THE EFFECT OF REGISTERED NURSE SUPPLY ON POPULATION HEALTH OUTCOMES: A DISTRIBUTED LAG MODEL APPROACH

by

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ABSTRACT

Registered nurses (RNs) are essential to providing care in the healthcare system. To date, research on the relationship between healthcare provider supply and population health has focused on physician supply. This study explored the effect of RN supply on population health outcomes in the U.S.

This is a retrospective, cross-sectional study of U.S. counties and county equivalents using national data. Seven population health outcomes (total and disease specific mortalities and low infant birth weight rate) were the response variables. The predictor variable, RN supply, and some control variables were anticipated to have an asynchronous effect on the seven outcome variables in the hypothesized relationship. Therefore, these variables were examined using three different models: contemporaneous; a three-year lagged; and a distributed lag (both contemporaneous and lagged variables). Quadratic terms for RN and physician supply variables were included. Because the Area Health Resource File (AHRF) outcome variables were skewed toward zero and left censored, Tobit regression analyses were used.

Data were obtained from 19 states using historical RN Supply data for 1,472 counties, representing 47% of the total target population of 3,108 U.S. counties and county equivalents. Regions with rural populations—the Midwest and Southeast—were overrepresented.

Higher RN supply is positively related to higher mortality rates from ischemic heart disease, other cardiovascular disease, and chronic lower respiratory disease in the distributed lag models. Higher RN supply is not significantly related to rates of low infant birth weight, infant mortality, or mortality from cerebrovascular disease in any model. Higher RN supply is positively related to total deaths in the contemporaneous and lagged model.

The results suggest a counter-intuitive, but non-linear relationship between RN supply and health outcomes. More research is needed to understand these relationships and policies must be devised to reduce the current and growing future RN shortage.

Key Words: healthcare workforce, clinician to population ratio, RN supply, mortality, health outcomes, Tobit regression, distributed lag model, left censored data

For my father who tolerated copious crayon scribbles on the walls of our humble country home in Tobago as practice for the work he knew I would eventually do.

I wish he were still here.

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LIST OF ABBREVIATIONS

AACN	American Association of Colleges of Nursing
AAMC	American Association of Medical Colleges
AHRF	Area Health Resources File
APRN	Advanced Practice Registered Nurse
BRFSS	Behavioral Risk Factor Surveillance System
CCNA	Center to Champion Nursing in America
CDC	Centers for Disease Control and Prevention
CVHI	Cardiovascular Health Risk Index
ED	Emergency Department
FIPS	Federal Information Processing Standard
IOM	Institute of Medicine
NCSBN	National Council of State Boards of Nursing
PCP	Primary Care Physician
PHI	Population Health Institute
RUCC	Rural Urban Continuum Code
RN	Registered Nurse

CHAPTER ONE: INTRODUCTION

Registered nurses (RNs) hold 13% of healthcare jobs and are the largest category of healthcare professionals. As of October 2015, more than three million RNs were practicing nursing in the United States (The Henry J. Kaiser Family Foundation, 2016 ; U.S. Bureau of Labor Statistics, 2015). RNs practice in settings ranging from schools and work sites, to clinics, hospitals, nursing homes, and in the community (American Association of Colleges of Nursing AACN, 2014). RNs are on the frontline of healthcare delivery and are often the first point of contact to treat, educate, and supervise follow-up care for patients (Institute of Medicine (U.S.) Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing, 2011). Proximity to the point of care means these professionals significantly affect population health outcomes by improving quality, reducing cost, and adding value as prescribed in the Institute for Health Improvement's Triple Aim[1] (Berwick, Nolan, & Whittington, 2008). However, predictions suggest there will not be an adequate supply of nurses to meet these needs (Center to Champion Nursing in America (CCNA), 2014; The Henry J. Kaiser Family Foundation, 2016, Auerbach, Buerhaus, & Staiger, 2015, 2017)

The nursing profession has an aging workforce, with decreasing job satisfaction and burnout causing RNs to leave direct patient care (Bodenheimer & Sinsky, 2014; Institute of Medicine (U.S.). Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing, 2011; McHugh, Kutney-Lee, Cimiotti, Sloane, & Aiken, 2011; Naylor & Kurtzman, 2010; Seago, Spetz, Ash, Herrera, & Keane, 2011; Unruh, 2005; Unruh & Zhang, 2013). Many

[1] Triple Aim embodies a new direction for healthcare that seeks to improve population health, improve patient experience and satisfaction, and reduce healthcare costs.

RNs have opted for reassignment—sometimes permanently—from clinical care to quality improvement, risk and patient safety, and administration (McHugh et al., 2011).

Increasing use of technology, professional domain revision, scope of practice expansion, and the debate over the role of advanced practice registered nurses (RNs with a master's or doctor of nursing practice degree who can diagnose and treat both simple and complex medical conditions [APRNs]) complicate determining the extent of the pending shortage of RNs. Another issue is the capacity of education programs to train new RNs at a rate adequate to meet expected demand (Institute of Medicine (U.S.). Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing, 2011; Rosseter, 2014).

These nursing workforce issues are similar to shortages in the physician workforce. Attention to the supply of clinicians and their importance to improving population health outcomes have focused on physician shortages, physician specialty and geographic maldistribution, and the need for additional residency slots to train doctors. (Chang et al., 2011; Dussault & Franceschini, 2006; Shi et al., 2005.; Starfield, Shi, Grover, & Macinko, 2005; Zurn, Dal Poz, Stilwell, & Adams, 2004). Nonetheless, RNs are involved in every aspect of care and are often the first point of contact.

Logic suggests RNs contribute significantly to population health, but there has been little research to support this belief. A body of literature is emerging that compares primary care outcomes for physicians with care outcomes for APRNs that supports expanding their scope of practice and removing physician supervision requirements (Bauer, 2010; Brooten, Youngblut, Kutcher, & Bobo, 2004; Dierick-Van Daele et al., 2010; Kleiner, Marier, Park, & Wing, 2014; Kuo, Loresto, Rounds, & Goodwin, 2013; Newhouse et al., 2011; Xue, Ye, Brewer, & Spetz, 2015). Other research has focused on the impact of RNs on patient and resident outcomes in hospitals and nursing homes. This results of this research strongly indicate that nursing plays a positive role in outcomes (Cho, Ketefian, Barkauskas, & Smith, 2015; Konetzka, Stearns, & Park, 2008).

Only three national studies examine the ratios of RNs and the health outcomes of the populations they serve (Bigbee, 2003;Bigbee, 2008; Bigbee et al., 2014; Fields, Bigbee, & Bell, 2015). The results were remarkable because they showed positive associations between higher RN supply and population health. However, one study used state population health rankings as the outcome measure (Bigbee, 2008); a second study may have overstated RN supply (Bigbee et al., 2014); another considered RNs as only one element of a healthcare workforce study (Fields et al, 2015). Thus, the association between RN supply and population health outcomes is uncertain and there continues to be many unanswered questions.

