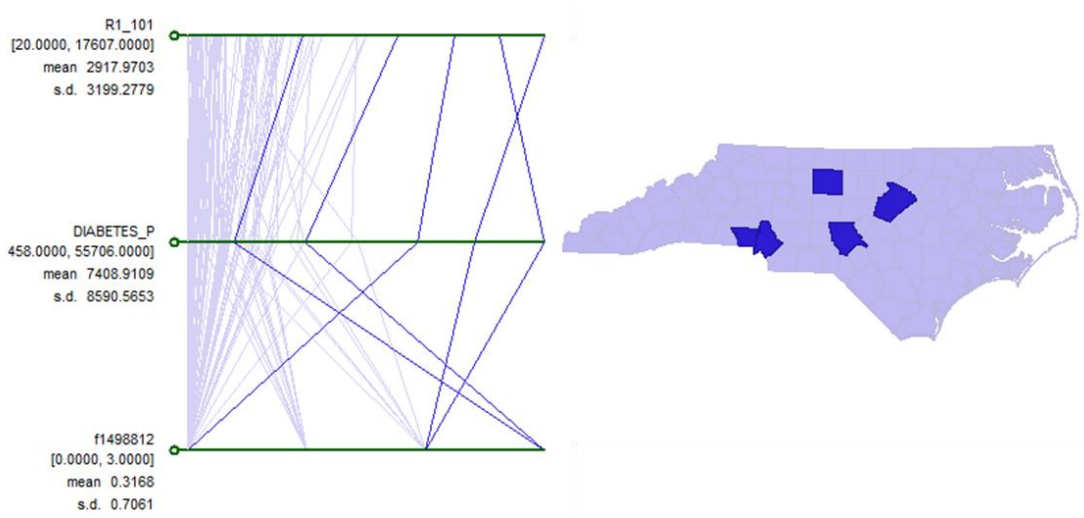


Prepared by: T. Farrow-Chestnut. (2017). Percent of the Population below Poverty Level. Data Source: Area Resource File (AHRF) 2011/12.

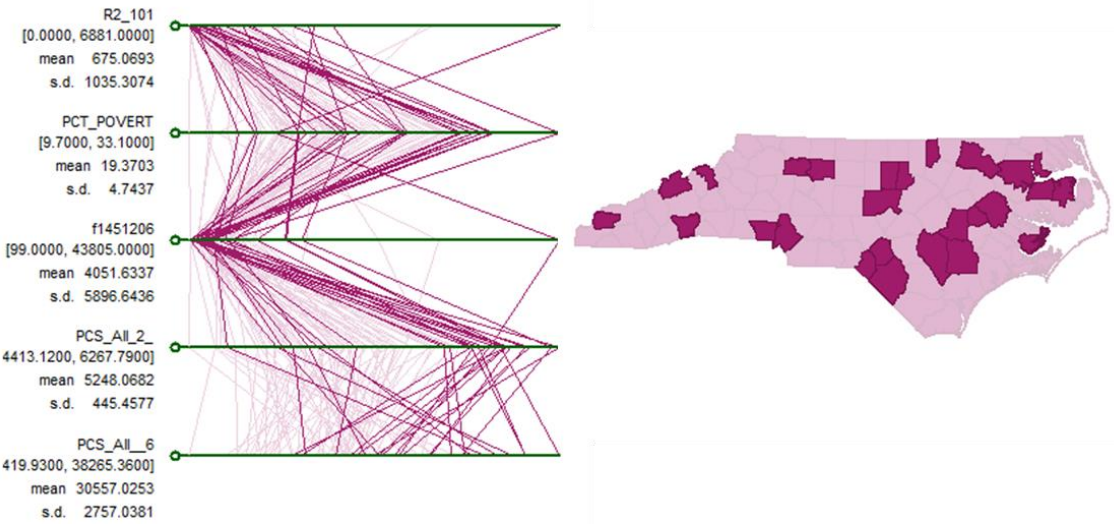


Prepared by: T. Farrow-Chestnut. (2017). Number of Toxic Waste Sites. Data Source: Area Resource File (AHRF) 2011/12.

APPENDIX G: PARALLEL PLOTS & MAPS – RACE/ETHNICITY



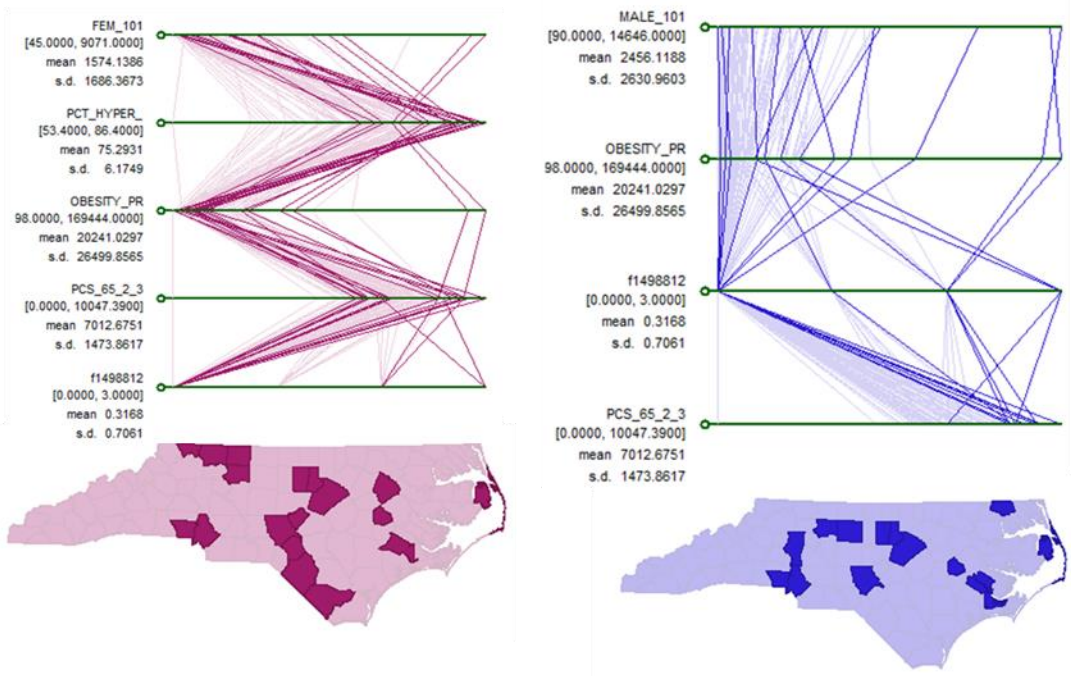
Parallel Plot and Map of Coronary Heart Disease non-Hispanic white final network model. Source: Farrow-Chestnut, 2017.



Parallel Plot and Map of Coronary Heart Disease non-Hispanic black final network model. Source: Farrow-Chestnut, 2017.

Parallel Plot and Map of Coronary Heart Disease Hispanic final network model. Source: Farrow-Chestnut, 2017.

APPENDIX H: PARALLEL PLOTS & MAPS - GENDER



A. Parallel Plot and Map of Coronary Heart Disease Female (left) final network model, B. Parallel Plot and Map of Coronary Heart Disease Male (right) final network model. Source: Farrow-Chestnut, 2017.

APPENDIX I: SINGLE-LEVEL DIAGNOSES, CCS

1 Tuberculosis
2 Septicemia (except in labor)
3 Bacterial infection; unspecified site
4 Mycoses
5 HIV infection
6 Hepatitis
7 Viral infection
8 Other infections; including parasitic
9 Sexually transmitted infections (not HIV or hepatitis)
10 Immunizations and screening for infectious disease
11 Cancer of head and neck
12 Cancer of esophagus
13 Cancer of stomach
14 Cancer of colon
15 Cancer of rectum and anus
16 Cancer of liver and intrahepatic bile duct
17 Cancer of pancreas
18 Cancer of other GI organs; peritoneum
19 Cancer of bronchus; lung
20 Cancer; other respiratory and intrathoracic
21 Cancer of bone and connective tissue
22 Melanomas of skin
23 Other non-epithelial cancer of skin
24 Cancer of breast
25 Cancer of uterus
26 Cancer of cervix
27 Cancer of ovary
28 Cancer of other female genital organs
29 Cancer of prostate
30 Cancer of testis
31 Cancer of other male genital organs
32 Cancer of bladder
33 Cancer of kidney and renal pelvis
34 Cancer of other urinary organs
35 Cancer of brain and nervous system
36 Cancer of thyroid
37 Hodgkin`s disease
38 Non-Hodgkin`s lymphoma
39 Leukemias
40 Multiple myeloma
41 Cancer; other and unspecified primary
42 Secondary malignancies
43 Malignant neoplasm without specification of site
44 Neoplasms of unspecified nature or uncertain behavior
45 Maintenance chemotherapy; radiotherapy
46 Benign neoplasm of uterus
47 Other and unspecified benign neoplasm

48 Thyroid disorders
49 Diabetes mellitus without complication
50 Diabetes mellitus with complications
51 Other endocrine disorders
52 Nutritional deficiencies
53 Disorders of lipid metabolism
54 Gout and other crystal arthropathies
55 Fluid and electrolyte disorders
56 Cystic fibrosis
57 Immunity disorders
58 Other nutritional; endocrine; and metabolic disorders
59 Deficiency and other anemia
60 Acute posthemorrhagic anemia
61 Sickle cell anemia
62 Coagulation and hemorrhagic disorders
63 Diseases of white blood cells
64 Other hematologic conditions
650 Adjustment disorders
651 Anxiety disorders
652 Attention-deficit, conduct, and disruptive behavior disorders
653 Delirium, dementia, and amnestic and other cognitive disorders
654 Developmental disorders
655 Disorders usually diagnosed in infancy, childhood, or adolescence
656 Impulse control disorders, NEC
657 Mood disorders
658 Personality disorders
659 Schizophrenia and other psychotic disorders
660 Alcohol-related disorders
661 Substance-related disorders
662 Suicide and intentional self-inflicted injury
663 Screening and history of mental health and substance abuse codes
670 Miscellaneous mental health disorders
76 Meningitis (except that caused by tuberculosis or sexually transmitted disease)
77 Encephalitis (except that caused by tuberculosis or sexually transmitted disease)
78 Other CNS infection and poliomyelitis
79 Parkinson`s disease
80 Multiple sclerosis
81 Other hereditary and degenerative nervous system conditions
82 Paralysis
83 Epilepsy; convulsions
84 Headache; including migraine
85 Coma; stupor; and brain damage
86 Cataract
87 Retinal detachments; defects; vascular occlusion; and retinopathy
88 Glaucoma
89 Blindness and vision defects
90 Inflammation; infection of eye (except that caused by tuberculosis or sexually transmitteddisease)
91 Other eye disorders
92 Otitis media and related conditions

93 Conditions associated with dizziness or vertigo
94 Other ear and sense organ disorders
95 Other nervous system disorders
96 Heart valve disorders
97 Peri-; endo-; and myocarditis; cardiomyopathy (except that caused by tuberculosis or sexually transmitted disease)
98 Essential hypertension
99 Hypertension with complications and secondary hypertension
100 Acute myocardial infarction
101 Coronary atherosclerosis and other heart disease
102 Nonspecific chest pain
103 Pulmonary heart disease
104 Other and ill-defined heart disease
105 Conduction disorders
106 Cardiac dysrhythmias
107 Cardiac arrest and ventricular fibrillation
108 Congestive heart failure; nonhypertensive
109 Acute cerebrovascular disease
110 Occlusion or stenosis of precerebral arteries
111 Other and ill-defined cerebrovascular disease
112 Transient cerebral ischemia
113 Late effects of cerebrovascular disease
114 Peripheral and visceral atherosclerosis
115 Aortic; peripheral; and visceral artery aneurysms
116 Aortic and peripheral arterial embolism or thrombosis
117 Other circulatory disease
118 Phlebitis; thrombophlebitis and thromboembolism
119 Varicose veins of lower extremity
120 Hemorrhoids
121 Other diseases of veins and lymphatics
122 Pneumonia (except that caused by tuberculosis or sexually transmitted disease)
123 Influenza
124 Acute and chronic tonsillitis
125 Acute bronchitis
126 Other upper respiratory infections
127 Chronic obstructive pulmonary disease and bronchiectasis
128 Asthma
129 Aspiration pneumonitis; food/vomitus
130 Pleurisy; pneumothorax; pulmonary collapse
131 Respiratory failure; insufficiency; arrest (adult)
132 Lung disease due to external agents
133 Other lower respiratory disease
134 Other upper respiratory disease
135 Intestinal infection
136 Disorders of teeth and jaw
137 Diseases of mouth; excluding dental
138 Esophageal disorders
139 Gastroduodenal ulcer (except hemorrhage)
140 Gastritis and duodenitis
141 Other disorders of stomach and duodenum

142 Appendicitis and other appendiceal conditions
143 Abdominal hernia
144 Regional enteritis and ulcerative colitis
145 Intestinal obstruction without hernia
146 Diverticulosis and diverticulitis
147 Anal and rectal conditions
148 Peritonitis and intestinal abscess
149 Biliary tract disease
150 Liver disease; alcohol-related
151 Other liver diseases
152 Pancreatic disorders (not diabetes)
153 Gastrointestinal hemorrhage
154 Noninfectious gastroenteritis
155 Other gastrointestinal disorders
156 Nephritis; nephrosis; renal sclerosis
157 Acute and unspecified renal failure
158 Chronic kidney disease
159 Urinary tract infections
160 Calculus of urinary tract
161 Other diseases of kidney and ureters
162 Other diseases of bladder and urethra
163 Genitourinary symptoms and ill-defined conditions
164 Hyperplasia of prostate
165 Inflammatory conditions of male genital organs
166 Other male genital disorders
167 Nonmalignant breast conditions
168 Inflammatory diseases of female pelvic organs
169 Endometriosis
170 Prolapse of female genital organs
171 Menstrual disorders
172 Ovarian cyst
173 Menopausal disorders
174 Female infertility
175 Other female genital disorders
176 Contraceptive and procreative management
177 Spontaneous abortion
178 Induced abortion
179 Postabortion complications
180 Ectopic pregnancy
181 Other complications of pregnancy
182 Hemorrhage during pregnancy; abruptio placenta; placenta previa
183 Hypertension complicating pregnancy; childbirth and the puerperium
184 Early or threatened labor
185 Prolonged pregnancy
186 Diabetes or abnormal glucose tolerance complicating pregnancy; childbirth; or the puerperium
187 Malposition; malpresentation
188 Fetopelvic disproportion; obstruction
189 Previous C-section
190 Fetal distress and abnormal forces of labor

191 Polyhydramnios and other problems of amniotic cavity
192 Umbilical cord complication
193 OB-related trauma to perineum and vulva
194 Forceps delivery
195 Other complications of birth; puerperium affecting management of mother
196 Other pregnancy and delivery including normal
197 Skin and subcutaneous tissue infections
198 Other inflammatory condition of skin
199 Chronic ulcer of skin
200 Other skin disorders
201 Infective arthritis and osteomyelitis (except that caused by tuberculosis or sexually transmitted disease)
202 Rheumatoid arthritis and related disease
203 Osteoarthritis
204 Other non-traumatic joint disorders
205 Spondylosis; intervertebral disc disorders; other back problems
206 Osteoporosis
207 Pathological fracture
208 Acquired foot deformities
209 Other acquired deformities
210 Systemic lupus erythematosus and connective tissue disorders
211 Other connective tissue disease
212 Other bone disease and musculoskeletal deformities
213 Cardiac and circulatory congenital anomalies
214 Digestive congenital anomalies
215 Genitourinary congenital anomalies
216 Nervous system congenital anomalies
217 Other congenital anomalies
218 Liveborn
219 Short gestation; low birth weight; and fetal growth retardation
220 Intrauterine hypoxia and birth asphyxia
221 Respiratory distress syndrome
222 Hemolytic jaundice and perinatal jaundice
223 Birth trauma
224 Other perinatal conditions
225 Joint disorders and dislocations; trauma-related
226 Fracture of neck of femur (hip)
227 Spinal cord injury
228 Skull and face fractures
229 Fracture of upper limb
230 Fracture of lower limb
231 Other fractures
232 Sprains and strains
233 Intracranial injury
234 Crushing injury or internal injury
235 Open wounds of head; neck; and trunk
236 Open wounds of extremities
237 Complication of device; implant or graft
238 Complications of surgical procedures or medical care
239 Superficial injury; contusion

240 Burns
241 Poisoning by psychotropic agents
242 Poisoning by other medications and drugs
243 Poisoning by nonmedicinal substances
244 Other injuries and conditions due to external causes
245 Syncope
246 Fever of unknown origin
247 Lymphadenitis
248 Gangrene
249 Shock
250 Nausea and vomiting
251 Abdominal pain
252 Malaise and fatigue
253 Allergic reactions
254 Rehabilitation care; fitting of prostheses; and adjustment of devices
255 Administrative/social admission
256 Medical examination/evaluation
257 Other aftercare
258 Other screening for suspected conditions (not mental disorders or infectious disease)
259 Residual codes; unclassified
260 E Codes: All (external causes of injury and poisoning)
2601 E Codes: Cut/pierceb
2602 E Codes: Drowning/submersion
2603 E Codes: Fall
2604 E Codes: Fire/burn
2605 E Codes: Firearm
2606 E Codes: Machinery
2607 E Codes: Motor vehicle traffic (MVT)
2608 E Codes: Pedal cyclist; not MVT
2609 E Codes: Pedestrian; not MVT
2610 E Codes: Transport; not MVT
2611 E Codes: Natural/environment
2612 E Codes: Overexertion
2613 E Codes: Poisoning
2614 E Codes: Struck by; against
2615 E Codes: Suffocation
2616 E Codes: Adverse effects of medical care
2617 E Codes: Adverse effects of medical drugs
2618 E Codes: Other specified and classifiable
2619 E Codes: Other specified; NEC
2620 E Codes: Unspecified
2621 E Codes: Place of occurrence

Source: https://www.hcup-us.ahrq.gov/toolssoftware/ccs/CCSCategoryNames_FullLabels.pdf