Since there are greater numbers of RNs than any other healthcare professional, it is essential to understand the relationship between RN supply and population health outcomes. This knowledge could be used to influence healthcare workforce policy analyses and population health improvement strategies.

The Research Problem

Prior research found that population health outcomes are improved with higher primary care physician to population ratios, but not with higher specialist physician to population ratios (Shi et al., 2004; Starfield, Shi, Grover, & Mackino, 2005; Starfield, Shi &Mackino, 2005). The relationship between primary care supply and population health outconess is even less clear when regional variation is considered (Ricketts & Holmes, 2007). Considering the impending shortage of primary care physicians, the potential for RNs to fill the gap—particularly in managing chronic disease—demands explication (Cooper, 2015; Dall et al., 2013; AAMC, 2015). If there is a relationship between physician supply and health outcomes, it is conceivable there is also a relationship between RN supply and population health outcomes.

Definitions

The terms used in this research are defined below:

Registered Nurses (RNs)

RNs “complete a program of study at a community college (associate degree), diploma school of nursing (diploma), or a four-year college or university (baccalaureate) degree and must pass a national, standardized licensing examination in the state in which they begin practice” (Institute of Medicine (U.S.) (IOM) Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing, 2011, p. 68). With this preparation, RNs work in settings that span the continuum of healthcare delivery. Typical activities include patient observation, assessment, education, medication administration, wellness promotion, and disease prevention. Many RNs are certified in subspecialty areas of nursing including pediatrics, critical care, obstetrics, and surgery. This definition excludes licensed practical nurses (LPNs), licensed vocational nurses (LVNs), and certified nursing assistants (CNAs).

Advanced Practice Registered Nurse (APRN)

Some RNs continue their education beyond the baccalaureate degree in nursing (BSN) to obtain graduate degrees in nursing – Master of Science in nursing (MSN) and Doctor of Nursing Practice (DNP). There are four types of APRNs. Nurse practitioners (NPs) provide a broad range of services in various settings. These RNs are trained to diagnose and treat common health problems, order and interpret common diagnostic tests, write prescriptions, and make referrals (IOM, 2011). They provide services similar to primary care physicians. However, their legal scope of practice varies by state. Certified registered nurse anesthetists (CRNAs) are trained to provide anesthesia and related care to patients at different levels of acuity. Clinical nurse specialists (CNS) provide care across the continuum and are responsible for diagnosis, management, and treatment of disease, health promotion, and health education. Certified nurse-midwives (CNMs) can provide primary, gynecologic and obstetric care to women, as well as newborn care. They can also provide reproductive care to the male partners and treatment for sexually transmitted diseases (Bauer, 2010; Center to Champion Nursing in America (CCNA), 2014.)

RN Supply

RN supply is based on a model from Health Resources and Services Administration (HRSA), which is part of the U.S. Department of Health and Human Services. The model estimates the number of available full-time equivalent licensed RNs by age, education, practice setting, and employment participation and adjusts for expected separations from the workforce and new graduates (Bureau of Health Resources and Service Administration, 2004). RN supply can also measure the characteristics of health providers (such as gender, age, race, full/part time work, educational preparation etc.) in a defined area (Lewin Group, 2010).

RN supply in this study includes licensed registered nurses (both part and full time). Location of nurses within the professional registry data is listed as residential address. In this study, RN to population ratios (per 100,000) are used as the standard of comparison for variations in population distribution (Fields et al., 2015).

Primary Care Physician

Primary care physicians include general family medicine, general practice, internal medicine, and pediatrics. Thus, the definition of a primary care physician as distinct from a specialist physician is not completely explained by education, training, and certification, since primary care physicians may have a specialty or sub-specialty (such as pediatrics and obstetrics/gynecology) and board certification (Association of American Medical Colleges (AAMC), 2015; 3; Chang, Stukel, Flood, & Goodman, 2015; Chang et al., 2011). The distinction has more to do with their role in healthcare delivery. According to the American Academy of Family Physicians (AAFP), a primary care physician "provides definitive care to the undifferentiated patient at the point of first contact, and takes continuing responsibility for providing the patient's comprehensive care. This care may include chronic, preventive, and acute care in both inpatient and outpatient settings. Such a physician must be specifically trained to provide comprehensive primary care services through residency or fellowship training in acute and chronic care settings". This study uses the AHRF definition of PCP as operationalized in previous studies (Starfield, Shi, Grover, et al., 2005; Starfield, Shi, & Macinko, 2005): "doctors in office-based practice in family medicine or general practice, general internal medicine, and general pediatrics". All other physicians are defined as specialists.

Population Health Outcomes

This term describes collective health consequences within the population group of interest. This health status results from individual exposure to numerous factors (health determinants such as access to medical care, socioeconomic status, and lifestyle, as well as genetic predisposition) as well as policies and other interventions at the group level (Kindig & Stoddart, 2003; Parrish, 2010). Examples of population health outcomes include mortality, morbidity, quality of life, and health status. For the purpose of this research, low infant birth weight, disease-specific and age-adjusted mortality rates were selected as population health outcome measures (Parrish, 2010). These are detailed in Chapter 2.

Significance of the Research, Research Questions, and Hypotheses

The study of the impact of clinician supply on population access and health outcomes has generated a significant body of literature about the role of doctors (Dussault & Franceschini, 2006; Laditka, 2004; Macinko et al., 2007; Shi et al., 2004; Starfield, Shi, Grover, et al., 2005; Starfield, Shi, & Macinko, 2005). However, little is known about RNs and their role in population health outcomes (Bigbee, 2008; Bigbee et al., 2014; Fields et al., 2015). This is curious given RN participation in every aspect of healthcare delivery, and in settings as diverse as community health and primary care services and acute and long-term care (Institute of Medicine [U.S.]. Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing, 2011; Rice & Unruh, 2015). To date, RN studies of the link to population health have used self-assessed health status, county health ranking, and gender-specific interventions as outcome measures. Only two RN supply studies used regression analysis with disease specific or total mortality rates as outcome measures, as has been done in physician supply research.

The purpose of this research is to identify the effect of RN supply on population health outcomes in the U.S., by examining the association with various types of mortality and low infant birth weight. It will build on prior research examining relationships between nurse staffing and patient outcomes at facility levels. It will add to evidence regarding the effects of RN supply on the micro level (e.g., hospital/health facility level), and inform the field about RN supply on the macro level (e.g., population health, and healthcare delivery). The results will help inform policies to help ensure RN workforce adequacy and its effective use as suggested in the IOM report, *The Future of Nursing (2010).*

Demonstrating the relationship between RN supply and population health outcomes will provide essential information to encourage measures to improve RN recruitment and retention. It will also suggest a reconsideration of the scope of practice restrictions that require qualified nonphysicians to be directly or indirectly supervised by a physician. Reducing these restrictions will increase the number of clinicians who can affect healthcare outcomes and improve population health as prescribed in the Triple Aim (see page 1).

Population health outcomes are numerous, complex and interrelated. Thus, no one measure of population health can accurately reflect the health of the counties being studied. This research selects seven measures of health outcomes. The measures have been selected to be largely gender neutral. The measures include total and disease-specific mortality rates, infant mortality and low infant birth weight; thus, compensating for the limitations of previous studies.

This study will add to the knowledge base by answering the research question:

What is the relationship between RN supply and population health outcomes?

The research question will be answered by testing seven hypotheses:

H1: Higher county-level RN to population ratios are related to lower rates of low birth weight infants.

H2: Higher county-level RN to population ratios are related to lower infant mortality rates.

H3: Higher county-level RN to population ratios are related to lower total mortality rates.

H4: Higher county-level RN to population ratios are related to lower rates of mortality due to cerebrovascular disease.

H5: Higher county-level RN to population ratios are related to lower rates of mortality due to ischemic heart disease.

H6: Higher county-level RN to population ratios are related to lower rates of mortality due to cardiovascular disease.

H7: Higher county-level RN to population ratios are related to lower rates of mortality due to chronic lower respiratory disease.

Description of Study

This exploratory study is a cross-sectional analysis of secondary national data at the county level and will include lagged dependent variables. Data on population health outcomes will be obtained from the Area Health Resources File (AHRF) for the 3108 counties and county equivalents in 48 contiguous states and the District of Columbia for 2010 through 2014. The data from the AHRF will be matched by the five-digit Federal Information Processing Standard (FIPS) code to data on RN supply from the State Boards of Nursing (NCSBN) for the years 2010 and 2013.

Chapter Summary

This chapter identifies the significance of RNs in healthcare delivery and access to healthcare, and briefly describes how some factors including RN supply may affect population health outcomes. The chapter describes the significant contribution this research will make to the knowledge about healthcare workforce issues and the link to population health, as measured by several population health outcomes. Finally, the chapter proposes research questions and hypotheses to study the relationship between RN supply and population health outcomes.

CHAPTER TWO: THEORETICAL FRAMEWORK AND LITERATURE REVIEW

This chapter discusses the theoretical framework and literature pertaining to the relationship between RN supply and population health outcomes. The theoretical framework discusses definitions of population health and theories explicating the relationship among the variables used in the research model.

The literature review analyzes previous research linking clinician-to-population ratios, including RN supply, to health outcomes. It includes research on the supply of general practice (PCP) and specialist physicians and population health for two reasons. First, the link between physician supply and population health has been explored and provides important insight on the research to be undertaken. Second, PCP supply is an essential independent variable in the research design detailed in Chapter Three. Since factors other than workforce supply influence population health, the literature review includes previous research exploring those factors.

Theoretical Framework

With few exceptions, studies of clinician supply and population health outcomes have been atheoretical. Standard economic location theory (SELT) was referenced by researchers in some studies examining physician location choice and the relationship to health outcomes (Beckmann, 1971; Dussault & Franceschini, 2006; Newhouse, Williams, Bennett, & William, 1982). However, unlike other aspects of physician supply research that provide a conceptual basis for this study, this theory is inadequate to predict the relationship between RN supply and population health outcomes. SELT neither explains the relationship among the determinants of population health outcomes nor does it explain the relationships that occur among individual and community level determinants or between the individual and community level determinants.

Many theories inform the framework for this study. The following section discusses definitions and measures of population health and present frameworks that identify factors contributing to population health. Donabedian framework links workforce supply to population health.

Definitions of Population Health and Population Health Outcome Measures

To develop a framework for population health to guide this research, an exploration of population health definitions and measures of population health outcomes is warranted. The following section reviews the definitions in the literature and suggests possible measures of population health outcomes as informed by prior works. Ultimately, population health outcome measures are selected for the conceptual framework for this study.

Population health has been defined and measured in various ways. Young (1998) suggested that population health is a model for considering comparative health outcomes among groups of people including the policies, studies, and resources devoted to these outcomes. In 1999, Dunn and Hayes extended the following definition for population health, including measuring health, as well as its determinants:

> "Population health refers to the health of a population as measured by health status indicators and as influenced by social, economic, and physical environments, personal health practices, individual capacity and coping skills, human biology, early childhood development, and health services. As an approach, population health focuses on interrelated conditions and factors that influence the health of populations over the life course, identifies systematic variations in their patterns of occurrence, and applies the resulting knowledge to develop and implement policies and actions to improve the health and well-being of those populations." (Dunn & Hayes, 1999 (p57).)

Kindig and Stoddart (2003) define population health as "the health outcomes of a group of individuals, including the distribution of such outcomes within the group" (p.381). Kindig and Stoddart (2003) use health outcomes instead of health status in their definition of population health, but do not identify health outcome measures. They assert that "health outcomes" captures more than the snapshot implied by "health status." They add that health outcomes should be construed as longitudinal, and suggest that health researchers should select measures appropriate to their research. They did not, however, suggest a single summative measure. Last (2001) defines health outcomes as 1) any result stemming from exposure to the cause or from interventions or preventive measures, or 2) all the identifiable changes in the health condition consequential to an intervention. The guidance from this definition is broad; population health outcome measures may include mortality or longevity and life expectancy, morbidity, quality of life, disability and self-reported health status.

To measure population health outcomes, both quality and length of life could be represented in equal proportion. However, health-related quality of life encompasses subjective concepts such as beauty, spirituality, culture, choice of environment. It could also be considered as the collective impact of life choices on well-being (Gold, Stevenson, and Fryback, 2002 as cited in (Remington & Booske, 2011)). The Centers for Disease Control and Prevention (CDC) defines health-related quality of life as "an individual's or group's perceived physical and mental health over time." Thus, as a construct perceived health-related quality of life or morbidity could prove difficult to measure since it is largely self-perception. On the other hand, objective indicators of morbidity, mortality, or the length of life may be more reliable measures of population health but less inclusive.

The challenge of measuring population health outcomes is illustrated by the Population Health Institute (PHI). They recommend five measures of outcomes: more measures for health-related quality of life than for length of life. Each of the five has equal weight:

1. Mortality determined from premature deaths, which is measured as years of potential life lost before age 75.
2. Morbidity as self-reported health status of fair or poor health.
3. Morbidity as the average number of days reported as physically unwell during the past month.
4. Morbidity as the average number of days reported as mentally unwell during the past month.
5. Morbidity as low birthweight infants which captures health at birth. (Remington & Booske, 2011)

Self-reported health status is also used as a metric of population health. The PHI requires three instances of self-assessments for fair or poor health, feeling physically unwell, or feeling mentally unwell. Although information about this "point in time" assessment of health could be derived from population health surveys such as the Behavioral Risk Factor Surveillance System (BRFSS), those assessments could be unreliable. Inter-region and inter-population comparisons become problematic because the interpretation of questions and responses is highly variable. Also, survey responses are amenable to bias as participants may overrate or underrepresent responses to cast themselves in favorable light – reporting bias. Therefore, self-reported health outcomes have not been selected as dependent variables for this study.