APPENDIX J: ALL VARIABLES LIST

#	Variable	Label
1	FIPS	County
2	Nodes	Nodes
3	Edges	Edges
4	Avg_Degree	Avg Degree
5	Avg_Weighted_Degree	Avg Weighted Degree
6	Network_Diameter	Network Diameter
7	Graph_Density	Graph Density
8	Modularity	Modularity
9	Number_of_Communities	Number of Communities
10	Number_of_Weakly_Connected_Compo	Number of Weakly Connected Components
11	Number_of_Stronlgy_Connected_Com	Number of Stronlgy Connected Component
12	Avg_Clustering_Coeff	Avg Clustering Coeff
13	Average_Path_length	Average Path length
14	Page_Rank	Page Rank
15	Group	
16	COUNTY	
17	Mortality_Z_Score	Mortality Z-Score
18	Morbidity_Z_Score	Morbidity Z-Score
19	Behaviors_Z_Score	Behaviors Z-Score
20	ClinicalCare_Z_Score	ClinicalCare Z-Score
21	SocioEcon_Z_Score	SocioEcon Z-Score
22	Physical_EnvZ_Score	Physical EnvZ-Score
23	Smoking_Z_Score	Smoking Z-Score
24	Diet_Z_Score	Diet Z-Score
25	Alcohol_Z_Score	Alcohol Z-Score
26	Sex_Z_Score	Sex Z-Score
27	Access_Z_Score	Access Z-Score
28	Quality_Z_Score	Quality Z-Score
29	Education_Z_Score	Education Z-Score
30	Employment_Z_Score	Employment Z-Score
31	Income_Z_Score	Income Z-Score
32	Family_Z_Score	Family Z-Score
33	Community_Z_Score	Community Z-Score
34	Air_Z_Score	Air Z-Score
35	Built_Env_Z_Score	Built Env Z-Score
36	f1212910	TotMD2010
37	f1322810	PhysAssist2010
38	f1367501	NursePrac2001
39	f0861900	RegNurses2000
40	f0863100	LPNs_LVNs2000
41	f0954510	InpatientDays2010
42	f0959610	TotExp
43	f0453010	Population2010
44	f1419608	MedicaidElig2008
45	f1420608	Medicare_MedicaidDuallyElig2008
46	f1193308	3-Yr IsHrt2008-10
47	f1193307	3-Yr IsHrt2007-09

48	f1193306	3-Yr IsHrt2006-08
49	f1193305	3-Yr IsHrt2005-07
50	f1193303	3-Yr IsHrt2003-05
51	f1316508	3-Yr OtherCardDis2008-10
52	f1316507	3-Yr IsHrt2007-09
53	f1316506	3-Yr IsHrt2006-08
54	f1316505	3-Yr IsHrt2005-07
55	f1316503	3-Yr IsHrt2003-05
56	f1255810	TotDeaths2010
57	f0978110	PCI2010
58	f1474810	Pers<652010
59	f1474910	Pers<65wHS2010
60	f1475110	PercPers<65woHS2010
61	f1444006	Pers25+2006-10
62	f1445006	Pers25+w/<HSDipl2006-10
63	f1445106	Pers25+w/HSDiplMore2006-10
64	f1451006	TotCivLab2006-10
65	f1451206	UnemployedCivLab2006-10
66	f1458006	Agr/Frst/Fish/Hunt/Mine2006-10
67	f1367000	Agr/Frst/Fish/Hunt/Mine2000
68	f1458106	Construction2006-10
69	f0879800	Construction2000
70	f1458206	Educ/HlthCare/SocAssist2006-10
71	f1367100	Health/SocialService2000
72	f1458306	Manufacturing2006-10
73	f0858900	Manufacturing2000
74	f1458406	OtherInd2006-10
75	f1462206	Mangmt/Prof2006-10
76	f0859000	WhiteCollar2000
77	f1387610	PopDensity2010
78	f1498812	TxcSite2012
79	f1498912	TxcSiteNot2012
80	f1526411	DaysAQ2011
81	f1526511	#DaysAQGood2011
82	f1526611	PercGoodAQD 2011
83	f1526208	DailyFPartMat2008
84	f1526306	Days8hrAOzone2006
85	Mortal_Z	Mortal_Z
86	Morb_Z	Morb_Z
87	HthBeh_Z	HthBeh_Z
88	ClnCar_Z	ClnCar_Z
89	SoEcon_Z	SoEcon_Z
90	PhyEnv_Z	PhyEnv_Z
91	Smoke_Z	Smoke_Z
92	DietEx_Z	DietEx_Z
93	Acccar_Z	Acccar_Z
94	FmScSp_Z	FmScSp_Z
95	ComCar_Z	ComCar_Z
96	AirQua_Z	AirQua_Z
97	BuiltE_Z	BuiltE_Z
98	Deaths	Deaths
99	PrDth_Pop	PrDth_Pop

100	YPLL_Rate	YPLL Rate
101	Z_Score	Z-Score
102	__Smokers	% Smokers
103	Z_Score5	Z-Score5
104	AdObes__	AdObes_%
105	Z_Score6	Z-Score6
106	Population	Population
107	Rates_per_100_000	Rates per 100,000
108	Z_Score9	Z-Score9
109	Uninsured__	Uninsured_%
110	Z_Score11	Z-Score11
111	PCP_No__	PCP No_%
112	PCP_Rate	PCP Rate
113	Population1	Population1
114	PCP_No	PCP No
115	PCP_Rate1	PCP Rate1
116	Z_Score12	Z-Score12
117	No_of_Medicare_enrollees	No of Medicare enrollees
118	ACSC_Rate	ACSC Rate
119	Z_Score13	Z-Score13
120	__HbA1c	% HbA1c
121	Z_Score14	Z-Score14
122	HS_Enrollment	HS_Enrollment
123	Diplomas	Diplomas
124	Z_Score16	Z-Score16
125	Unemployed__	Unemployed_%
126	Z_Score18	Z-Score18
127	GINI	GINI
128	Z_Score20	Z-Score20
129	__No_Social_Emotional_Support	% No Social-Emotional Support
130	Z_Score21	Z-Score21
131	PM_Days	PM Days
132	Z_Score25	Z-Score25
133	Ozone_Days	Ozone Days
134	Z_Score26	Z-Score26
135	__Healthy_Food	% Healthy Food
136	Z_Score27	Z-Score27
137	RCL	RCL
138	Spindex	Spindex
139	Diverse	Diverse
140	Inative	Inative
141	Iasian	Iasian
142	Iblack	Iblack
143	Ihisp	Ihisp
144	Ipacif	Ipacif
145	Iwhite	Iwhite

APPENDIX K: DESCRIPTIVE STATISTICS

Variable	Label	N	Mean	Std Dev	Minimum	Maximum
FEM_101	Hrt Dis WTD DEGREE label 101 for Female	0	.	.	.	.
FEM_102	Hrt Dis WTD DEGREE label 102 for Female	100	872.35	1087.25	8	5739
FEM_103	Hrt Dis WTD DEGREE label 103 for Female	100	450.11	606.37902	5	4136
FEM_104	Hrt Dis WTD DEGREE label 104 for Female	99	72.818182	115.63007	1	913
FEM_105	Hrt Dis WTD DEGREE label 105 for Female	100	233.45	289.74766	3	1744
FEM_106	Hrt Dis WTD DEGREE label 106 for Female	100	1642.32	1920.88	36	11335
FEM_107	Hrt Dis WTD DEGREE label 107 for Female	96	56.6875	128.75724	1	1147
FEM_108	Hrt Dis WTD DEGREE label 108 for Female	100	2213.87	2521.5	64	15531
MALE_101	Hrt Dis WTD DEGREE label 101 for Male	100	2445.78	2642.15	90	14646
MALE_102	Hrt Dis WTD DEGREE label 102 for Male	100	720.94	843.86014	18	4420
MALE_103	Hrt Dis WTD DEGREE label 103 for Male	100	317.07	391.71262	4	2544
MALE_104	Hrt Dis WTD DEGREE label 104 for Male	100	51.44	83.327796	1	645
MALE_105	Hrt Dis WTD DEGREE label 105 for Male	100	266.42	331.431	6	1992
MALE_106	Hrt Dis WTD DEGREE label 106 for Male	100	1544.08	1787.46	81	10646
MALE_107	Hrt Dis WTD DEGREE label 107 for Male	97	62.907217	82.445952	1	477
MALE_108	Hrt Dis WTD DEGREE label 108 for Male	100	2015.65	2299.95	77	14273
R456_101	Hrt Dis WTD DEGREE label 101 for R456	88	124.73864	465.11485	1	4255
R456_102	Hrt Dis WTD DEGREE label 102 for R456	75	62.746667	208.76368	1	1754
R456_103	Hrt Dis WTD DEGREE label 103 for R456	67	23.373134	67.698493	1	526
R456_104	Hrt Dis WTD DEGREE label 104 for R456	52	6.8269231	13.4787	1	85
R456_105	Hrt Dis WTD DEGREE label 105 for R456	69	18.028986	56.016272	1	445
R456_106	Hrt Dis WTD DEGREE label 106 for R456	88	87.670455	272.29669	1	2309
R456_107	Hrt Dis WTD DEGREE label 107 for R456	38	7.6315789	13.767217	1	72
R456_108	Hrt Dis WTD DEGREE label 108 for R456	86	141.56977	493.07295	1	4338
R3_101	Hrt Dis WTD DEGREE label 101 for R3	73	34.068493	58.007023	1	359
R3_102	Hrt Dis WTD DEGREE label 102 for R3	66	27.409091	42.235595	1	237
R3_103	Hrt Dis WTD DEGREE label 103 for R3	55	9.7090909	21.239091	1	157
R3_104	Hrt Dis WTD DEGREE label 104 for R3	34	2.6764706	4.146708	1	24
R3_105	Hrt Dis WTD DEGREE label 105 for R3	52	6.2692308	9.6245507	1	61
R3_106	Hrt Dis WTD DEGREE label	78	27.602564	44.804435	1	281

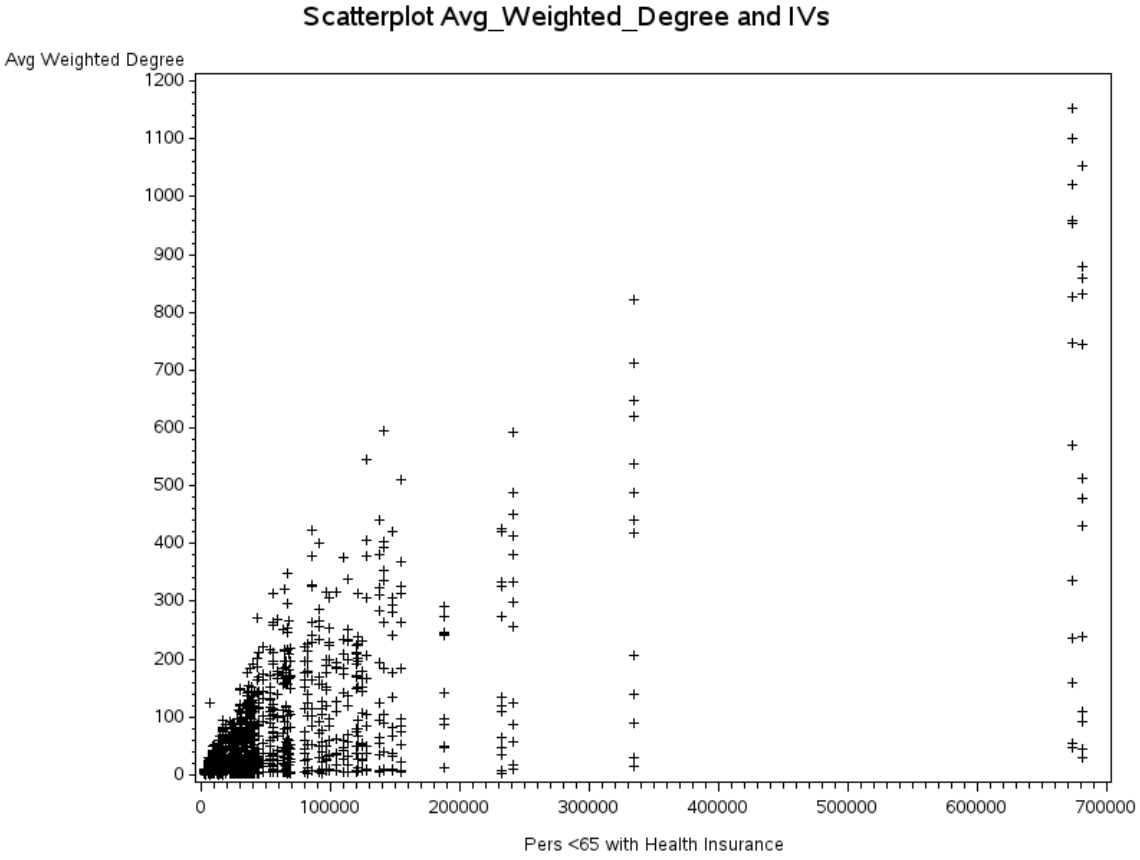
	106 for R3					
R3_107	Hrt Dis WTD DEGREE label 107 for R3	23	4.4347826	5.1063782	1	18
R3_108	Hrt Dis WTD DEGREE label 108 for R3	79	40.405063	80.910764	1	636
R2_101	Hrt Dis WTD DEGREE label 101 for R2	99	661.64646	1023.68	1	6881
R2_102	Hrt Dis WTD DEGREE label 102 for R2	92	459.97826	748.38963	1	4237
R2_103	Hrt Dis WTD DEGREE label 103 for R2	92	227.3913	396.77023	1	2947
R2_104	Hrt Dis WTD DEGREE label 104 for R2	86	36.011628	72.636807	1	491
R2_105	Hrt Dis WTD DEGREE label 105 for R2	88	106.05682	162.40664	2	1096
R2_106	Hrt Dis WTD DEGREE label 106 for R2	96	563.20833	909.33232	1	6423
R2_107	Hrt Dis WTD DEGREE label 107 for R2	81	37.530864	80.436013	1	503
R2_108	Hrt Dis WTD DEGREE label 108 for R2	98	1237.21	1919.94	2	13672
R1_101	Hrt Dis WTD DEGREE label 101 for R1	100	2915.63	3215.31	20	17607
R1_102	Hrt Dis WTD DEGREE label 102 for R1	98	1017.31	1159.63	2	5618
R1_103	Hrt Dis WTD DEGREE label 103 for R1	99	507.32323	628.62035	1	3608
R1_104	Hrt Dis WTD DEGREE label 104 for R1	96	129.70833	449.41386	2	4308
R1_105	Hrt Dis WTD DEGREE label 105 for R1	97	379.57732	474.97633	5	2814
R1_107	Hrt Dis WTD DEGREE label 107 for R1	96	143.97917	681.01947	1	6692
R1_108	Hrt Dis WTD DEGREE label 108 for R1	100	2591.44	2943.05	3	15351
AWD_AGE_65	AWD_AGE_65	100	138.76408	154.00338	8.013	959.647
AWD_AGE_17_44	AWD_AGE_17_44	100	37.7508	48.917281	2.229	336.855
AWD_AGE_45_64	AWD_AGE_45_64	100	87.24178	108.30924	4.986	746.901
AWD_FEMALE	AWD_FEMALE	100	144.95294	173.951	7.212	1154.48
AWD_INS_MDCAID	AWD_INS_MDCAID	100	27.84578	33.262807	2.253	236.077
AWD_INS_MDCARE	AWD_INS_MDCARE	100	148.56543	159.40166	9.443	1020.84
AWD_INS_PRIVATE	AWD_INS_PRIVATE	100	64.82987	96.056497	2.726	569.881
AWD_INS_SLFPY	AWD_INS_SLFPY	100	17.68737	22.783752	0.904	159.901
AWD_MALE	AWD_MALE	100	124.15724	145.90163	6.846	954.435
AWD_RACE_1	AWD_RACE_1	100	177.92317	199.14817	8.287	1101.19
AWD_RACE_2	AWD_RACE_2	100	63.71164	105.77743	0.75	827.453
AWD_RACE_3	AWD_RACE_3	100	4.56709	6.5020213	0	54.256
AWD_RACE_456	AWD_RACE_456	100	9.02696	25.52286	0.5	241.852
f1474910	Pers <65 with Health Insurance	100	65474.98	104151.29	2238	681123
f0892110	Hospital Beds 2010	100	285.48	466.74078	0	2489
f0954510	InpatientDays2010	100	72281.98	129762.34	0	699921
f0453010	Population2010	100	95354.83	141743.07	4407	919628
f1419608	MedicaidElig2008	100	19005.77	22754.29	1178	156932