Mortality is a measure of deaths in a defined population over time. The raw calculation of deaths is the crude mortality rate. However, the crude death rate does not allow accurate comparison among groups. Age distributions vary in populations, and older populations will have more deaths. Thus, adjusting for age distribution – age-adjusted mortality rates – standardizes mortality rates and allows accurate comparisons (Miller & Stokes, 1978). Other calculations of mortality include disease-specific mortality rates, calculated for all deaths from the same cause. This metric shows how specific types of morbidity affect total mortality.

While mortality captures end of life, other population health outcomes capture health outcomes at birth – infant mortality and low infant birth weight. Infant mortality is a robust representation of overall population health (Reidpath & Allotey, 2003). It is calculated from the mortality of children less than age one. This measure is linked to other population health outcomes, such as life expectancy. It is also an indicator of the adequacy of clinical care (Chen & Lowenstein, 1985; Shi et al., 2004). Low infant birth weight is measured as infants born weighing 2500 grams, or less. As a population health outcome, low infant birth weight serves as an indicator of maternal health and health behaviors, health access, socio-economic status, environment, as well as a prediction for the infant's health outcomes. Thus, a variety of associations can be drawn from low infant birth weight (Shi et al., 2004).

Previous research has followed the advice offered by Kindig and Stoddart and used several measures of health outcomes: total and disease-specific mortality rates, self-assessed health status, low infant birth weight, and early breast, cervical, colorectal, and skin cancer detection (Gulliford, 2002; Starfield, Shi, Grover, et al., 2005; Starfield, Shi, & Macinko, 2005). Mortality rates are usually age-adjusted and listed as the rate of deaths per 1,000 population (Starfield, Shi, & Macinko, 2005). This study will follow that precedent and use the following population health outcome measures as guided by the literature: age-adjusted mortality rates, specific mortality rates for cerebrovascular disease, ischemic and other cardiovascular disease, chronic lower respiratory disease, diabetes, low infant birth weight, and infant mortality. These outcomes, as substantiated in the preceding discussion, are listed in Table 1.

Table 1 Specific Population Health Outcome Measures

Outcome Variables	Measurement	Reference
Total age-adjusted mortality	Rates of total mortality in the county adjusted by age	Shi et al., 2005
Mortality -cerebrovascular disease	Rates of mortality due to cerebrovascular disease in the county, 3-year average	Macinko, Starfield & Shi, 2007
Mortality - ischemic heart disease	Rates of mortality due to ischemic heart disease in the county, 3-year average	Shi et al., 2005:
Mortality - other cardio-vascular disease	Rates of mortality due to other cardio-vascular disease in the county, 3-year average	Shi et al., 2005:
Mortality - chronic lower respiratory disease	Rates of mortality due to chronic lower resp. disease in the county, 3-year average	Proxy for air quality and health behaviors such as smoking
Low infant birth weight	Rates of birth < 2500 grams, 3-year average	Shi, Macinko, Xu, Regan, Politzer & Wulu, 2004
Infant mortality	Rates of mortality under one year of age in county, 5-year average	Shi, Macinko, Xu, Regan, Politzer & Wulu, 2004

Kindig and Stoddart Framework for Determinants of Population Health

The definition of population health by Kindig and Stoddart (2003) above is an early indication in the literature that population health is multidimensional and is influenced by many broad categories of health determinants – factors that affect health (Last, 2001, Kindig, 2007). An association between a health determinant and a health condition is shown when the presence or absence of the determinant or a change in the level of the determinants affects the degree of the health condition. This relationship between certain factors and population health forms the basis of a broad framework for the determinants of population health (Kindig et al., 2008).

Kindig and Stoddart considered the research on the determinants of population health an equation. The left side of the equation – health determinants, the right side of the equation – health outcomes; or both sides of the equation – the total effect of various health determinants on health outcomes, and concluded that the whole equation is the most appropriate for population health research.

According to Kindig 2007, the categories of health determinants are physical and environmental, healthcare access, social or socio-economic, genetic, behavioral or lifestyle, and biological. Confounding the causal relationship between a specific determinant and health condition is that various broad categories of determinants themselves have important associations and intervening relationships between and among them (Kindig, 2007; Kindig et al., 2008).

The environment includes external factors that ultimately affect health outcomes: healthcare system, physical setting, and community. The healthcare system includes the state and federal policies and the configuration of services that affect healthcare utilization. Included in the system are availability and distribution of the healthcare workforce (including physician and nurse supply). The physical setting includes elements that could affect the health status of individuals where they live and work: societal norms, neighborhood walkability, economic conditions and poverty/wealth, stress levels, environmental quality, and violence (Kindig et al., 2008; Phillips, Morrison, Andersen, & Aday, 1998). Kindig and Stoddart concluded that population health as a health outcome concept should be defined broadly. Concomitantly, they asserted that attention to multiple determinants of health outcomes (regardless of how measured [i.e., both sides of the equation] is necessarily intrinsic to the field of population health research). Determinants include medical care, public health interventions, social environment (e.g., income, education, employment, social support, and culture), physical environment (e.g., urban design, and clean air and water), genetics, and individual behavior (Health, Durch, Bailey, & Stoto, 1997).

Population Health Institute Framework

The Population Health Institute (PHI) at the University of Wisconsin developed a comprehensive framework of factors that influence population health. PHI used this framework to rank population health in Wisconsin counties from 2003. Now, in collaboration with the Robert Wood Johnson Foundation, PHI's framework is being used to rank the population health of counties nationwide from 2010 to 2016 – County Health Rankings Approach. The framework (described from this point as the PHI Framework) includes factors affecting population health such as social and economic conditions, health behavior, physical environment, and access to, and quality of, healthcare (see Figure 1).

The social and economic factors in this model include the domains of community safety, education, income, employment, and family and social support. The community safety domain includes neighborhood felonies (e.g. murder, manslaughter, rape, and assault) as well as accidental injury rates. A fear of crime may cause residents additional stress or cause them to limit time spent outdoors with deleterious effects to their health (Egerter, Barclay, Grossman-Kahn, & Braveman, 2011). The education domain illustrates the link between educational achievements and longevity and fewer chronic conditions (Egerter, Braveman, Sadegh-Nobari, Grossman-Kahn, & Dekker, 2011; Meara, Richards, & Cutler, 2008). The employment domain recognizes that freedom of choice supports overall quality of life, which is linked to the prevailing economic conditions as well as educational preparation as well as income (An, Braveman, Dekker, Egerter, & Grossman-Kahn, 2011). Finally, the income domain includes the resources that support additional living decisions such as choice of residence, other basic physiological needs, and asset accretion. Income disparities are known to be associated with higher mortality risks (Lynch et al., 2004; Shi, Macinko, Starfield, Xu, & Politzer, 2003; Shi et al., 2003). The family and social support domain includes the concept of social capital – collective pooling of resources in networked relationships. Residents in areas with greater social capital have better networks that connect them to information and resources that facilitate healthier behaviors and prevent social exclusion (Carpiano, 2006; Kawachi, Kennedy, & Glass, 1999).

The health behavior factors in the PHI Framework include domains for excessive alcohol and illicit drug use or prescription drug misuse, diet and exercise, sexual activity, tobacco use, and sleep deprivation. Collectively, lifestyle choices in these domains can negatively influence population health outcomes. For example, excessive alcohol consumption is positively associated in motor vehicle injuries and deaths, increased risk of chronic disease, risky sexual behavior, as well as a precursor to intimate partner violence (Centers for Disease Control and Prevention, 2015). Some environmental and lifestyle choices and behaviors are linked to low birth weight. For example, smoking, substance abuse, or poor nutrition have been associated with low infant birth weight (Bailey & Byrom, 2007). Low birth weight can increase the risk of cardiovascular and respiratory conditions in adulthood, predicting morbidity and mortality (Irving, Belton, Elton, & Walker, 2000; Kotecha, Dunstan, & Kotecha, 2012; Paneth, 1995).

The physical environment factors in the PHI framework include air and water quality, housing, and transit. Access to clean air and potable water are basic to maintaining good health.

Increased mortality risks are associated with poor air quality, particularly in populations with chronic lung conditions (Chen, Goldberg, & Villeneuve, 2008). Poor air quality in built-up neighborhoods results from highways, poor sanitation, and areas that lack green space (Lovasi et al., 2012; Vlahov et al., 2007). Another part of the physical environment domain is housing and transit. These factors can affect health, too. Although well-built homes provide shelter from the elements, they can also sicken occupants with the presence of allergens such as mold, or from exposure to lead or radon (Braveman, Dekker, Egerter, Sadegh-Nobari, & Pollack, 2011). Transit describes the private vehicles or public transit systems that connect residents with home, school, or work and leisure activities, and also neighborhood walkability. Absence of sidewalks and reliance on vehicles is associated with increased obesity and cardiovascular disease (De Snyder et al., 2011; Lovasi et al., 2012).

The last domain in the PHI framework is about quality of, and access to, medical care. Higher quality care is linked with fewer medical errors and the provision of evidence-based care. Access to care includes factors such as health insurance coverage, and out of pocket costs (University of Wisconsin Population Health Institute, 2016). Also included is the availability and proximity of clinicians including physicians and nurses — the variable of interest in this research — as a population to provider ratio (RN supply).

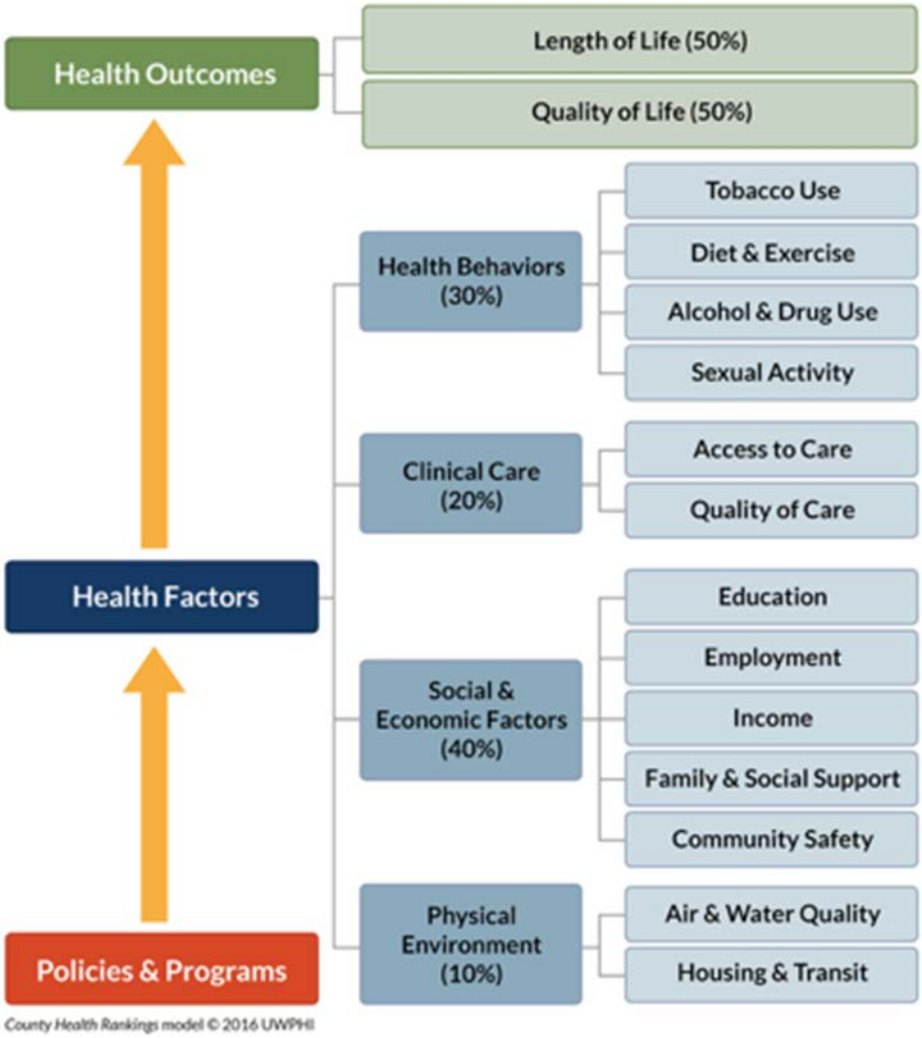

Figure 1 University of Wisconsin Population Health Institute. County Health Rankings & Roadmaps 2017.

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Eco-epidemiological Theory

Population health outcomes emerge from the complex interplay of determinants at multiple levels, from the biological to the societal level of individuals aggregated within social networks, affected by location, and influenced differently over time. (Fink, Keyes, & Cerdá, 2016). Ecological theories acknowledge these relationships and allow nuanced exploration of these interactions, and explanations of the association between social environment and health outcomes (Brailsford et al., 2011; Carpiano & Daley, 2006; Macdonald, Newburn-Cook, Allen, & Reutter, 2013).

Eco-epidemiological theory is one of this group of theories. As developed by Susser and Susser (1996), the theory hypothesizes a system wherein the community, group, and individual levels of determinants influence each other – a nested system. According to these authors, "[E]cology embraces the interrelations of all living things. Epidemiology could be described as human ecology, or that large part of human ecology relating to states of health"(Susser, 1973) (p. 30). Eco-epidemiology then is "the conceptual approach combining molecular, societal, and population-based aspects to study a health related problem" (Bain & Awah, 2014). The theory has been used to explain the clustering of morbidity and mortality and facilitate analysis of hierarchical factors (Bain & Awah, 2014; Diez-Roux, 2000; Diez Roux, 2007; Phelan, Link, Diez-Roux, Kawachi, & Levin, 2004).

In contrast, the risk factor paradigm of epidemiology describes the perspective that multiple determinants at the individual level can be associated with population health outcomes without mediating factors. Susser disagreed. His eco-epidemiological theory is built on the concept that population health is more than the aggregation of individual health outcomes as advanced by Morris 1957 in *Uses of Epidemiology* (March & Susser, 2006). Susser added levels of organization by asserting that determinants of health for the individual could be different from those determinants for the population.