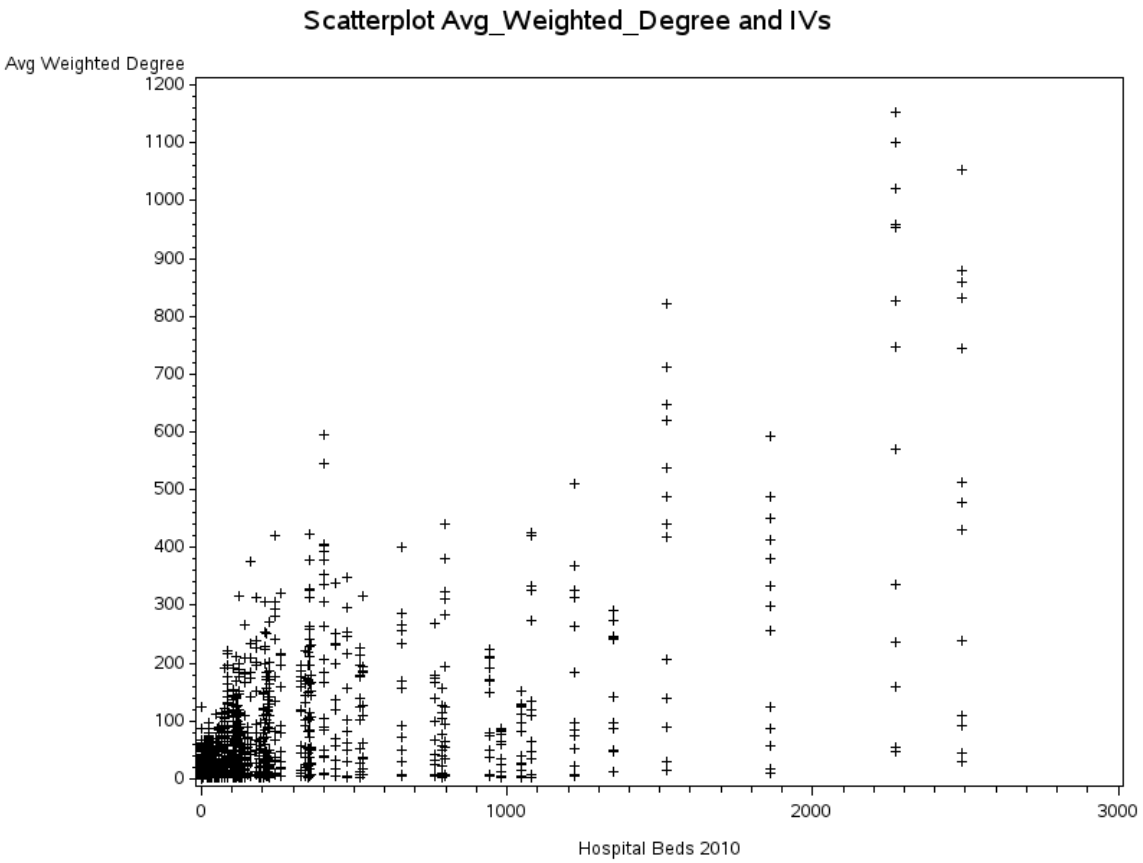
f1420608	Medicare_MedicaidDuallyEligi2008	100	3163.31	2907.51	216	17687
f1193308	3-Yr IsHrt2008-10	100	108.06	101.89436	0	521
f1316508	3-Yr OtherCardDis2008-10	100	79.79	87.077151	0	559
f0978110	PCI2010	100	31220.11	4799.04	23925	46713
f1474810	Pers<652010	100	80974.14	126061.76	3054	826480
f1475110	PercPers<65woHS2010	100	20.302	2.6668553	15.5	30.1
f1451006	TotCivLab2006-10	100	46402.29	74424.27	1805	497840
f1451206	UnemployedCivLab2006-10	100	4061.42	5925.53	99	43805
f1387610	PopDensity2010	100	195.451	260.39378	9.5	1755.5
f1498812	TxcSite2012	100	0.32	0.7089614	0	3
f1498912	TxcSiteNot2012	100	0.01	0.1	0	1
f1526411	DaysAQ2011	100	131.12	155.71479	0	365
f1526511	#DaysAQGood2011	100	109.3	130.77882	0	358
f1526611	PercGoodAQD 2011	100	37.5442	42.029452	0	100
f1526208	DailyFPartMat2008	100	12.8654	0.418174	12.16	13.7
f1526306	Days8hrAOzone2006	100	2.18	4.1956688	0	23
PCS_All_0_1	MULTIMORBIDITY _PCSpend_All_0_1	100	1875.71	278.34853	1278.14	3616.94
PCS_All_2_3	MULTIMORBIDITY _PCSpend_All_2_3	100	5254.44	443.04958	4413.12	6267.79
PCS_All_4_5	MULTIMORBIDITY _PCSpend_All_4_5	100	11822.45	1129.44	8940.18	14697.11
PCS_All__6	MULTIMORBIDITY _PCSpend_All_>6	100	30507.31	2725.04	24419.93	38265.36
PCS_65_0_1	MULTIMORBIDITY _PCSpend_<65_0_1	98	2347.19	626.8684	1273.09	7050.29
PCS_65_2_3	MULTIMORBIDITY _PCSpend_<65_2_3	98	7164.89	1092.65	4682.76	10047.39
PCS_65_4_5	MULTIMORBIDITY _PCSpend_<65_4_5	98	14542.74	2671.46	8283.74	21739.19
PCS_65__6	MULTIMORBIDITY _PCSpend_<65_>6	98	36181.19	6194.89	24352.55	60248.76
PCS_65_0_10	MULTIMORBIDITY _PCSpend_>65_0_1	98	1687.97	227.57341	1202.19	2381.23
PCS_65_2_30	MULTIMORBIDITY _PCSpend_>65_2_3	98	4810.18	427.72007	4011.06	5841.04
PCS_65_4_50	MULTIMORBIDITY _PCSpend_>65_4_5	98	11216.51	1051.71	8728.72	14081.89
PCS_65__60	MULTIMORBIDITY _PCSpend_>65_>6	98	29456.23	2581.49	23503.57	35794.55
Urban_Rural_Status	Urban_Rural_Status	100	3.4	0.7521014	1	4
_Pop_65	%Pop>65	100	16.756	4.136468	7.4	27.1
_POVERTY	%POVERTY	100	19.329	4.7493178	9.7	33.1
_HYPER_HOSP_DISC	%HYPER_HOSP_DISC	100	75.355	6.1743748	53.4	86.4
_HEARTDIS_HOSP_DISC	%HEARTDIS_HOSP_DISC	100	72.815	2.9612438	63.9	77.8
_WO_HS	%WO_HS	100	17.497	4.9100486	8	29.3
_ADULT_SMOKE	%ADULT_SMOKE	100	22.709	4.905369	11.9	44.4
DIABETES_PREV	DIABETES_PREV	100	7417.7	8633.39	458	55706
_DIABETES_PREV	%DIABETES_PREV	100	11.943	1.9803711	6.7	16.1

OBESITY_PREV	OBESITY_PREV	100	20289.57	26628.84	1098	169444
_OBESITY_PREV	%OBESITY_PREV	100	30.365	3.8233037	20.8	40.7
LEIS_PHY_INACTIVE	LEIS_PHY_INACTIVE	100	17767.73	21392.94	1049	137305
INDDIS_white_black	INDDIS_white_black	100	33.475	14.957498	0	64.9
INDDIS_white_indian	INDDIS_white_indian	100	24.534	15.635192	0	85.8
INDDIS_white_asian	INDDIS_white_asian	100	28.371	11.467189	0	56.7
INDDIS_white_hispanic	INDDIS_white_hispanic	100	27.364	13.685999	0	59.1
INDDIS_white_blackwhite	INDDIS_white_blackwhite	100	27.443	10.758133	0	59.2
INDDIS_white_asianwhite	INDDIS_white_asianwhite	100	30.344	14.438461	0	80.5
INDDIS_white_indianwhite	INDDIS_white_indianwhite	100	19.228	8.5684656	0	55.7
INDDIS_black_indian	INDDIS_black_indian	100	34.997	15.601926	0	88.2
INDDIS_black_asian	INDDIS_black_asian	100	36.693	16.212293	0	76
INDDIS_black_hispanic	INDDIS_black_hispanic	100	29.488	12.576548	0	60.7
INDDIS_black_blackwhite	INDDIS_black_blackwhite	100	25.094	10.800485	0	52.7
INDDIS_black_asianwhite	INDDIS_black_asianwhite	100	41.968	16.170068	0	84.1
INDDIS_black_indianwhite	INDDIS_black_indianwhite	100	35.58	14.45925	0	67.7
INDDIS_amind_asian	INDDIS_amind_asian	100	36.501	15.621033	0	85.3
INDDIS_amind_hispan	INDDIS_amind_hispan	100	32.511	14.572056	0	77.7
INDDIS_amind_blackwhite	INDDIS_amind_blackwhite	100	31.724	14.879368	0	78.9
INDDIS_amind_asianwhite	INDDIS_amind_asianwhite	100	36.173	18.087916	0	93.4
INDDIS_amind_indianwhite	INDDIS_amind_indianwhite	100	25.92	12.138236	0	71.1
INDDIS_asian_hispanic	INDDIS_asian_hispanic	100	35.265	15.170721	0	75
INDDIS_asian_blackwhite	INDDIS_asian_blackwhite	100	31.984	12.27799	0	61.6
INDDIS_asian_asianwhite	INDDIS_asian_asianwhite	100	33.648	16.601597	0	90.3
INDDIS_asian_indianwhite	INDDIS_asian_indianwhite	100	33.662	12.738733	0	63.1
INDDIS_hispanic_blackwhite	INDDIS_hispanic_blackwhite	100	27.471	12.046554	0	56.2
INDDIS_hispanic_asianwhite	INDDIS_hispanic_asianwhite	100	38.202	17.1852	0	85.1
INDDIS_hispanic_indianwhite	INDDIS_hispanic_indianwhite	100	29.853	13.301458	0	58.6
INDDIS_blackwhite_asianwhite	INDDIS_blackwhite_asianwhite	100	35.794	15.524915	0	80
INDDIS_blackwhite_indianwhite	INDDIS_blackwhite_indianwhite	100	29.417	12.284959	0	65.4
INDDIS_asianwhite_indianwhitecou	INDDIS_asianwhite_indianwhitecounty	100	34.875	15.74397	0	97.7
f0956610	OutpatVisitsGenHosp2010	100	202242.39	361519.24	0	1840625
f0957210	EmerDepartVisitsGenHosps2010	100	43673.59	64743.48	0	444155
f1475010	Pers<65woutHlthIns2010	100	15499.19	22094.43	816	152458
f0453710	PctWht_2010	100	71.475	17.724704	29	96.6
f0453810	PctBlk_AAm_2010	100	20.612	16.591499	0.2	62.5
f0453910	PctAmIndAlaNat_2010	100	1.613	4.8947644	0.2	38.4
f1345710	PctAsian_2010	100	1.008	1.1418291	0.1	6.7

f0454210	PctHispLat_2010	100	6.487	3.8493514	1.3	20.6
f1463910	PctWht_Non-HispLat_2010	100	69.07	17.679529	27	95.2
f1353310	AmIn_Lumbee_Pop2010	100	529.05	3792.97	0	37833