These differences augment the analytical challenge with an equal risk of opposing fallacies: an *ecological fallacy* – inference about the individual from population comparisons; or an *atomistic fallacy* – inference about the population from individual comparisons (March & Susser, 2006; Susser, 2004; Susser & Susser, 1996a; Susser & Susser, 1996b; Susser, 1973, 1998). Nonetheless, the multilevel conceptualization facilitated by eco-epidemiological theory addresses the risks of these fallacies for the researcher. The eco-epidemiological perspective provides a heightened awareness of the ecological risks and an understanding that no determinant is without relationships (Diez-Roux, 1998; McLaren & Hawe, 2005). The perspective assures that within the nested environment, a set of factors could be construed in a logical structure or function (Bain & Awah, 2014). Finally, the perspective supports a broad framework for population health and that population level factors are used to determine population health outcomes.

Donabedian Structure-Process-Outcomes Framework

Donabedian's seminal conceptualization of quality assessment and management, which he titled structure-process-outcome, is one such broad framework. The Donabedian framework for quality assessment is robust enough to include macro population health measures such as longevity, morbidity, and mortality, as well as the use and distribution of healthcare services. Thus, the framework and its proposed measures are applicable to this research.

As first published in 1966, the concept of structure →process→ outcome was intended to evaluate the quality of the medical care process at the individual level, i.e. patient interaction with a clinician. Community-level services delivery were not included (Donabedian, 1966;

Donabedian, 1978). However, the conceptualization can be used to frame the variables in the logic model of this study. Moreover, the robustness of Donabedian's framework allows structure to be used to study outcomes. The framework persists in explication despite an incomplete understanding of the relationship between structure and process, or process and outcome, or structure and outcome (Donabedian, 1978; Wyszewianski & Donabedian, 1981).

As conceived by Donabedian and applied here, structure is the setting and organization of healthcare delivery, including managerial processes that support delivery of services. This domain includes physical facilities and the related equipment, financial and information resources, as well as the number, type, and qualifications of human resources. The number of hospital beds, insurance coverage, hospital ownership and organization structure are also in this domain (Donabedian, 1978; Duff, 1992; Macinko, Starfield, & Shi, 2003; Spetz et al., 2013; Zinn & Mor, 1998). In this study, RN supply and PCP supply are important elements of structure.

Donabedian described process as the work of the clinicians in patient management and delivery of services, i.e., what is done to and for patients (Donabedian, 1978; Duff, 1992; Zinn & Mor, 1998). This domain includes the accessibility of care, care coordination and continuity, as well as communication with providers (Gustafson & Hundt, 1995). However, the framework assumes a sequential process from structure to outcomes and this study is concerned with the relationship between an essential structural component and outcomes. An assumption made by the Donabedian framework is that given good structure, good clinical care follows (Donabedian, 1978; Spetz et al., 2013; Zinn & Mor, 1998). In this sense, process is analogous to the black box paradigm of eco-epidemiological theory, in which a relationship is known to exist, but is not well understood.

Donabedian defined outcomes as the effect of care on individuals and populations (Berwick & Fox, 2016; Donabedian, 1978). Outcomes have been categorized as the appraisal of the health outcomes in terms of quality and satisfaction, or technical (also clinical) and interpersonal, or positive and negative. Outcomes such as mortality (the dependent variables in this study), morbidity, and disability are considered technical outcomes. Negative outcomes are objective. Discomfort or dissatisfaction are interpersonal or positive outcomes and are subjective. (Zinn & Mor, 1998).

A half century after being introduced, the structure-process-outcome sequence remains fundamental to quality measurement, quality improvement, and health systems research (Berwick & Fox, 2016). This makes the Donabedian framework is relevant to study the relationship between RN supply and population health outcomes.

Integrated Framework for the Relationship between RN Supply and Population Health

The Donabedian and population health conceptual frameworks can be integrated to suggest the relationship between RN supply and population health outcomes. The Donabedian framework classifies the number, type, and qualifications of clinicians – RN supply and PCP supply – as part of the structure domain i.e. the setting and organization of healthcare delivery. Setting and organization of healthcare delivery also describes whether the location under review is urban or rural. RN supply and PCP supply, as well as urbanicity have been selected as three structural elements to predict the availability and proximity to care. These control structural measures, urbanicity, and the demographic and socio-economic measures, are discussed in the literature review and in Chapter Three.

Given Donabedian's corollary that good outcomes follow good structure and the need for parsimony, it is possible to omit process measures from this study. This omission is necessary because process measures are difficult to quantify at the population level.

The PHI framework, as well as the Kindig treatise on population health, include a category of health determinants for healthcare access such as insurance coverage and clinician supply. These determinants connect the ability of patients to have access to medical care with population health outcomes.

Eco-epidemiological theory reinforces the conclusion that the relationship between RN supply and population health outcomes is embedded within ecological variables. Susser's theory also serves as a reminder that the variables to be included in the framework must be at comparable levels. That is to say that the variables should describe the environment of the county, the unit of analysis. The clustering of total mortality, disease-specific mortalities, and low infant birth weight among counties should be explained, at least in part, by the nested relationship of the individual in their environment and RN supply in the healthcare facility concentration.

Additionally, the influence of socio-economics, genetics, and health behaviors on health outcomes cannot be overlooked. Control measures have been selected that serve as proxies for these factors and allow fair comparisons between counties. This domain found in the PHI and Kindig frameworks-- demographics and socio-economics--includes population level measures for ethnicity, age, income, and education.

Figure 1 depicts the relevance of the theoretical frameworks for this study. Donabedian's structure, process, and outcomes framework and the PHI and Kindig frameworks link RN supply to population health outcomes, while the population health frameworks suggest that health behaviors, socio-economics and genetics also play an important role in health outcomes.

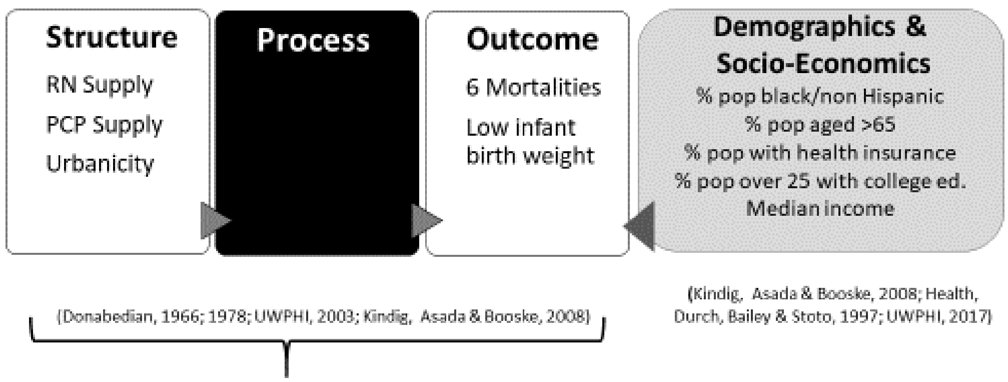

Figure 2 Integrated Framework for the Relationship between RN Supply and Population Health Outcomes.