APPENDIX L: SCATTERPLOTS – DEP. & IND. VARIABLES

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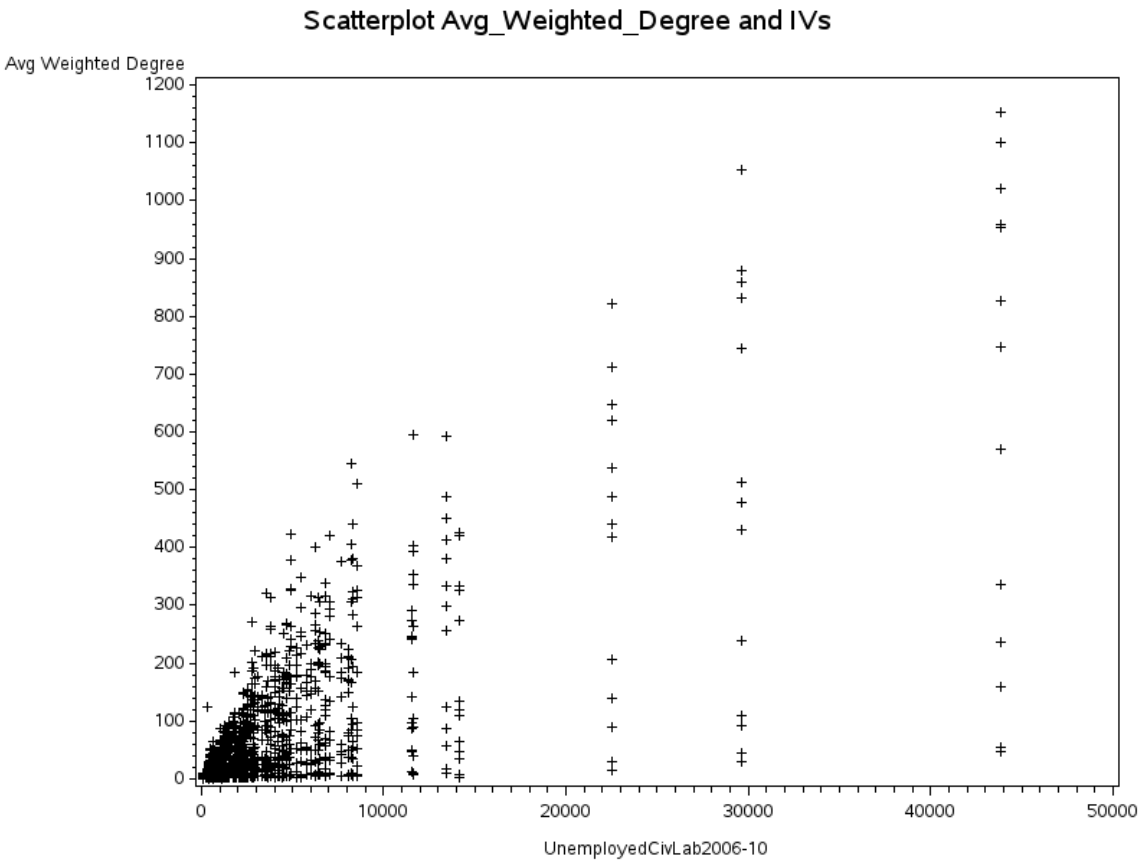
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
1000
2000
3000
Hospital Beds 2010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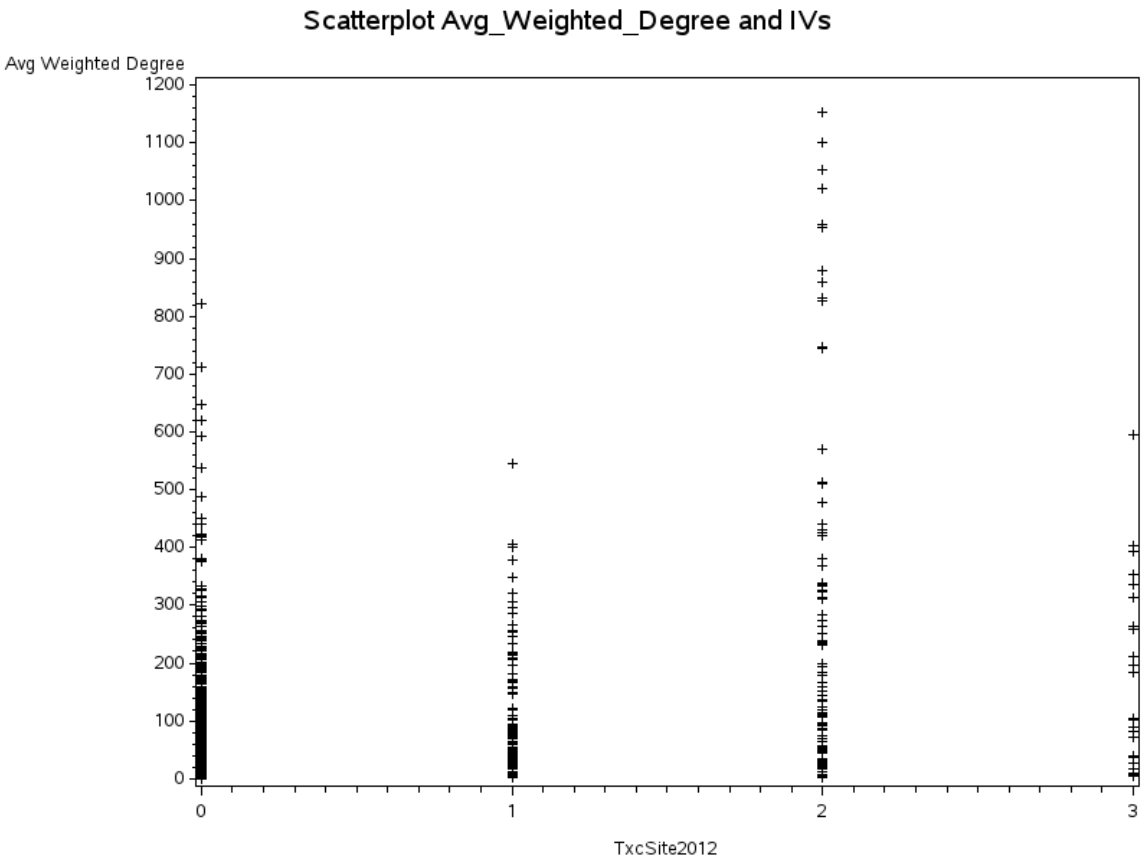
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
10000
20000
30000
40000
50000
UnemployedCivLab2006-10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Avg Weighted Degree
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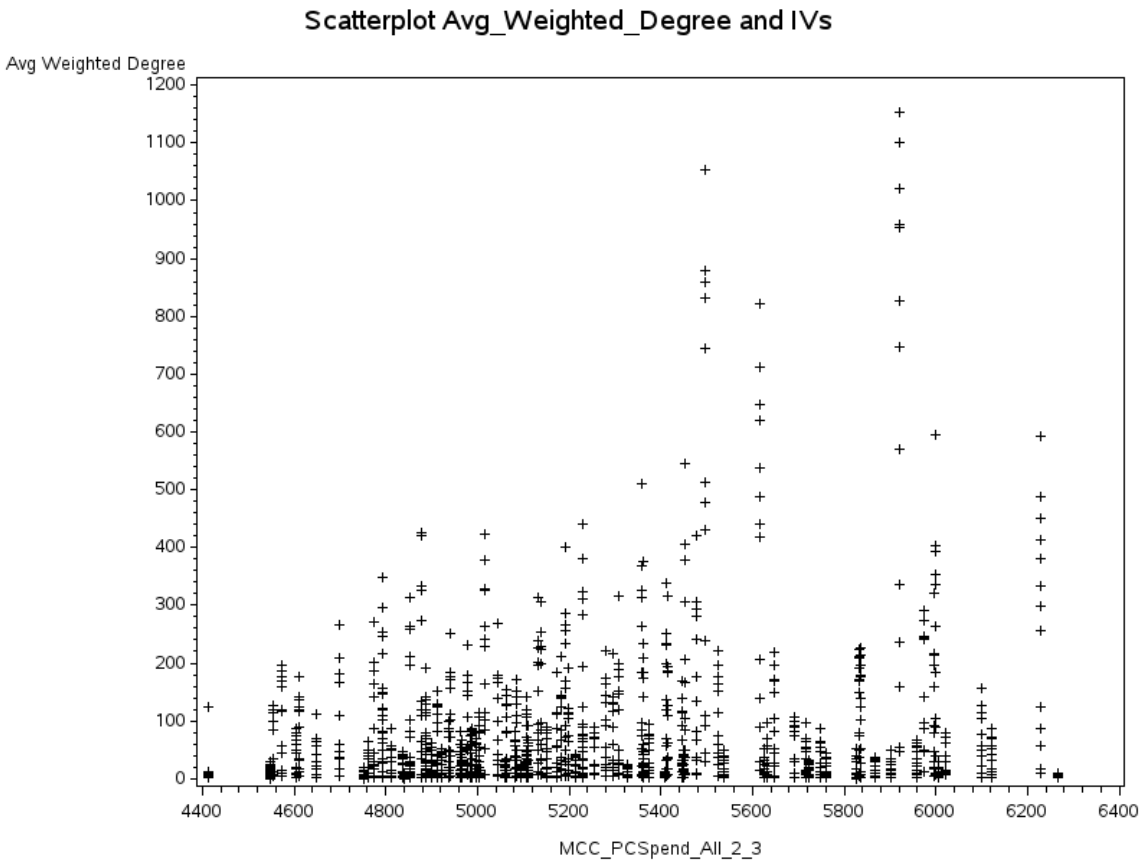
1100
1000
900
800
700
600
500
400
300
200
100
0
0
1
2
3
TxcSite2012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Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
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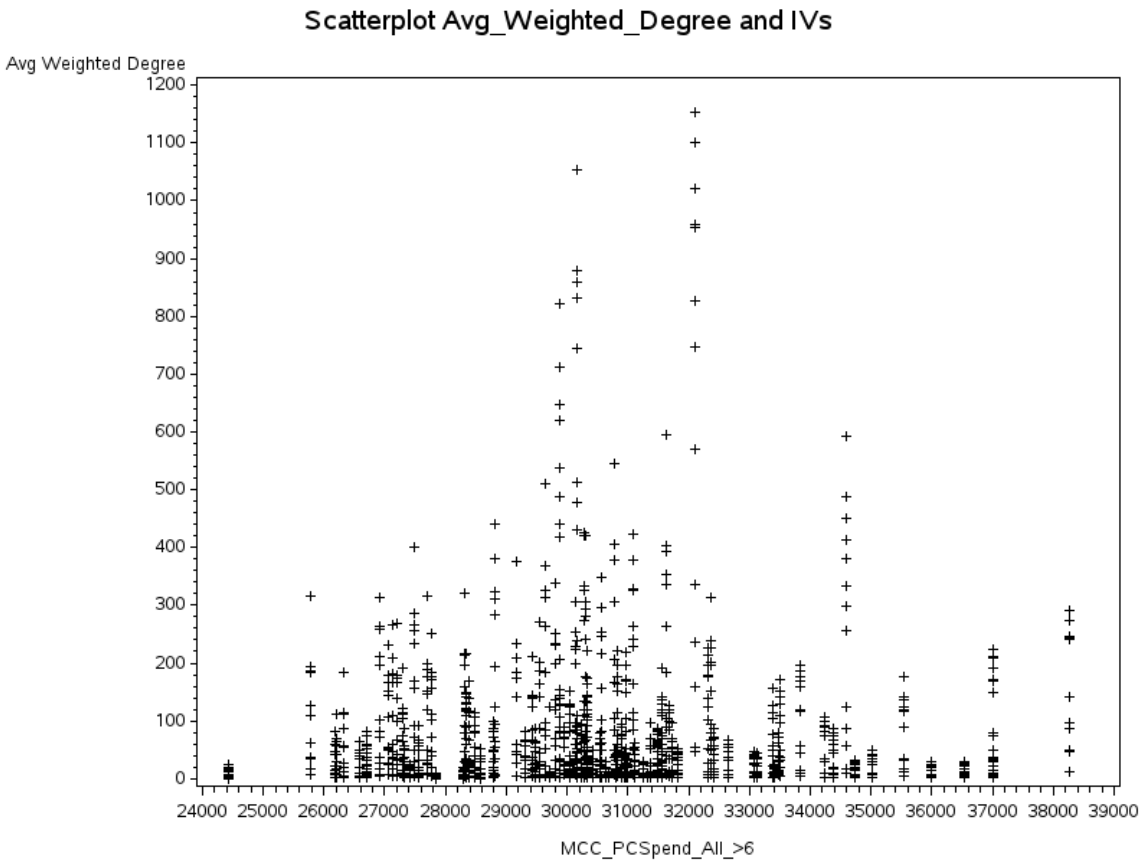
4400
4600
4800
5000
5200
5400
5600
5800
6000
6200
6400
MCC_PCSpend_All_2_3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Avg Weighted Degree
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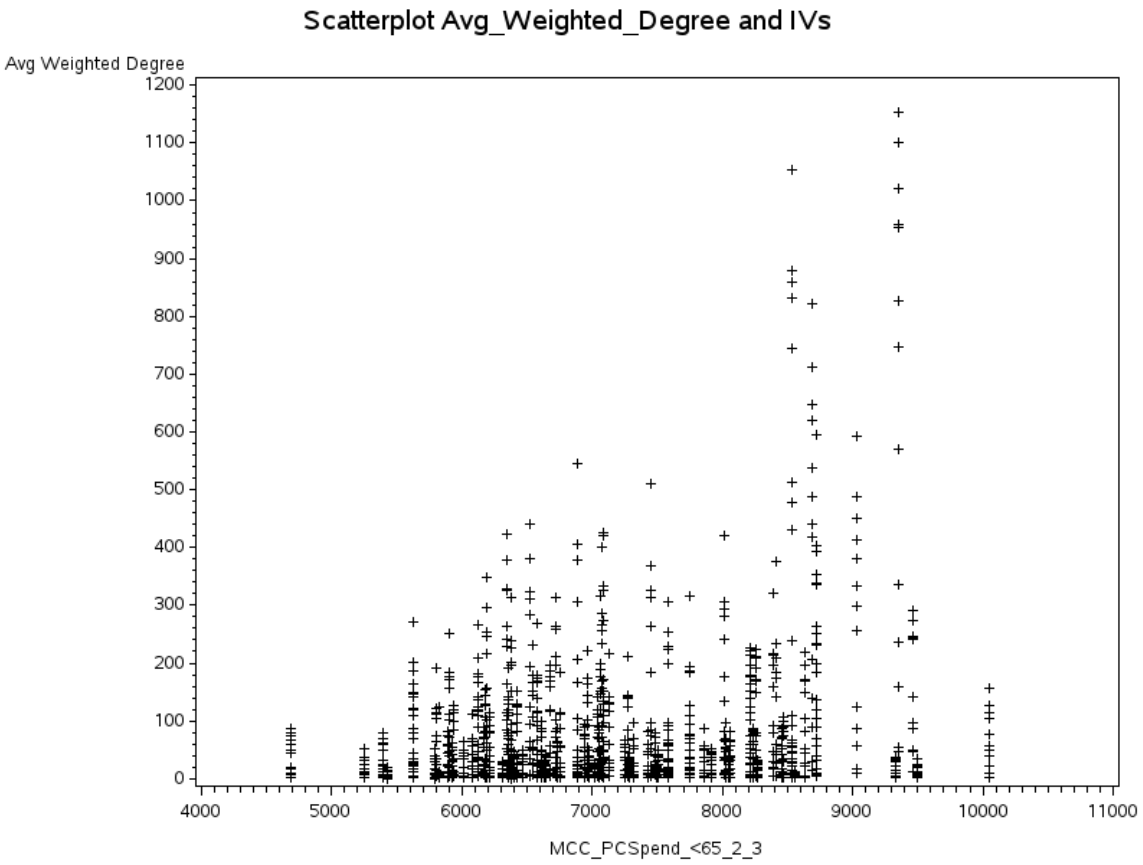
1100
1000
900
800
700
600
500
400
300
200
100
0
24000 25000 26000 27000 28000 29000 30000 31000 32000 33000 34000 35000 36000 37000 38000 39000
MCC_PCSpend_All_>6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Avg Weighted Degree
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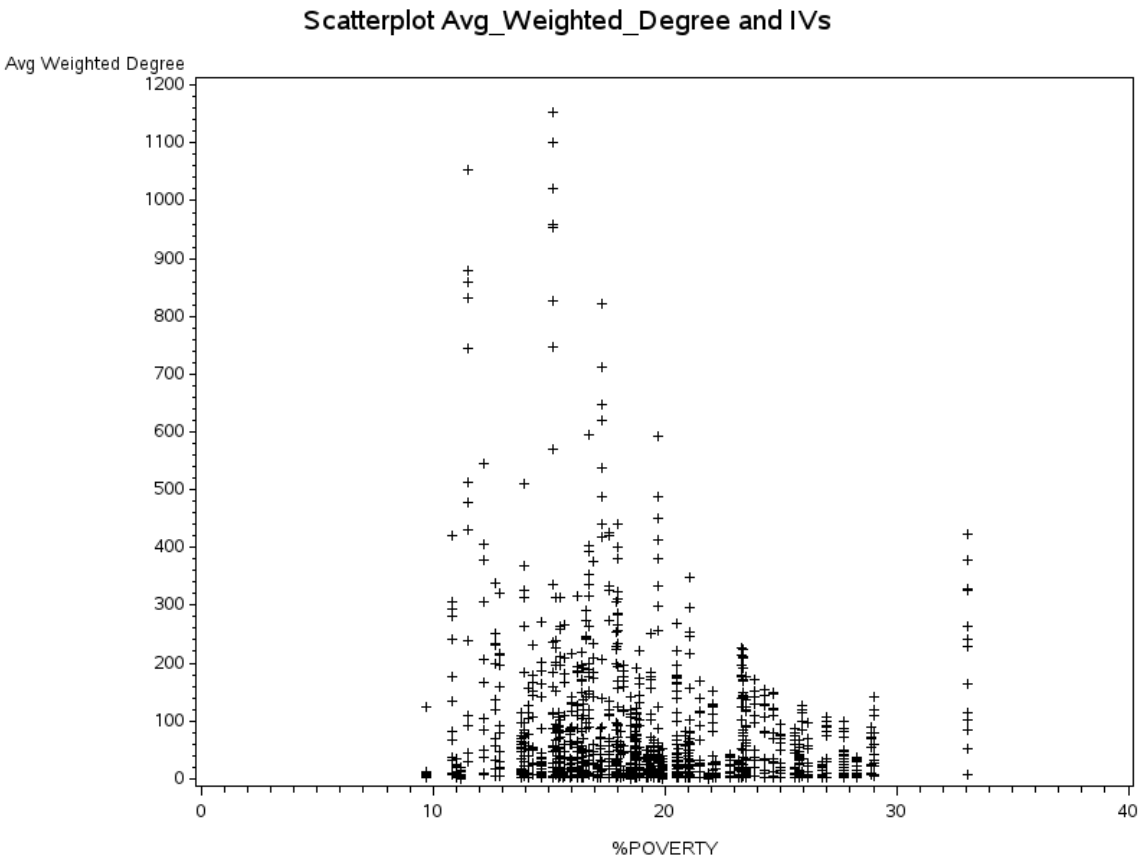
1100
1000
900
800
700
600
500
400
300
200
100
0
4000
5000
6000
7000
8000
9000
10000
11000
MCC_PCSpend_<65_2_3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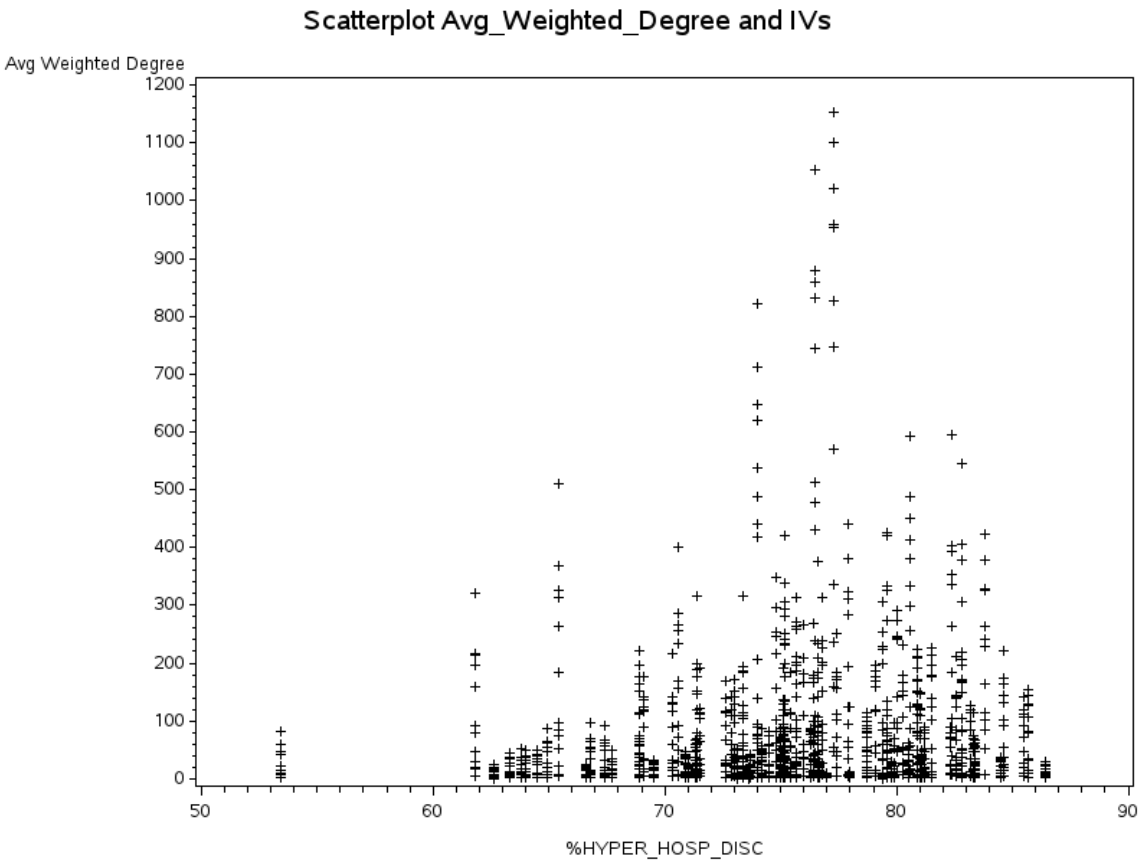
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
10
20
30
40
%POVERTY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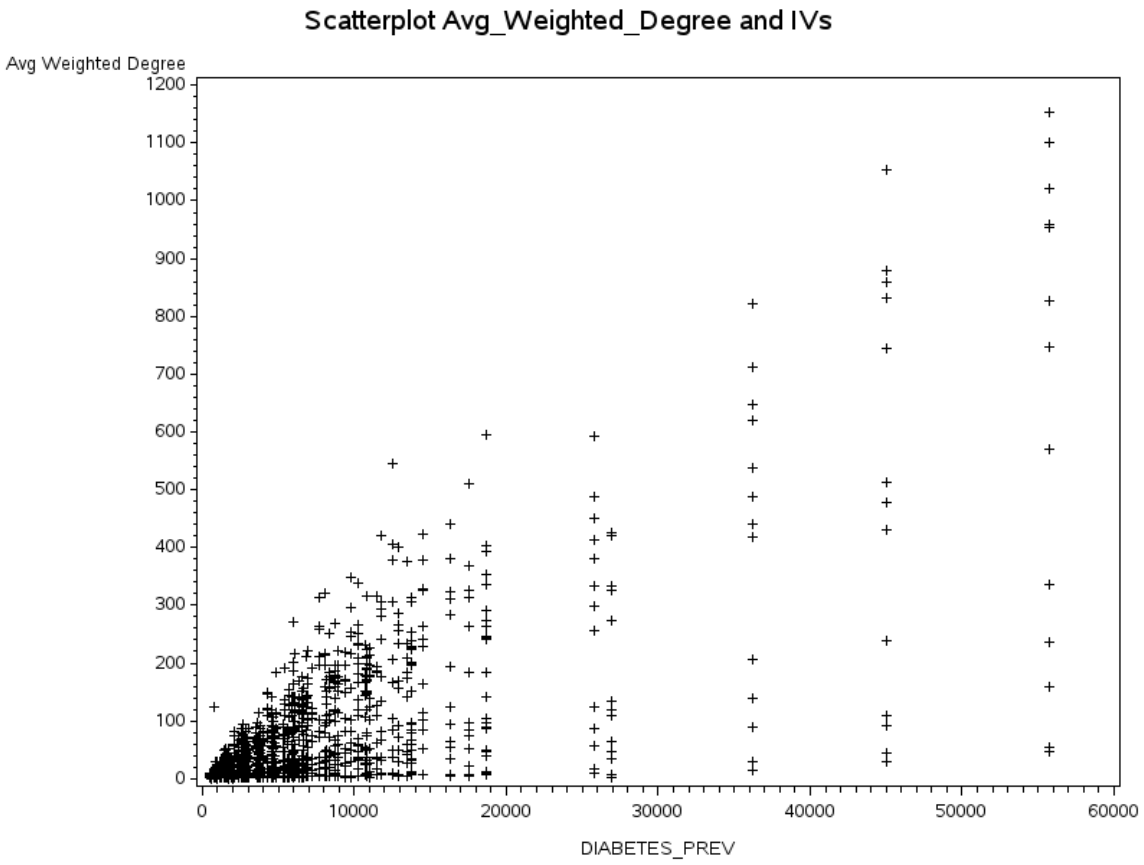
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
50
60
70
80
90
%HYPER_HOSP_DISC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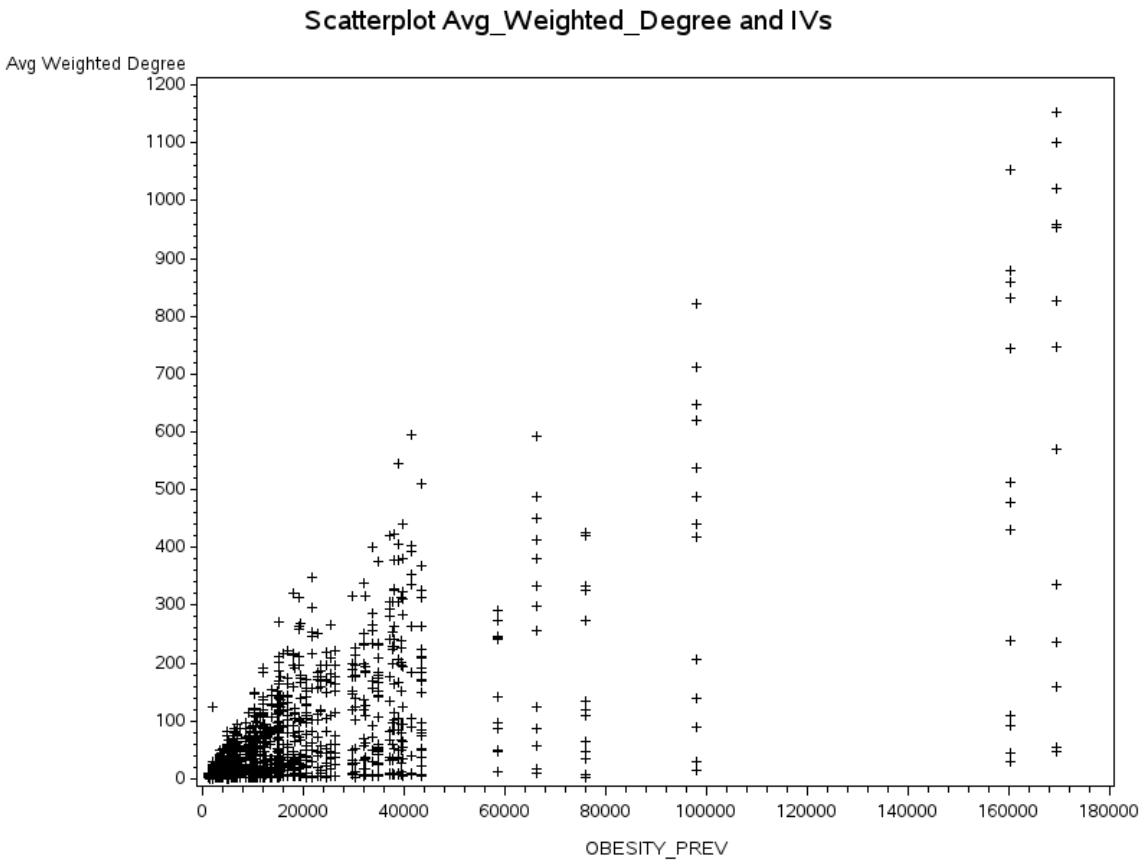
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
10000
20000
30000
40000
50000
60000
DIABETES_PREV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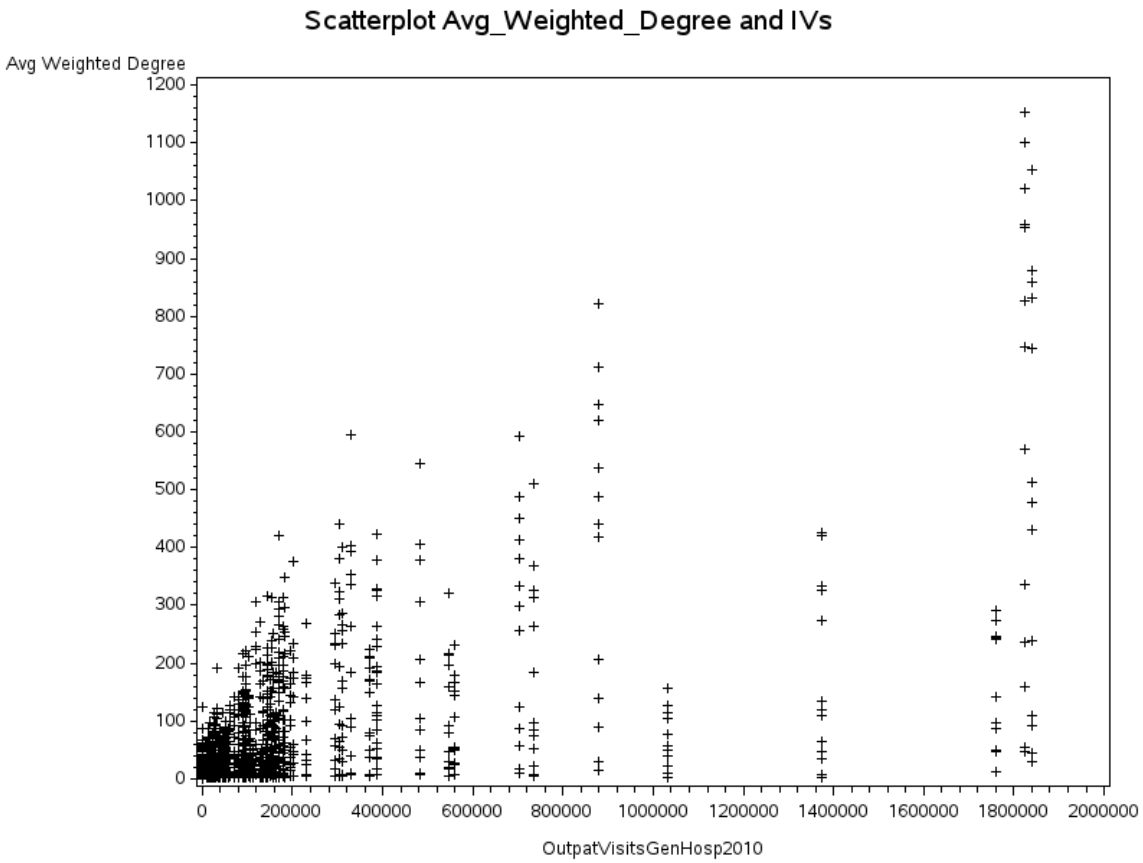
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
20000
40000
60000
80000
100000
120000
140000
160000
180000
OBESITY_PREV