Literature Review

This section examines the previous literature regarding relationships between RN supply and population health, PCP supply and population health, and other factors that contribute to population health. There is limited research correlating RN supply and population health. Previous studies about RNs and RN supply focused on the RN's role in the hospital and on patient-level outcomes, adjusted for staffing levels (Cho, Ketefian, Barkauskas, & Smith, 2015; Park et al., 2012; Schreuders, Bremner, Geelhoed, & Finn, 2014; Spetz, Harless, Herrera, & Mark, 2013; Unruh, 2003). Other studies have researched the scope of practice for advanced practice registered nurses (APRNs) - nurses with additional graduate level training and certification - and compared APRNs to physicians in terms of primary care outcomes (Carr-Hill & Currie, 2013; Naylor & Kurtzman, 2010; Pohl, Hanson, Newland, & Cronenwett, 2010; Xue et al., 2015). Only three studies examine the supply of RNs and the health status of the populations they serve (Bigbee, 2008; Bigbee et al., 2014; Fields et al., 2015). Another study considers the effect of RN supply's effect on organizational nurse staffing (Blegen et al., 2008).

Most research on the supply of providers and their effect on population health focuses on physicians. These pioneering studies were reviewed to understand an analogous situation. This corpus of physician-focused studies is helpful since one research question will test if the association between physician supply and improved population health status or health outcomes can be extended to the RN supply.

The criteria used to include articles in the literature review were: 1) peer- reviewed, and 2) used U.S. data for multiple states. Further, articles needed to show a statistical association between RN or physician supply and health outcomes while controlling for ecological variables such as income, education, poverty, and income disparity.

Previous Studies of RN Supply and Population Health Outcomes

The few studies about RN supply (RN to population ratios), or those that considered RNs as a part of a healthcare workforce affecting population health had promising results. Those three studies are discussed individually.

One study was an exception to the multistate study criterion noted above. It examined RN-to-population and demographic and health status data for counties in Nevada. Bigbee (2003) found RN supply is positively correlated with female preventive healthcare, but was not significantly correlated with self-reported health status or age-adjusted death rates. The findings suggest greater RN supply might be associated with improved population health. Given small sample size and data from only one state, the study cannot be generalized. A subsequent study used states as the unit of analysis. Bigbee (2008) examined the relationship between RN-to-population ratio and population health and compared those data to physician-to-population ratio. Population health was measured as the health ranking of states published by the Population Health Institute at the University of Wisconsin. The results showed that a high concentration of nurses (RN supply) was associated with improved population health, but regression analysis is needed to explain the relationship further.

In another study, Bigbee and colleagues explored the relationship between RN-to-population ratios and population health in a cross-sectional study of national data from counties in 33 states. Using regression models that included nurse education (percentage of RNs with a BSN or higher degree) and experience (number of years since graduation), these researchers found significant positive associations for self-rated health, breast cancer screening rates, and lower teen birth rates and nurse supply, while controlling for population education, income, race/ethnicity , and PCP supply (Bigbee et al., 2014). Limitations of this study included overstating the number of nurses (each license was counted as an RN even if RNs were licensed in more than one state, and the data were only available for 33 states); and the confounding effect of geography (RNs were sited based on residence).

The most recent study (2015) analyzed the link between provider-to-population ratios (included were ratios for RNs, physicians, and dentists), rurality, and population health in 33 states with the most complete provider data. Measures of population health outcomes included self-rated health assessments, screening rate for mammograms, teen birthrate, and all-cause premature death rate–years of potential life lost if death occurred before age 75. Regression models were adjusted for county rurality. The results found counties with the highest concentrations of RNs, i.e., greater RN supply, had statistically significant better health outcomes (Fields et al., 2015).

Advanced Practice Registered Nurse

Several studies in nursing workforce research focused on APRNs and their role in providing accessible, high-quality primary care. This literature supports expanding APRN scope of practice and removing physician supervision requirements, as well as their importance in improving population health outcomes.

In addition to suggesting the importance of RNs in improving population health, some of these studies compare the quality of care provided by APRNs and doctors (Bauer, 2010; Brooten et al., 2004; Newhouse et al., 2011; Xue et al., 2015). Study results show the care of APRNs equivalent to care provided by physicians with similar patient satisfaction levels, competent diagnoses, treatment strategies, and positive outcomes at lower costs (Brooten et al., 2004; Carter & Chochinov, 2007; Newhouse et al., 2011).

Other studies report that APRNs are more likely to serve in rural and underserved areas (Stange, 2014) and that an increasing proportion of primary care is being delivered by APRNs (Xue et al., 2015). These results support that APRNs, whose numbers are included in RN supply, have an important role in expanding access to healthcare, and improving health behavior (Brooten et al., 2004; Kleiner et al., 2014), thereby improving population health outcomes.

In summary, there is limited research as to RN supply or RN to population ratios and the health of a population. Only two studies have used multiple regression analyses, and the researchers included gender-dependent population health outcome measures (teen birth rates, mammography screening) and health status self-assessments. However, both found a positive relationship between higher RN supply and population health.

Physician Supply and Population Health Outcomes

As noted in the introduction, the research linking PCP supply and population health outcomes is a conceptual basis for this study in the assumption that RN supply bears a similar relationship to population health. In addition, PCP supply is a critical independent variable for the study.

Primary Care Physicians

Health policy experts assert that the supply of PCPs is insufficient for the U.S. population. The American Association of Medical Colleges projects a shortage of PCPs of betweeen12,500 and 31,100 by 2025 (Association of American Medical Colleges [AAMC), 2015]. Unlike some developed countries in which healthcare workforce policy is shaped by government decision-making, the U.S. takes a fragmented, decentralized approach. This method leaves decisions about whether and in what to specialize and where to practice to the individual physician (Brennan & Berwick, 1996; Ricketts & Fraher, 2013; Schlesinger, 2004.; Squires, 2011).

Others suggest the issue is not sufficiency, but maldistribution. Physicians are spread disproportionately across the U.S. This maldistribution affects parity of access to healthcare, particularly in rural areas and economically depressed urban centers. Research suggests that as many as seven million (2%) of Americans live in areas where demand for primary care outpaces supply by at least ten percent (Huang & Finegold, 2013). It is unrealistic to expect there will be no variation in physician distribution, but there are disparities in access that may be only a function of zip code and county or state of residence. Fewer physicians mean fewer choices for a doctor, longer wait times for appointments, greater travel distances, shorter appointment times, and higher charges as physicians become more selective about insurance coverage, or refuse to accept Medicare and Medicaid (Cooper, 2004; Rosenthal et al., 2005).

Previous research links fewer PCPs to worse health outcomes (Chang, Stukel, Flood, & Goodman, 2011; Macinko, Starfield, & Shi, 2007; Shi et al., 2003; Starfield, Shi, & Macinko, 2005). Macincko et al., (2007) reviewed ten articles published between 1985 and 2005 that had the key terms “primary care physician supply” or “primary care supply”. They reanalyzed those studies to predict the effect of health outcomes when there was a one-unit increase in PCPs per 10,000 population. The results confirmed the association of greater supply with improved health outcomes at the macro level, regardless of how health outcomes are defined – disease / total mortality, low birth weight infants, life expectancy and self-reported health – unit of analysis, urbanicity/rurality, and definitions of primary care physician (Macinko et al., 2007).