Scatterplot Avg_Weighted_Degree and IVs
Avg Weighted Degree
1200
1100
1000
900
800
700
600
500
400
300
200
100
0
0
200000
400000
600000
800000
1000000
1200000
1400000
1600000
1800000
2000000
OutpatVisitsGenHosp2010

APPENDIX M: PEARSON CORRELATION COEFFICIENTS

Pearson Correlation Coefficients, N = 1300

Prob > |r| under H0: Rho=0

	Avg_Weighted_Degree	f1420608	f1316508	f1451006	f1498812	f1526411	f1526306	DIABETES_PREV	f0956610	f0957210	f1345710	f1353310	f0453010	f1419608	f1387610
Avg_Weighted_Degree	1	0.68956													
		<.0001													
Avg Weighted Degree		1													
f1420608															
			0.70281	0.69225	0.36053	0.24721	0.43923	0.70902	0.58255	0.69273	0.46639	0.11904	0.6951		
Medicare_MedicaidDualyElig2008			<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
f1316508			1	0.88645	0.45582	0.39665	0.51766	0.95873	0.7825	0.91883	0.58023	0.20851	0.8972		
				<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
3-Yr. OtherCardDis2008-10				1	0.51307	0.38412	0.5702	0.97705	0.84024	0.95643	0.64892	0.0615	0.95476		
					<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
f1451006					0.44966	0.34905	0.5753	0.96621	0.85934	0.95204	0.70279	0.0381	0.99728		
					<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
TotCivLab2006-10					1	0.15235	0.26569	0.49059	0.44908	0.48941	0.2526	-0.02553	0.4718		
						<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
f1498812						1	0.43694	0.45377	0.36439	0.39547	0.24302	-0.00286	0.41049		
							<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
TxcSite2012							0.36881	0.33944	0.31109	0.33573	0.20357	-0.00448	0.34811		
							<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
f1526411							1	0.57511	0.45897	0.56759	0.38639	-0.04368	0.56399		
								<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		
DaysAQ2011								1	0.85509	0.96596	0.66722	0.11548	0.97497		
									<.0001	<.0001	<.0001	<.0001	<.0001		
f1526511									1	0.8805	0.80835	0.08382	0.87023		
										<.0001	<.0001	<.0001	<.0001		
#DaysAQGood2011										1	0.70679	0.0863	0.95592		
											<.0001	<.0001	<.0001		
f1526306											1	-0.00371	0.7042		
												<.0001	<.0001		
DaysOfExOzone2006												1	0.05874		
													<.0001		
DIABETES_PREV													1		
f0956610															
OutpatVisitsGenHosp2010															
f0957210															
EmerDepartVisitsGenHosps2010															
f1345710															
PctAsian_2010															
f1353310															
Amib_Lumbee_Pop2010															
f0453010															
Population2010															

APPENDIX N: CORRELATION COEFFICIENTS - FEMALE & MALE

AWD_FEMALE	100	**AWD_MALE**	100
f1474910	0.88913	f1474910	0.9112
Pers <65 with Health Insurance	100	Pers <65 with Health Insurance	100
f0892110	0.79301	f0892110	0.80774
Hospital Beds 2010	100	Hospital Beds 2010	100
f0954510	0.78588	f0954510	0.80014
InpatientDays2010	100	InpatientDays2010	100
f0453010	0.89788	f0453010	0.92052
Population2010	100	Population2010	100
f1419608	0.93789	f1419608	0.93905
MedicaidElig2008	100	MedicaidElig2008	100
f1420608	0.9414	f1420608	0.93835
Medicare_MedicaidDuallyElig2008	100	Medicare_MedicaidDuallyElig2008	100
f1193308	0.93988	f1193308	0.95587
3-Yr IsHrt2008-10	100	3-Yr IsHrt2008-10	100
f1316508	0.91159	f1316508	0.93154
3-Yr OtherCardDis2008-10	100	3-Yr OtherCardDis2008-10	100
f0978110	0.44909	f0978110	0.46566
PCI2010	100	PCI2010	100
f1474810	0.89404	f1474810	0.91549
Pers<652010	100	Pers<652010	100
f1475110	-0.24746	f1475110	-0.25529
PercPers<65woHS2010	100	PercPers<65woHS2010	100
f1451006	0.88252	f1451006	0.90832
TotCivLab2006-10	100	TotCivLab2006-10	100
f1451206	0.90183	f1451206	0.91595
UnemployedCivLab2006-10	100	UnemployedCivLab2006-10	100
f1387610	0.82084	f1387610	0.84164
PopDensity2010	100	PopDensity2010	100
f1498812	0.50893	f1498812	0.52
TxcSite2012	100	TxcSite2012	100
f1498912	0.42553	f1498912	0.46642
TxcSiteNot2012	100	TxcSiteNot2012	100
f1526411	0.37463	f1526411	0.38536
DaysAQ2011	100	DaysAQ2011	100
f1526511	0.32257	f1526511	0.33292
#DaysAQGood2011	100	#DaysAQGood2011	100

f1526611	0.25661	f1526611	0.26434
PercGoodAQD 2011	100	PercGoodAQD 2011	100
f1526208	0.06335	f1526208	0.07895
DailyFPartMat2008	100	DailyFPartMat2008	100
f1526306	0.49851	f1526306	0.51958
Days8hrAOzone2006	100	Days8hrAOzone2006	100
PCS_All_0_1	0.00827	PCS_All_0_1	0.04607
MULTIMORBIDITY _PCSpend_All_0_1	100	MULTIMORBIDITY _PCSpend_All_0_1	100
PCS_All_2_3	0.11827	PCS_All_2_3	0.14798
MULTIMORBIDITY _PCSpend_All_2_3	100	MULTIMORBIDITY _PCSpend_All_2_3	100
PCS_All_4_5	0.03319	PCS_All_4_5	0.04205
MULTIMORBIDITY _PCSpend_All_4_5	100	MULTIMORBIDITY _PCSpend_All_4_5	100
PCS_All__6	0.04621	PCS_All__6	0.00502
MULTIMORBIDITY _PCSpend_All_>6	100	MULTIMORBIDITY _PCSpend_All_>6	100
PCS_65_0_1	0.02732	PCS_65_0_1	0.04415
MULTIMORBIDITY _PCSpend_<65_0_1	98	MULTIMORBIDITY _PCSpend_<65_0_1	98
PCS_65_2_3	0.23199	PCS_65_2_3	0.25575
MULTIMORBIDITY _PCSpend_<65_2_3	98	MULTIMORBIDITY _PCSpend_<65_2_3	98
PCS_65_4_5	0.18759	PCS_65_4_5	0.19667
MULTIMORBIDITY _PCSpend_<65_4_5	98	MULTIMORBIDITY _PCSpend_<65_4_5	98
PCS_65__6	0.17853	PCS_65__6	0.16764
MULTIMORBIDITY _PCSpend_<65_>6	98	MULTIMORBIDITY _PCSpend_<65_>6	98
PCS_65_0_10	-0.01169	PCS_65_0_10	0.05331
MULTIMORBIDITY _PCSpend_>65_0_1	98	MULTIMORBIDITY _PCSpend_>65_0_1	98
PCS_65_2_30	0.03556	PCS_65_2_30	0.07899
MULTIMORBIDITY _PCSpend_>65_2_3	98	MULTIMORBIDITY _PCSpend_>65_2_3	98
PCS_65_4_50	-0.04103	PCS_65_4_50	-0.02326
MULTIMORBIDITY _PCSpend_>65_4_5	98	MULTIMORBIDITY _PCSpend_>65_4_5	98
PCS_65__60	-0.03309	PCS_65__60	-0.07324
MULTIMORBIDITY _PCSpend_>65_>6	98	MULTIMORBIDITY _PCSpend_>65_>6	98
Urban_Rural_Status	-0.55448	Urban_Rural_Status	-0.58326
Urban_Rural_Status	100	Urban_Rural_Status	100
_Pop_65	-0.51561	_Pop_65	-0.48566
%Pop>65	100	%Pop>65	100
_POVERTY	-0.17224	_POVERTY	-0.22451
%POVERTY	100	%POVERTY	100
_HYPER_HOSP_DISC	0.22293	_HYPER_HOSP_DISC	0.20162
%HYPER_HOSP_DISC	100	%HYPER_HOSP_DISC	100
_HEARTDIS_HOSP_DISC	-0.02588	_HEARTDIS_HOSP_DISC	-0.00497
%HEARTDIS_HOSP_DISC	100	%HEARTDIS_HOSP_DISC	100

_WO_HS	-0.30482	_WO_HS	-0.34304
%WO_HS	100	%WO_HS	100
_ADULT_SMOKE	-0.2947	_ADULT_SMOKE	-0.3045
%ADULT_SMOKE	100	%ADULT_SMOKE	100
DIABETES_PREV	0.94319	DIABETES_PREV	0.95449
DIABETES_PREV	100	DIABETES_PREV	100
_DIABETES_PREV	-0.30267	_DIABETES_PREV	-0.35946
%DIABETES_PREV	100	%DIABETES_PREV	100
OBESITY_PREV	0.92526	OBESITY_PREV	0.93909
OBESITY_PREV	100	OBESITY_PREV	100
_OBESITY_PREV	-0.05723	_OBESITY_PREV	-0.13286
%OBESITY_PREV	100	%OBESITY_PREV	100
LEIS_PHY_INACTIVE	0.93751	LEIS_PHY_INACTIVE	0.95073
LEIS_PHY_INACTIVE	100	LEIS_PHY_INACTIVE	100
f0956610	0.75355	f0956610	0.75266
OutpatVisitsGenHosp2010	100	OutpatVisitsGenHosp2010	100
f0957210	0.89256	f0957210	0.902
EmerDepartVisitsGenHosps2010	100	EmerDepartVisitsGenHosps2010	100
f1475010	0.90975	f1475010	0.92813
Pers<65woutHlthIns2010	100	Pers<65woutHlthIns2010	100
f0453710	-0.19658	f0453710	-0.12937
PctWht_2010	100	PctWht_2010	100
f0453810	0.08449	f0453810	0.02584
PctBlk_AAm_2010	100	PctBlk_AAm_2010	100
f0453910	0.08704	f0453910	0.05149
PctAmIndAlaNat_2010	100	PctAmIndAlaNat_2010	100
f1345710	0.58074	f1345710	0.59708
PctAsian_2010	100	PctAsian_2010	100
f0454210	0.36285	f0454210	0.34973
PctHispLat_2010	100	PctHispLat_2010	100
f1463910	-0.22585	f1463910	-0.15892
PctWht_Non-HispLat_2010	100	PctWht_Non-HispLat_2010	100
f1353310	0.2352	f1353310	0.19549
AmIn_Lumbee_Pop2010	100	AmIn_Lumbee_Pop2010	100

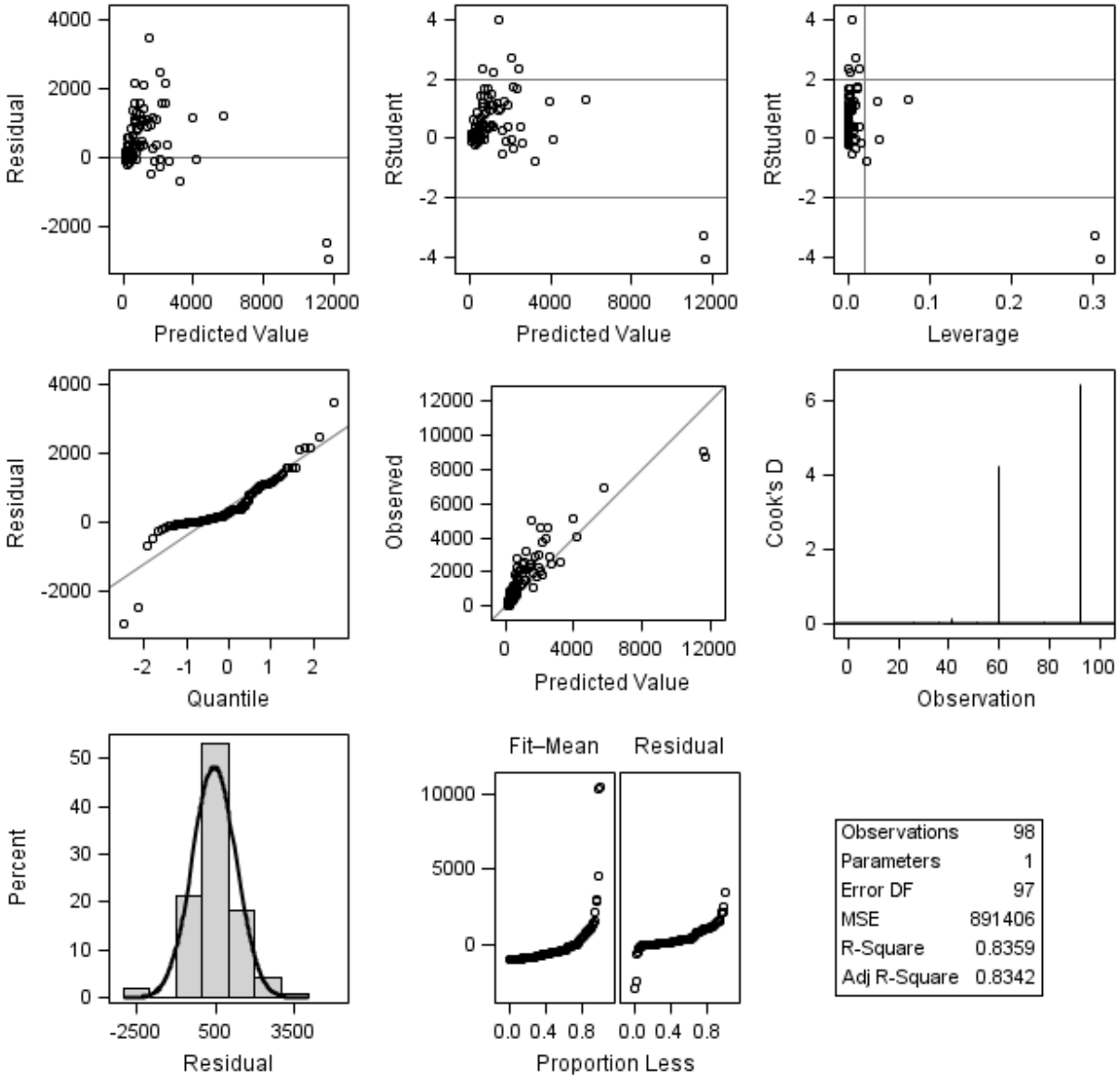
APPENDIX O: BIVARIATE ANALYSIS RESULTS

Models	Estimate	StdErr	tValue	Probt	Labels
MODEL1	0.000967	2.2E-05	43.95	<.0001	Pers <65 with Health Insurance
MODEL2	0.20331	0.0054	37.62	<.0001	Hospital Beds 2010
MODEL3	0.000741	2.01E-05	36.82	<.0001	InpatientDays2010
MODEL4	0.000704	1.56E-05	45.15	<.0001	Population2010
MODEL5	0.00413	8.72E-05	47.34	<.0001	MedicaidElig2008
MODEL6	0.02796	0.000619	45.14	<.0001	Medicare_MedicaidDuallyElig2008
MODEL7	0.80571	0.01802	44.71	<.0001	3-Yr IsHrt2008-10
MODEL8	1.0329	0.02198	47	<.0001	3-Yr OtherCardDis2008-10
MODEL9	0.00277	0.000112	24.71	<.0001	PCI2010
MODEL10	0.000798	1.79E-05	44.52	<.0001	Pers<652010
MODEL11	3.86383	0.18273	21.15	<.0001	PercPers<65woHS2010
MODEL12	0.00136	3.08E-05	44.24	<.0001	TotCivLab2006-10
MODEL13	0.01686	0.000366	46.01	<.0001	UnemployedCivLab2006-10
MODEL14	0.35664	0.00861	41.43	<.0001	PopDensity2010
MODEL15	97.96908	4.79656	20.42	<.0001	TxcSite2012
MODEL16	484.8917	40.59677	11.94	<.0001	TxcSiteNot2012
MODEL17	0.39795	0.0179	22.23	<.0001	DaysAQ2011
MODEL18	0.4494	0.02182	20.6	<.0001	#DaysAQGood2011
MODEL19	1.28707	0.06709	19.18	<.0001	PercGoodAQD 2011
MODEL20	6.38456	0.28397	22.48	<.0001	DailyFPartMat2008
MODEL21	18.64573	0.74379	25.07	<.0001	Days8hrAOzone2006
MODEL22	0.04364	0.00194	22.55	<.0001	MULTIMORBIDITY _PCSpend_All_0_1
MODEL23	0.0159	0.00069	23.04	<.0001	MULTIMORBIDITY _PCSpend_All_2_3
MODEL24	0.00698	0.000308	22.71	<.0001	MULTIMORBIDITY _PCSpend_All_4_5
MODEL25	0.00268	0.00012	22.4	<.0001	MULTIMORBIDITY _PCSpend_All_>6
MODEL26	0.0333	0.00152	21.96	<.0001	MULTIMORBIDITY _PCSpend_<65_0_1
MODEL27	0.01184	0.000496	23.88	<.0001	MULTIMORBIDITY _PCSpend_<65_2_3
MODEL28	0.00576	0.000244	23.59	<.0001	MULTIMORBIDITY _PCSpend_<65_4_5
MODEL29	0.00229	9.88E-05	23.19	<.0001	MULTIMORBIDITY _PCSpend_<65_>6
MODEL30	0.04837	0.00215	22.53	<.0001	MULTIMORBIDITY _PCSpend_>65_0_1
MODEL31	0.01718	0.000755	22.75	<.0001	MULTIMORBIDITY _PCSpend_>65_2_3
MODEL32	0.00729	0.000325	22.43	<.0001	MULTIMORBIDITY _PCSpend_>65_4_5
MODEL33	0.00275	0.000124	22.16	<.0001	MULTIMORBIDITY _PCSpend_>65_>6
MODEL34	19.64937	1.118	17.58	<.0001	Urban_Rural_Status
MODEL35	3.99028	0.22421	17.8	<.0001	%Pop>65
MODEL36	3.7869	0.19124	19.8	<.0001	%POVERTY
MODEL37	1.10073	0.04822	22.83	<.0001	%HYPER_HOSP_DISC
MODEL38	1.12797	0.05029	22.43	<.0001	%HEARTDIS_HOSP_DISC

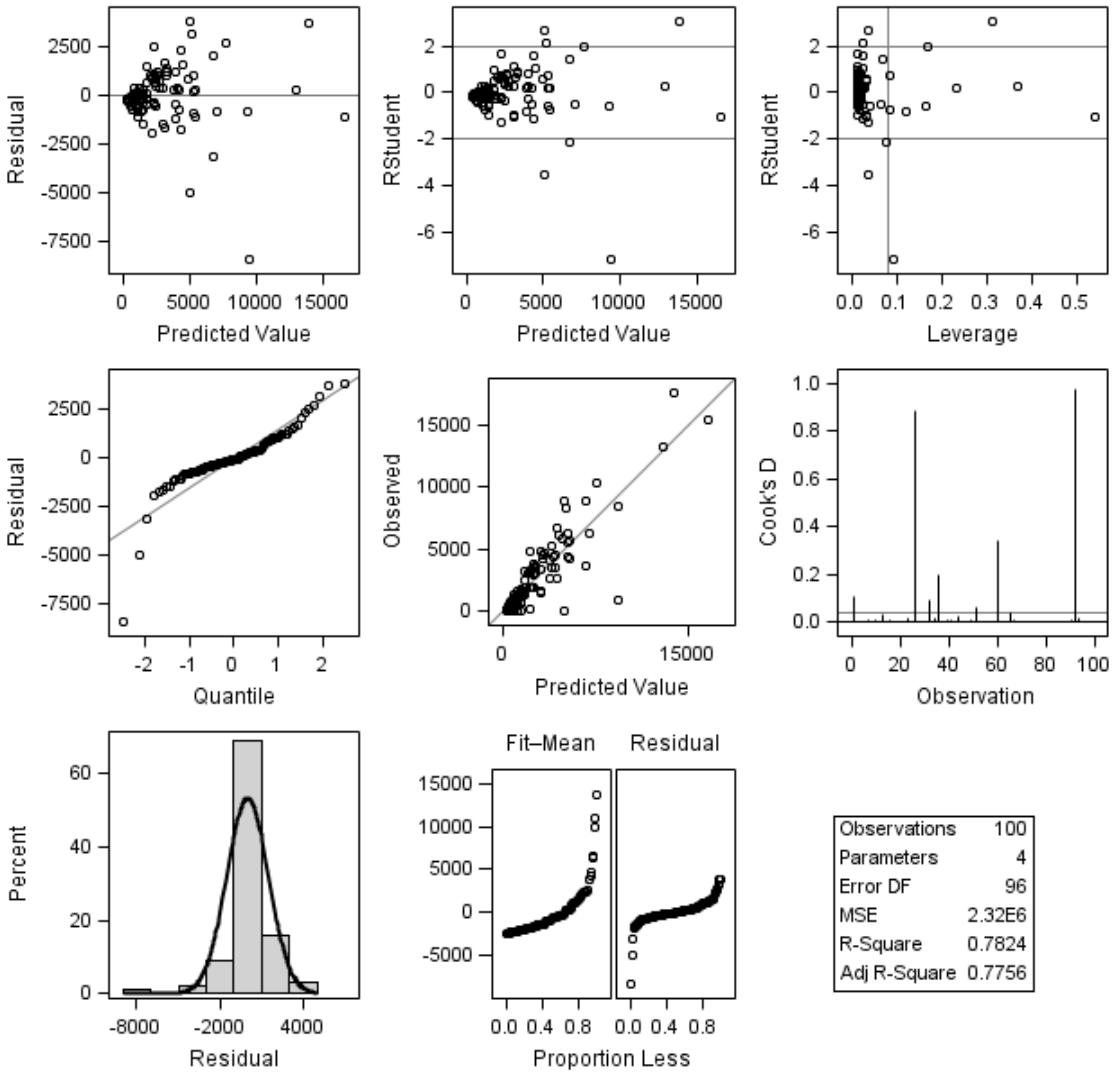
MODEL39	3.92467	0.21372	18.36	<.0001	%WO_HS
MODEL40	3.16921	0.16414	19.31	<.0001	%ADULT_SMOKE
MODEL41	0.01077	0.000226	47.67	<.0001	DIABETES_PREV
MODEL42	6.19872	0.31258	19.83	<.0001	%DIABETES_PREV
MODEL43	0.00363	7.82E-05	46.43	<.0001	OBESITY_PREV
MODEL44	2.5926	0.12129	21.38	<.0001	%OBESITY_PREV
MODEL45	0.0044	9.31E-05	47.23	<.0001	LEIS_PHY_INACTIVE
MODEL46	0.000255	7.51E-06	34	<.0001	OutpatVisitsGenHosp2010
MODEL47	0.00154	3.42E-05	44.93	<.0001	EmerDepartVisitsGenHosps2010
MODEL48	0.0045	9.7E-05	46.44	<.0001	Pers<65woutHlthIns2010
MODEL49	1.03241	0.05088	20.29	<.0001	PctWht_2010
MODEL50	2.55668	0.14868	17.2	<.0001	PctBlk_AAm_2010
MODEL51	5.49133	0.82021	6.7	<.0001	PctAmIndAlaNat_2010
MODEL52	65.91351	2.15608	30.57	<.0001	PctAsian_2010
MODEL53	11.4617	0.47366	24.2	<.0001	PctHispLat_2010
MODEL54	1.05291	0.05275	19.96	<.0001	PctWht_Non-HispLat_2010
MODEL55	0.00695	0.00111	6.28	<.0001	AmIn_Lumbee_Pop2010

APPENDIX P: FIT DIAGNOSTICS

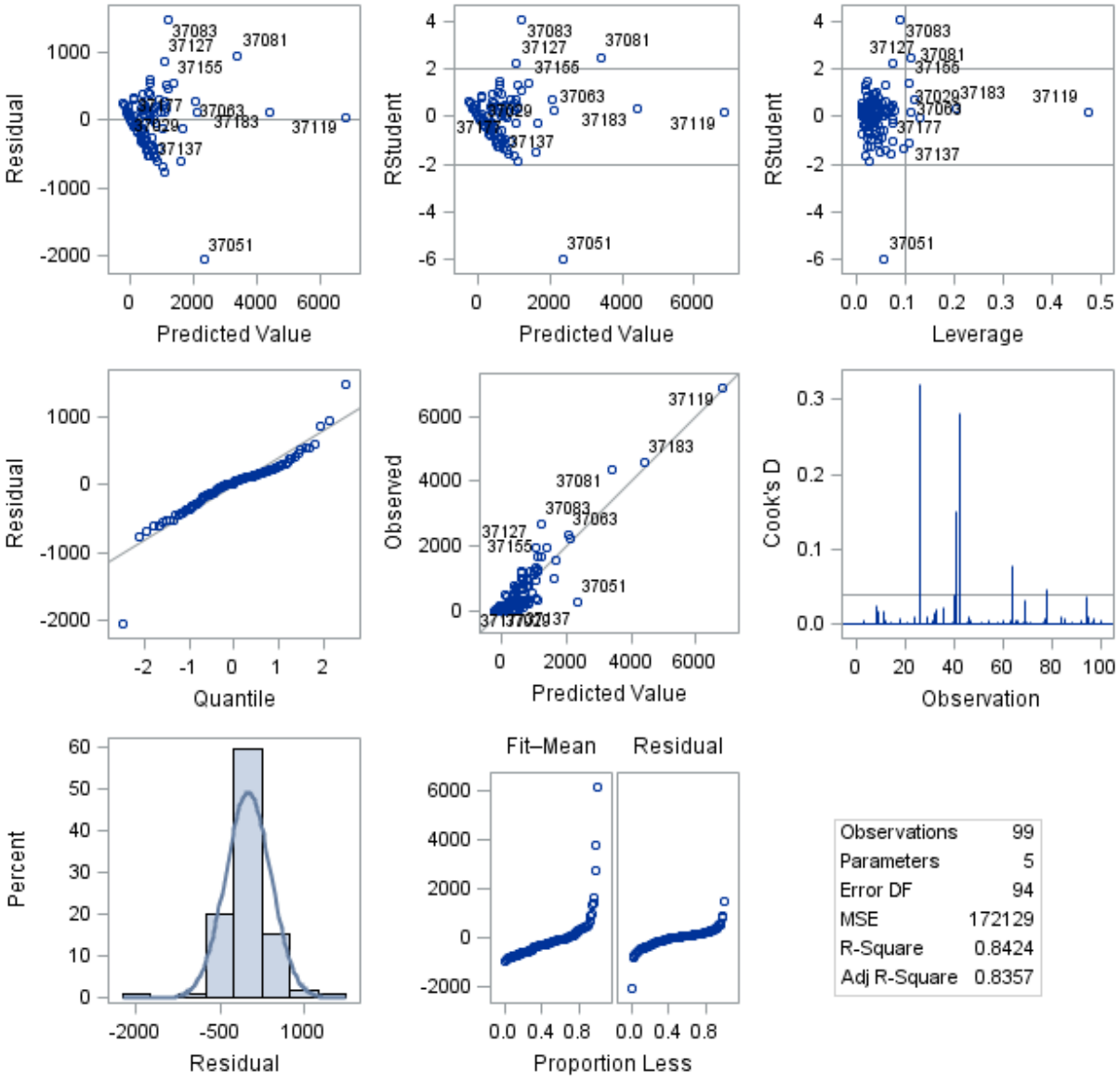
Female coronary heart disease model



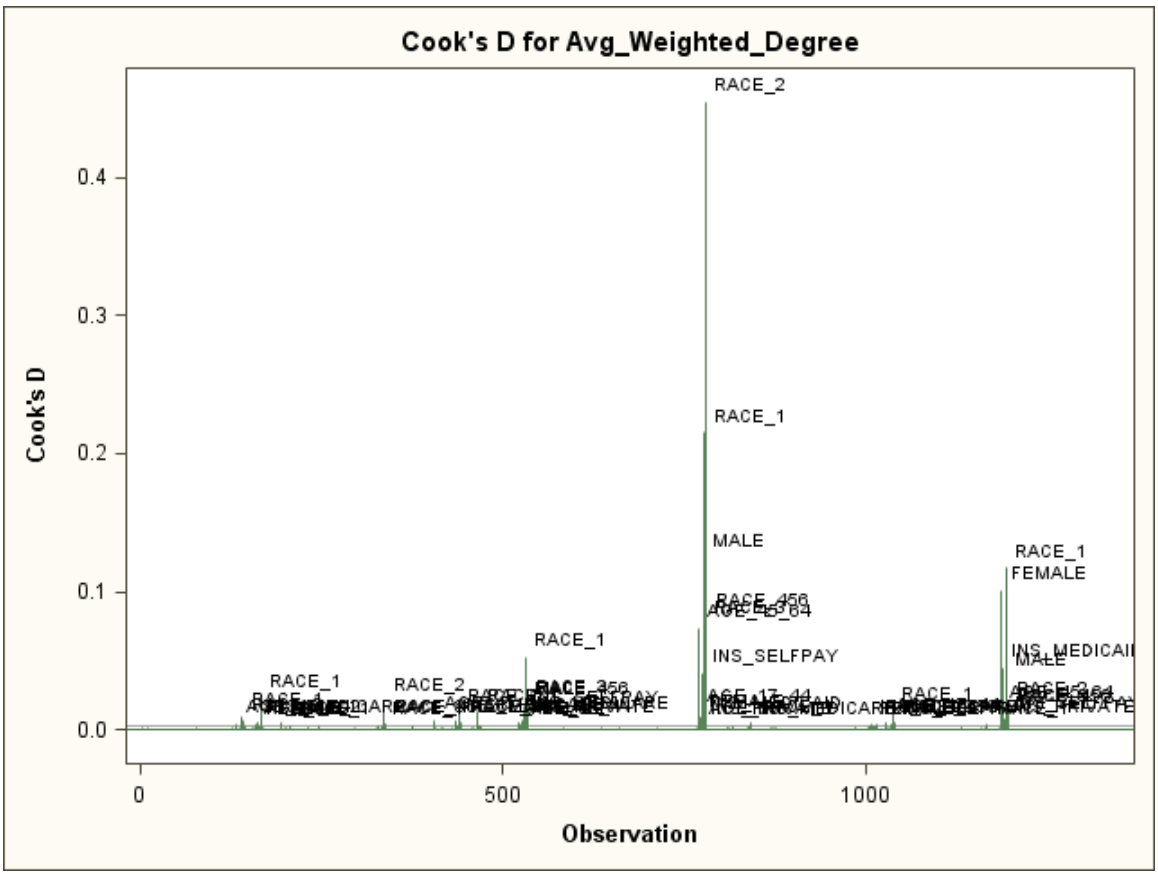
Non-Hispanic white coronary heart disease

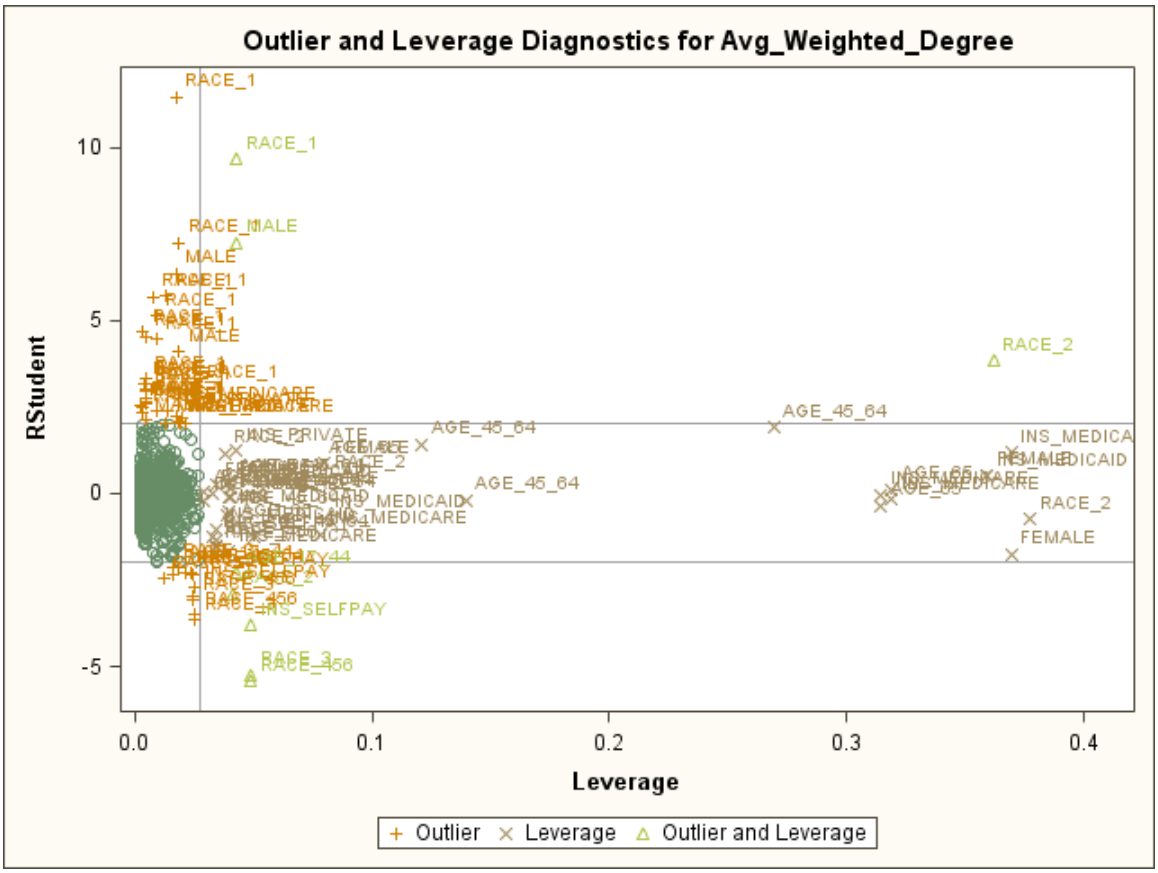


Non-Hispanic black coronary heart disease



APPENDIX Q: OUTLIER DIAGNOSTICS - COOK'S D & LEVERAGE




Outlier and Leverage Diagnostics for Avg_Weighted_Degree
RStudent
Leverage
10
5
0
-5
0.0
0.1
0.2
0.3
0.4
RACE_1
RACE_2
MALE
FEMALE
AGE_45_64
INS_PRIVATE
INS_MEDICAID
INS_MEDICARE
INS_SELFPAY
Outlier
Leverage
Outlier and Leverage

APPENDIX R: FINAL MODELS

Dependent Variable: **FEMALE**_101 Hrt Dis WTD DEGREE label 101 for FEMALE								
Number of Observations Used	98							
Number of Observations with Missing Values	2							

Analysis of Variance								
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Model	4	245169044	61292261	172.19	<.0001			
Error	93	33104695	355964					
Corrected Total	97	278273739						
Root MSE	596.62757	R-Square	0.881					
Dependent Mean	1592.602	Adj R-Sq	0.8759					
Coeff Var	37.46244							

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	Intercept	1	-78.17554	867.53631	-0.09	0.9284	-1800.9307	1644.5796
HYPER HOSP_DISC	%HYPER_HOSP _DISC	1	22.22701	9.88094	2.25	0.0268	2.60543	41.8486
f1498812	TxcSite2012	1	215.15509	95.82374	2.25	0.0271	24.86813	405.44205
PCS_65_2_3	MULTIMORBID ITY _PCSpend_<65_2 _3	1	-0.17664	0.05978	-2.96	0.004	-0.29534	-0.05794
OBESITY_ PREV	OBESITY_PREV	1	0.05767	0.00276	20.9	<.0001	0.05219	0.06315

Dependent Variable: **MALE**_101 Hrt Dis WTD DEGREE label 101 for Male								
Number of Observations Read	100							
Number of Observations Used	98							
Number of Observations with Missing Values	2							
Analysis of Variance								
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Model	3	610287328	203429109	274.38	<.0001			
Error	94	69693639	741422					
Corrected Total	97	679980966						
Root MSE	861.05847	R-Square	0.8975					
Dependent Mean	2493.44898	Adj R-Sq	0.8942					
Coeff Var	34.53283							
Parameter Estimates								
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	Intercept	1	2164.0121	601.08769	3.6	0.0005	970.5384	3357.4858
f1498812	TxcSite2012	1	364.38632	138.2921	2.63	0.0098	89.80412	638.96853
PCS_65_2_3	MULTIMORBIDITY _PCSpend_<65_ 2_3	1	-0.23577	0.08611	-2.74	0.0074	-0.40675	-0.06479
OBESITY_ PREV	OBESITY_ PREV	1	0.09187	0.00394	23.33	<.0001	0.08406	0.09969

Dependent Variable: **R1**_101 Hrt Dis WTD DEGREE label 101 for R1								
Number of Observations Read	100							
Number of Observations Used	100							
Analysis of Variance								
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Model	2	785772703	392886351	160.32	<.0001			
Error	97	237709873	2450617					
Corrected Total	99	1023482575						
Root MSE	1565.44474	R-Square	0.7677					
Dependent Mean	2915.63	Adj R-Sq	0.763					
Coeff Var	53.69147							

Parameter Estimates								
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	Intercept	1	506.3982	206.90218	2.45	0.0162	95.75465	917.04176
f1498812	TxcSite2012	1	657.01276	254.67355	2.58	0.0114	151.55626	1162.46926
DIABETES_PREV	DIABETES_PREV	1	0.29645	0.02091	14.18	<.0001	0.25494	0.33796

Dependent Variable: **R2**_101 Hrt Dis WTD DEGREE label 101 for R2								
Number of Observations Read	100							
Number of Observations Used	99							
Number of Observations with Missing Values	1							
Analysis of Variance								
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Model	4	86516696	21629174	125.66	<.0001			
Error	94	16180151	172129					
Corrected Total	98	102696847						
Root MSE	414.88464	R-Square	0.8424					
Dependent Mean	661.64646	Adj R-Sq	0.8357					
Coeff Var	62.70488							

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	Intercept	1	-851.40949	617.42118	-1.38	0.1712	-2077.3137	374.49474
PCS_All__6	MULTIMORBIDITY _PC Spend_All_ >6	1	0.06615	0.0169	3.91	0.0002	0.03259	0.09971
f1451206	Unemployed CivLab 2006-10	1	0.16225	0.00754	21.52	<.0001	0.14728	0.17722
PCS_All_2_3	MULTIMORBIDITY _PC Spend_All _2_3	1	-0.34943	0.10457	-3.34	0.0012	-0.55707	-0.1418
_POVERTY	%POVERTY	1	34.35079	9.54307	3.6	0.0005	15.40281	53.29877

Dependent Variable: **R3**_101 Hrt Dis WTD DEGREE label 101 for R3

Number of Observations Read	100
Number of Observations Used	73
Number of Observations with Missing Values	27

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	202498	67499	117.11	<.0001
Error	69	39769	576.36338		
Corrected Total	72	242267			

Root MSE	24.00757	R-Square	0.8358
Dependent Mean	34.06849	Adj R-Sq	0.8287
Coeff Var	70.46854		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	Intercept	1	-1.05235	3.53267	-0.3	0.7667	-8.09983	5.99513
f1474910	Pers <65 with Health Insurance	1	0.00065344	0.00005432	12.03	<.0001	0.00054506	0.00076181
f0892110	Hospital Beds 2010	1	-0.02311	0.01215	-1.9	0.0613	-0.04734	0.00112
f0956610	OutpatVisitsGen Hosp2010	1	-4.137E-05	0.00001492	-2.77	0.0072	-7.114E-05	-0.0000116

APPENDIX S: SPATIAL REGRESSION RESULTS

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set: **HD_RACE_2_RESID**

Dependent Variable:	R2_101	Number of Observations:	101
Mean dependent var:	675.069	Number of Variables:	5
S.D. dependent var:	1030.17	Degrees of Freedom:	96

R-squared: 0.829839	F-statistic: 117.043
Adjusted R-squared: 0.822749	Prob(F-statistic): 4.92355e-036
Sum squared residual:1.82389e+007	Log likelihood: -754.562
Sigma-square: 189988	Akaike info criterion: 1519.12
S.E. of regression: 435.877	Schwarz criterion: 1532.2
Sigma-square ML: 180583	
S.E of regression ML: 424.951	

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	-888.866	643.269	-1.3818	0.17024
PCS_All__6	0.0783851	0.017304	4.52988	0.00002
f1451206	0.162554	0.00788195	20.6235	0.00000
PCS_All_2_	-0.412309	0.105427	-3.91085	0.00017
PCT_POVERT	34.7924	10.0198	3.47235	0.00078

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 37.744812
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	160.4765	0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	4	42.8677	0.00000
Koenker-Bassett test	4	10.6476	0.03082

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set: HD_RACE_2_RESID

Dependent Variable:	R2_101	Number of Observations:	101
Mean dependent var:	675.069	Number of Variables:	5
S.D. dependent var:	1030.17	Degrees of Freedom:	96

R-squared:	0.829839	F-statistic:	117.043
Adjusted R-squared:	0.822749	Prob(F-statistic):	4.92355e-036
Sum squared residual:	1.82389e+007	Log likelihood:	-754.562
Sigma-square:	189988	Akaike info criterion:	1519.12
S.E. of regression:	435.877	Schwarz criterion:	1532.2
Sigma-square ML:	180583		
S.E of regression ML:	424.951		

Variable	Coefficient	Std.Error	-Statistic	Probability
CONSTANT	-888.866	643.269	-1.3818	0.17024
PCS_All__6	0.0783851	0.017304	4.52988	0.00002
f1451206	0.162554	0.00788195	20.6235	0.00000
PCS_All_2_	-0.412309	0.105427	-3.91085	0.00017
PCT_POVERT	34.7924	10.0198	3.47235	0.00078

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 37.744812
TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	160.4765	0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	4	42.8677	0.00000
Koenker-Bassett test	4	10.6476	0.03082

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : HD_RACE_2_RESID_wt
(row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.0298	0.8066	0.41989
Lagrange Multiplier (lag)	1	0.1678	0.68209
Robust LM (lag)	1	0.0440	0.83392
Lagrange Multiplier (error)	1	0.2054	0.65040
Robust LM (error)	1	0.0816	0.77517
Lagrange Multiplier (SARMA)	2	0.2494	0.88278

SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set: HD_RACE_2_RESID
Spatial Weight: HD_RACE_2_RESID_wt
Dependent Variable: R2_101 Number of Observations: 101
Mean dependent var: 675.069307 Number of Variables: 5
S.D. dependent var: 1030.169363 Degrees of Freedom: 96
Lag coeff. (Lambda): 0.096507

R-squared: 0.830668 R-squared (BUSE) : -
Sq. Correlation: - Log likelihood: -754.415235
Sigma-square: 179704 Akaike info criterion: 1518.83
S.E of regression: 423.915 Schwarz criterion: 1531.91

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	-867.428	634.426	-1.36726	0.17154
PCS_All__6	0.0738598	0.0174285	4.23788	0.00002
f1451206	0.162574	0.00774029	21.0036	0.00000
PCS_All_2_	-0.392914	0.104253	-3.76887	0.00016
PCT_POVERT	35.6283	10.0204	3.55556	0.00038
LAMBDA	0.0965072	0.145145	0.664904	0.50611

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	4	42.4738	0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : HD_RACE_2_RESID_wt

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	0.2937	0.58785

APPENDIX T: ALL NETWORK STATISTICS FOR GROUPS

Sex													
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*	*Network Diameter*	*Graph Density*	*Modularity*	*Number of Communities*	*Number of Weakly*	*Number of Strongly*	*Avg Clustering Coeff*	*Avg Path Length*	*PageRank _highest*
Male													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	207.6	5964.7	27.9	124.2	5.0	0.1	1.4	5.8	1.1	56.0	0.4	2.1	0.0
Median	213.0	5369.5	25.4	78.0	5.0	0.1	0.1	6.0	1.0	52.5	0.4	2.1	0.0
Standard Deviation	16.55	3537.59	15.49	145.90	1.09	0.07	12.39	1.07	0.33	22.96	0.11	0.27	0.01
Skewness	-2.19	1.04	1.07	3.21	1.42	1.13	10.00	1.13	3.51	0.20	-0.26	1.00	1.73
Minimum	140	751	4.885	6.846	3	0.032	0.108	4	1	9	0.12	1.63	0.01
Maximum	223	18702	83.865	954.435	9	0.378	124	10	3	110	0.604	3.09	0.06
Coef of Variation	0.08	0.59	0.56	1.18	0.22	0.52	8.92	0.18	0.30	0.41	0.29	0.13	0.25
Female													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	214.8	6623.8	29.9	145.0	4.8	2.1	0.1	0.1	5.9	1.1	55.7	0.4	0.0
Median	220.5	5804.0	26.1	82.0	5.0	2.1	0.1	0.1	6.0	1.0	51.5	0.4	0.0
Standard Deviation	16.75	3887.02	16.44	173.95	0.91	0.26	0.07	0.03	0.99	0.36	23.97	0.11	0.03
Skewness	-2.00	1.00	1.03	3.29	0.67	0.80	1.14	2.03	0.50	3.03	0.28	-0.47	7.74
Minimum	151	776	5.139	7.212	3	1.61	0.034	0.098	4	1	10	0.127	0.01
Maximum	230	20546	89.33	1154.478	7	2.89	0.39	0.266	9	3	103	0.614	0.29
Coef of Variation	0.08	0.59	0.55	1.20	0.19	0.12	0.51	0.22	0.17	0.32	0.43	0.27	1.05
Race/ethnicity													
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*	*Network Diameter*	*Graph Density*	*Modularity*	*Number of Communities*	*Number of Weakly*	*Number of Strongly*	*Avg Clustering Coeff*	*Avg Path Length*	*PageRank _highest*
Non-Hispanic white													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	222.9	7551.9	66.0	177.9	4.9	0.1	0.1	5.7	1.2	52.4	0.4	2.1	0.0
Median	228.5	6752.5	58.5	96.1	5.0	0.1	0.1	6.0	1.0	48.0	0.4	2.0	0.0
Standard Deviation	15.15	4335.15	35.27	199.15	0.94	0.07	0.03	1.29	0.94	25.62	0.11	0.28	0.01
Skewness	-2.23	0.70	0.80	2.51	0.73	0.83	2.35	1.89	8.82	0.44	-0.51	-0.54	0.19
Minimum	164	482	11	8	3	0	0	4	1	8	0	1	0
Maximum	236	20724	176	1101	7	0	0	13	10	106	1	3	0
Coef of Variation	0.07	0.57	0.53	1.12	0.19	0.50	0.19	0.23	0.81	0.49	0.25	0.14	0.22
Non-Hispanic black													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	182.2	3739.9	34.8	63.7	5.3	0.1	0.2	6.5	2.8	68.3	0.3	2.3	0.0
Median	211.0	3454.0	32.4	38.7	5.0	0.1	0.2	6.0	1.0	67.0	0.3	2.2	0.0
Standard Deviation	59.34	3350.98	27.99	105.78	1.50	0.06	0.11	6.57	11.44	29.67	0.14	0.42	0.02
Skewness	-1.50	1.60	1.55	4.78	-0.38	1.75	1.66	9.30	7.44	0.82	-0.23	-0.38	8.62
Minimum	4	3	2	1	1	0	0	1	1	0	0	1	0
Maximum	235	18579	159	827	8	0	1	70	98	200	1	3	0
Coef of Variation	0.33	0.90	0.80	1.66	0.28	0.65	0.56	1.01	4.10	0.43	0.50	0.19	0.82
Hispanic													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	96.8	433.7	6.2	4.6	5.6	0.0	0.4	7.3	2.2	72.5	1.1	2.3	0.0
Median	100.5	231.5	4.4	2.8	7.0	0.0	0.4	7.5	2.0	84.5	0.1	2.5	0.0
Standard Deviation	56.12	678.58	5.99	6.50	3.10	0.06	0.15	2.98	2.56	33.36	10.19	0.93	0.05
Skewness	0.14	4.17	3.51	5.36	0.07	5.56	-0.44	1.67	7.28	-0.63	10.00	-0.13	3.53
Minimum	3	0	0	0	0	0	0	1	0	1	0	0	0
Maximum	227	5011	44	54	15	1	1	25	25	121	102	5	0
Coef of Variation	0.58	1.56	0.96	1.42	0.55	1.37	0.38	0.41	1.16	0.46	9.21	0.41	1.07
Non-Hispanic Asian, Pacific Islander, Native American, Other[a]													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	112.0	727.4	8.9	9.0	5.7	0.0	0.4	7.1	1.9	77.9	0.1	2.4	0.0
Median	115.5	330.0	5.8	3.9	6.5	0.0	0.4	7.0	2.0	89.0	0.1	2.7	0.0
Standard Deviation	60.95	1293.05	11.17	25.52	2.72	0.04	0.15	2.14	1.30	34.05	0.09	0.83	0.05
Skewness	-0.06	4.46	4.16	7.97	-0.32	5.09	0.04	-0.21	4.07	-0.60	1.78	-0.41	5.60
Minimum	3	2	1	1	1	0	0	1	1	3	0	1	0
Maximum	230	9862	86	242	11	0	1	15	11	129	1	4	0
Coef of Variation	0.54	1.78	1.26	2.83	0.48	0.96	0.40	0.30	0.70	0.44	0.85	0.35	1.20

Age group	Nodes	Edges	Avg Degree	Avg Weighted Degree	Network Diameter	Graph Density	Modularity	Number of Communities	Number of Weakly	Number of Strongly	Avg Clustering Coeff	Avg Path Length	PageRank _highest
17-44 years													
N	100	100	100	100	100	100	100	100	100	100	100	100	99
Mean	191.3	2716.3	26.8	37.8	6.4	0.1	0.2	6.7	1.5	77.2	0.2	2.6	0.0
Median	202.0	2280.5	23.2	23.5	6.0	0.1	0.2	7.0	1.0	80.5	0.3	2.5	0.0
Standard Deviation	35.05	2138.10	18.95	48.92	1.54	0.04	0.07	1.45	0.73	20.35	0.10	0.40	0.03
Skewness	-1.24	1.56	1.61	3.63	0.78	1.73	1.41	0.55	2.04	-0.58	0.38	0.54	8.01
Minimum	83	143	3	2	4	0	0	4	1	22	0	2	0
Maximum	234	12408	106	337	11	0	0	11	5	115	1	4	0
Coef of Variation	0.18	0.79	0.71	1.30	0.24	0.58	0.30	0.21	0.50	0.26	0.40	0.16	0.92
45-64 years													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	212.9	5054.9	22.7	87.2	5.4	0.1	0.2	6.0	1.2	66.0	0.3	2.3	0.0
Median	221.5	4633.0	20.9	54.7	5.0	0.1	0.1	6.0	1.0	63.5	0.4	2.2	0.0
Standard Deviation	22.82	3307.14	13.73	108.31	1.14	0.06	0.04	1.29	0.84	24.32	0.12	0.31	0.01
Skewness	-1.94	1.26	1.30	3.47	0.67	1.40	1.72	2.52	8.53	-0.09	-0.24	0.80	1.47
Minimum	130	545	4	5	4	0	0	4	1	13	0	2	0
Maximum	234	17988	77	747	9	0	0	14	9	109	1	3	0
Coef of Variation	0.11	0.65	0.60	1.24	0.21	0.55	0.27	0.22	0.72	0.37	0.33	0.14	0.24
65 years and over													
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Mean	211.3	6116.4	28.0	138.8	4.9	0.1	0.1	5.2	1.0	64.6	0.4	2.1	0.0
Median	216.5	5341.5	25.0	87.4	5.0	0.1	0.1	5.0	1.0	63.0	0.4	2.0	0.0
Standard Deviation	18.84	3405.42	14.09	154.00	0.88	0.06	0.02	0.95	0.20	19.51	0.10	0.21	0.00
Skewness	-1.68	0.97	0.96	2.99	0.28	1.00	2.04	0.51	4.77	-0.05	-0.35	0.90	0.15
Minimum	136	820	6	8	3	0	0	4	1	21	0	2	0
Maximum	235	18057	77	960	7	0	0	8	2	105	1	3	0
Coef of Variation	0.09	0.56	0.50	1.11	0.18	0.45	0.19	0.18	0.19	0.30	0.25	0.10	0.20

Health Insurance coverage	Nodes	Edges	Avg Degree	Avg Weighted Degree	Network Diameter	Graph Density	Modularity	Number of Communities	Number of Weakly	Number of Strongly	Avg Clustering Coeff	Avg Path Length	PageRank _highest
Private													
N	100.00	100.00	100.00	100.00	100.00	100.00	99.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean	207.2	4178.2	37.7	64.8	6.0	0.1	0.2	6.4	1.2	72.2	0.3	2.4	0.0
Median	216.5	3291.0	30.4	33.9	6.0	0.1	0.2	6.0	1.0	73.0	0.3	2.4	0.0
Standard Deviation	28.74	3308.88	27.40	96.06	1.57	0.06	0.06	1.28	0.43	25.67	0.12	0.42	0.01
Skewness	-1.67	1.64	1.66	3.57	1.24	1.74	1.46	0.59	1.82	-0.28	0.09	0.99	2.26
Minimum	106.00	246.00	4.64	2.73	4.00	0.02	0.11	4.00	1.00	12.00	0.06	1.71	0.01
Maximum	236.00	16644.00	141.05	569.88	13.00	0.30	0.38	10.00	3.00	118.00	0.56	4.09	0.08
Coef of Variation	0.14	0.79	0.73	1.48	0.26	0.65	0.32	0.20	0.36	0.36	0.41	0.17	0.27
Public													
Medicaid													
N	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean	186.3	2386.8	20.2	27.8	6.3	0.1	0.2	6.6	1.2	86.7	0.2	2.6	0.0
Median	196.0	2067.0	15.6	18.9	6.0	0.1	0.2	7.0	1.0	89.5	0.2	2.5	0.0
Standard Deviation	37.18	1914.81	15.48	33.26	1.59	0.03	0.08	1.39	0.49	18.35	0.10	0.41	0.01
Skewness	-1.09	1.74	2.02	3.47	1.39	1.88	1.25	0.44	1.97	-1.04	0.27	0.86	2.65
Minimum	79.00	153.00	2.33	2.25	4.00	0.02	0.13	4.00	1.00	25.00	0.06	1.77	0.02
Maximum	234.00	11200.00	95.73	236.08	12.00	0.21	0.47	11.00	3.00	120.00	0.50	4.16	0.07
Coef of Variation	0.20	0.80	0.77	1.19	0.25	0.53	0.33	0.21	0.40	0.21	0.44	0.16	0.24
Medicare													
N	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean	217.7	6671.4	59.5	148.6	4.8	0.1	0.1	5.4	1.1	61.3	0.4	2.1	0.0
Median	223.5	6030.0	54.2	99.1	5.0	0.1	0.1	5.0	1.0	58.5	0.4	2.0	0.0
Standard Deviation	18.06	3618.73	29.82	159.40	0.79	0.06	0.02	0.86	0.22	22.14	0.10	0.21	0.03
Skewness	-2.14	0.85	0.90	2.91	0.42	0.99	2.03	0.20	4.19	0.03	-0.38	0.75	9.64
Minimum	138.00	937.00	12.47	9.44	3.00	0.04	0.09	3.00	1.00	14.00	0.19	1.64	0.01
Maximum	234.00	19252.00	164.55	1020.84	7.00	0.35	0.22	8.00	2.00	110.00	0.61	2.70	0.31
Coef of Variation	0.08	0.54	0.50	1.07	0.16	0.46	0.18	0.16	0.21	0.36	0.24	0.10	1.14
Self Pay													
N	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean	164.3	1521.3	8.0	17.7	6.9	0.0	0.3	8.5	2.6	92.7	0.2	2.8	0.0
Median	175.5	1140.0	6.6	10.4	7.0	0.0	0.2	7.0	1.0	91.0	0.2	2.8	0.0
Standard Deviation	42.99	1424.40	5.99	22.78	1.68	0.02	0.10	10.78	10.57	44.68	0.09	0.46	0.02
Skewness	-0.72	2.13	1.98	3.65	0.17	2.13	1.21	9.68	9.92	7.76	0.57	-0.26	7.51
Minimum	59.00	96.00	0.64	0.90	3.00	0.00	0.14	5.00	1.00	31.00	0.01	1.48	0.02
Maximum	232.00	8535.00	36.79	159.90	11.00	0.16	0.59	114.00	107.00	500.00	0.45	3.83	0.24
Coef of Variation	0.26	0.94	0.75	1.29	0.24	0.52	0.36	1.27	4.03	0.48	0.52	0.17	0.58

Notes:

[a] Adults identifying as multiple races were inluded in the "other" race category

APPENDIX U: AVG WTD DEGREE NETWORK STATISTICS FOR ALL GROUPS

Sex				
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*
Male				
N	100	100	100	100
Mean	207.6	5964.7	27.9	124.2
Median	213.0	5369.5	25.4	78.0
Standard Deviation	16.55	3537.59	15.49	145.90
Skewness	-2.19	1.04	1.07	3.21
Minimum	140	751	4.885	6.846
Maximum	223	18702	83.865	954.435
Coef of Variation	0.08	0.59	0.56	1.18
Female				
N	100	100	100	100
Mean	214.8	6623.8	29.9	145.0
Median	220.5	5804.0	26.1	82.0
Standard Deviation	16.75	3887.02	16.44	173.95
Skewness	-2.00	1.00	1.03	3.29
Minimum	151	776	5.139	7.212
Maximum	230	20546	89.33	1154.478
Coef of Variation	0.08	0.59	0.55	1.20

Race/ethnicity				
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*
Non-Hispanic white				
N	100	100	100	100
Mean	222.9	7551.9	66.0	177.9
Median	228.5	6752.5	58.5	96.1
Standard Deviation	15.15	4335.15	35.27	199.15
Skewness	-2.23	0.70	0.80	2.51
Minimum	164	482	11	8
Maximum	236	20724	176	1101
Coef of Variation	0.07	0.57	0.53	1.12
Non-Hispanic black				
N	100	100	100	100
Mean	182.2	3739.9	34.8	63.7
Median	211.0	3454.0	32.4	38.7
Standard Deviation	59.34	3350.98	27.99	105.78
Skewness	-1.50	1.60	1.55	4.78
Minimum	4	3	2	1
Maximum	235	18579	159	827
Coef of Variation	0.33	0.90	0.80	1.66
Hispanic				
N	100	100	100	100
Mean	96.8	433.7	6.2	4.6
Median	100.5	231.5	4.4	2.8
Standard Deviation	56.12	678.58	5.99	6.50
Skewness	0.14	4.17	3.51	5.36
Minimum	3	0	0	0
Maximum	227	5011	44	54
Coef of Variation	0.58	1.56	0.96	1.42
Non-Hispanic Asian, Pacific Islander, Native American, Other[a]				
N	100	100	100	100
Mean	112.0	727.4	8.9	9.0
Median	115.5	330.0	5.8	3.9
Standard Deviation	60.95	1293.05	11.17	25.52
Skewness	-0.06	4.46	4.16	7.97
Minimum	3	2	1	1
Maximum	230	9862	86	242
Coef of Variation	0.54	1.78	1.26	2.83

Age group				
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*
17-44 years				
N	100	100	100	100
Mean	191.3	2716.3	26.8	37.8
Median	202.0	2280.5	23.2	23.5
Standard Deviation	35.05	2138.10	18.95	48.92
Skewness	-1.24	1.56	1.61	3.63
Minimum	83	143	3	2
Maximum	234	12408	106	337
Coef of Variation	0.18	0.79	0.71	1.30
45-64 years				
N	100	100	100	100
Mean	212.9	5054.9	22.7	87.2
Median	221.5	4633.0	20.9	54.7
Standard Deviation	22.82	3307.14	13.73	108.31
Skewness	-1.94	1.26	1.30	3.47
Minimum	130	545	4	5
Maximum	234	17988	77	747
Coef of Variation	0.11	0.65	0.60	1.24
65 years and over				
N	100	100	100	100
Mean	211.3	6116.4	28.0	138.8
Median	216.5	5341.5	25.0	87.4
Standard Deviation	18.84	3405.42	14.09	154.00
Skewness	-1.68	0.97	0.96	2.99
Minimum	136	820	6	8
Maximum	235	18057	77	960
Coef of Variation	0.09	0.56	0.50	1.11

Health Insurance coverage				
	Nodes	*Edges*	*Avg Degree*	*Avg Weighted Degree*
Private				
N	100.00	100.00	100.00	100.00
Mean	207.2	4178.2	37.7	64.8
Median	216.5	3291.0	30.4	33.9
Standard Deviation	28.74	3308.88	27.40	96.06
Skewness	-1.67	1.64	1.66	3.57
Minimum	106.00	246.00	4.64	2.73
Maximum	236.00	16644.00	141.05	569.88
Coef of Variation	0.14	0.79	0.73	1.48
Public				
Medicaid				
N	100.00	100.00	100.00	100.00
Mean	186.3	2386.8	20.2	27.8
Median	196.0	2067.0	15.6	18.9
Standard Deviation	37.18	1914.81	15.48	33.26
Skewness	-1.09	1.74	2.02	3.47
Minimum	79.00	153.00	2.33	2.25
Maximum	234.00	11200.00	95.73	236.08
Coef of Variation	0.20	0.80	0.77	1.19
Medicare				
N	100.00	100.00	100.00	100.00
Mean	217.7	6671.4	59.5	148.6
Median	223.5	6030.0	54.2	99.1
Standard Deviation	18.06	3618.73	29.82	159.40
Skewness	-2.14	0.85	0.90	2.91
Minimum	138.00	937.00	12.47	9.44
Maximum	234.00	19252.00	164.55	1020.84
Coef of Variation	0.08	0.54	0.50	1.07
Self Pay				
N	100.00	100.00	100.00	100.00
Mean	164.3	1521.3	8.0	17.7
Median	175.5	1140.0	6.6	10.4
Standard Deviation	42.99	1424.40	5.99	22.78
Skewness	-0.72	2.13	1.98	3.65
Minimum	59.00	96.00	0.64	0.90
Maximum	232.00	8535.00	36.79	159.90
Coef of Variation	0.26	0.94	0.75	1.29

Notes:

[a] Adults identifying as multiple races were inluded in the "other" race

APPENDIX V: PATIENT DISCHARGE STATISTICS

Patient Discharge Record Frequency by State/County FIPS code			
County Name	PSTCO	Frequency	Percent
Alamance	37001	18920	1.68
Alexander	37003	4163	0.37
Alleghany	37005	1449	0.13
Anson	37007	3809	0.34
Ashe	37009	3450	0.31
Avery	37011	2373	0.21
Beaufort	37013	6280	0.56
Bertie	37015	2830	0.25
Bladen	37017	4409	0.39
Brunswick	37019	12000	1.06
Buncombe	37021	26030	2.31
Burke	37023	10016	0.89
Cabarrus	37025	21183	1.88
Caldwell	37027	9311	0.83
Camden	37029	507	0.04
Carteret	37031	8263	0.73
Caswell	37033	1543	0.14
Catawba	37035	16993	1.51
Chatham	37037	5104	0.45
Cherokee	37039	2553	0.23
Chowan	37041	1849	0.16
Clay	37043	788	0.07
Cleveland	37045	14440	1.28
Columbus	37047	8400	0.75
Craven	37049	14599	1.29
Cumberland	37051	32911	2.92
Currituck	37053	895	0.08
Dare	37055	2014	0.18
Davidson	37057	16748	1.49
Davie	37059	4589	0.41
Duplin	37061	6720	0.6
Durham	37063	28268	2.51
Edgecombe	37065	9120	0.81

Forsyth	37067	42485	3.77
Franklin	37069	6151	0.55
Gaston	37071	29240	2.59
Gates	37073	576	0.05
Graham	37075	1030	0.09
Granville	37077	6214	0.55
Greene	37079	2404	0.21
Guilford	37081	57922	5.14
Halifax	37083	9737	0.86
Harnett	37085	12906	1.14
Haywood	37087	7614	0.68
Henderson	37089	12896	1.14
Hertford	37091	2914	0.26
Hoke	37093	3991	0.35
Hyde	37095	552	0.05
Iredell	37097	19240	1.71
Jackson	37099	3703	0.33
Johnston	37101	18413	1.63
Jones	37103	1666	0.15
Lee	37105	8892	0.79
Lenoir	37107	10202	0.9
Lincoln	37109	8463	0.75
McDowell	37111	5153	0.46
Macon	37113	3607	0.32
Madison	37115	2201	0.2
Martin	37117	3803	0.34
Mecklenburg	37119	89517	7.94
Mitchell	37121	2204	0.2
Montgomery	37123	3379	0.3
Moore	37125	11862	1.05
Nash	37127	13370	1.19
New Hanover	37129	21065	1.87
Northampton	37131	3513	0.31
Onslow	37133	16012	1.42
Orange	37135	10940	0.97
Pamlico	37137	1542	0.14
Pasquotank	37139	3539	0.31
Pender	37141	5681	0.5
Perquimans	37143	1317	0.12
Person	37145	5006	0.44

Pitt	37147	18648	1.65
Polk	37149	1704	0.15
Randolph	37151	14989	1.33
Richmond	37153	8985	0.8
Robeson	37155	22333	1.98
Rockingham	37157	13317	1.18
Rowan	37159	15698	1.39
Rutherford	37161	8428	0.75
Sampson	37163	9022	0.8
Scotland	37165	5815	0.52
Stanly	37167	7590	0.67
Stokes	37169	5209	0.46
Surry	37171	10787	0.96
Swain	37173	2655	0.24
Transylvania	37175	4006	0.36
Tyrrell	37177	461	0.04
Union	37179	18645	1.65
Vance	37181	6299	0.56
Wake	37183	83793	7.43
Warren	37185	1950	0.17
Washington	37187	1741	0.15
Watauga	37189	3864	0.34
Wayne	37191	16288	1.44
Wilkes	37193	9531	0.85
Wilson	37195	11455	1.02
Yadkin	37197	5241	0.46
Yancey	37199	2256	0.2