Chang et al. (2011) measured the link between the adult primary care physician workforce with individual patient outcomes for a sample of Medicare beneficiaries older than 65. They defined PCPs as general internal medicine and family physicians and health outcomes measures as mortality, ambulatory sensitive condition hospitalizations[2], and Medicare spending, and confirmed that a higher level of PCPs was associated with better healthcare outcomes. Because the study was limited to fee-for-service patients, the results cannot be generalized to younger populations, or populations with different types of insurance coverage. However, the direction of the association between increased physician supply and improved healthcare outcomes confirms previous studies.

In summary, these studies used the metric of PCP supply that was a derived ratio of the number of physicians per 10,000 people. They show a consistent positive relationship between more PCPs or primary care and positive population health outcomes (low birth weight infants, and better self-assessed health status). Higher PCP supply was negatively associated with higher total, cancer, heart disease, stroke, and infant mortality rates. The associations suggested between PCP supply and population health may persist over units of analysis including state, county, and metropolitan statistical area.

Specialist Physicians

The relationship between PCP supply and better population health does not hold for the specialist physician supply. A 2005 study by Starfield and colleagues examined data for almost 100% of U.S. counties for 1996-2000 and used age-adjusted, standardized all-cause mortality

[2] Ambulatory care-sensitive conditions are 18 chronic conditions that, if effectively managed in the outpatient setting, should not require hospitalization: asthma, diabetes, hypertension, congestive heart failure, and chronic obstructive pulmonary disease are examples.

rates (deaths/1000 population), and heart disease and cancer mortality as health outcome measures. The study also compared numbers of PCPs and specialty physicians, adjusted for socio-demographic variables associated with higher mortality rates. The results are thought provoking. Higher specialist to population ratios were associated with higher all-cause and age-adjusted mortality rates, higher cardiovascular disease and cancer mortality rates, higher infant mortality and greater incidence of infants with low birth weights (Shi, Macinko, Starfield, Xu, & Politzer, 2003; Shi, 1994; Starfield, Shi, Grover, et al., 2005). The relationship is not statistically significant when socio-demographic variables are used as controls. This contrasts with the findings regarding population health outcomes of PCPs discussed above.

More importantly, the 2005 Starfield et al. study was repeated two years later using multiple regression and geographically weighted regression (GWR) models. The presence of a relationship was confirmed. However, the direction of association was not consistent across the country and showed clusters in heavily populated areas using GWR. PCPs are consistently associated with lower mortality on the East Coast, the mid-West, and in Washington State. The study found other regions with varying strengths of the relationship between type of provider and population health outcomes and regions with no relationship (Ricketts & Holmes, 2007). The authors suggest the findings that differ from the Starfield et al. (2005) study result from geographic clusters, analytic methods, or variable specification differences. Therefore, the relationship between clinician supply and mortality required further exploration to identify causation or find additional correlates.

Table 2 RN & PCP Supply Impact on Population Health Outcomes Literature

Author, Year	Study Focus	Variables	Design	Results
RN Supply				
Bigbee, 2003	Relationship between RN Supply and population health indices	RN supply Self-reported health status % pregnant women seeking prenatal care Accidental death rate Avg life expectancy Age-adjusted death rate # of sick days/year Suicide rate	Correlational secondary analysis using 17 counties in Nevada as unit of analysis	County RN supply significantly correlated with % of pregnant women obtaining prenatal care in the first trimester, & accidental death rate County RN supply was not significantly related to self-reported health status, Avg. life expectancy, age-adjusted death rate, # sick days per year, and suicide rate. Direction of all correlation coefficients supportive of RN supply's effect on population health
Bigbee, 2008	Relationship between RN supply and population health indices	RN supply MD supply state health rankings	Correlational secondary analysis using states as unit of analysis	Significant association between RN supply and state health ranking
Bigbee et al., 2014	Relationship between RN supply and population health indices	RN-Supply (RN, Public Health RN, School RN) Physician to Population ratio PCP to population ratio (DV[3]) Mammography screening rates	Cross-sectional secondary data analysis using counties (2,017) as unit of analysis in linear regression models adjusted for education, income,	Significant association between RN supply and population health indices

[3] DV – Dependent Variable

Author, Year	Study Focus	Variables	Design	Results
		Self-report of fair or poor health Teen birth rate	race/ethnicity, PCP per capita	
Fields, Bigbee, & Bell, 2015	Relationship between clinician-to-population ratios (RN, MD, DMD supply), rurality and population health in U.S. counties	County level provider to population ratios Rurality Years of potential life lost Self-report of fair or poor health Teen birth rate Mammography rates	Cross-sectional secondary data analysis using counties as unit of analysis in linear regression models adjusted for education, income, race/ethnicity	Highest RN-to-population ratio associated with significantly better health measures in most urban/rural categories; the degree of associations generally increasing with county rurality.
Primary Care Physician (PCP) Supply				
Chang, Suckel, Flood & Goodman, 2011	Association between the adult PCP workforce and individual patient outcomes in 6,542 primary care service areas	PCP per 100k population (DV) Primary care FTEs per 100k beneficiaries (DV) Mortality ASCH hospitalizations Medicare program spending Controlling for age, sex, race. chronic condition, zip code area median income, hospital area specialty workforce, hospital area bed supply, spending	Cross-sectional analysis of outcomes of a 2007 20% sample of fee-for-service Medicare beneficiaries> 65 yrs (N=5,132, 936), using 2 measures of adult PCP (general internists and family physicians) across Primary Care Service Areas (N=6542): (1) AMA Masterfile nonfederal, office-based physicians/total population and (2) office-based primary care clinical FTEs per Medicare beneficiary	Higher levels of PCPworkforce were generally associated with more favorable patient outcomes

Author, Year	Study Focus	Variables	Design	Results
Macinko, Starfield, & Shi, 2007	Examination of PCP supply effect size and the predicted effect on health outcomes of a one-unit increase in PCP per 10,000 population		Meta-analysis of data from published studies of the impact of PCP supply on health outcomes in the U.S. Articles from a search of the PubMed database in January 2005 for titles including the terms “PCP supply” or “primary care supply” for articles published between 1985 and 2005. Ten articles met the inclusion criteria.	PCP supply was associated with improved health outcomes, including all-cause, cancer, heart disease, stroke, and infant mortality; low birth weight; life expectancy; and self-rated health in all units of analysis. Pooled results for all-cause mortality suggest that an increase of one PCP per 10,000 population was associated with an average mortality reduction of 5.3%.
Shi, Macinko, Starfield, Politzer, Wulu & Zu, 2003	Association between availability of primary care and income inequality on several categories of mortality in 3081 U.S. counties	All-cause mortality (DV) Heart disease mortality (DV) Cancer mortality (DV) Primary care resources Income inequality Socio-demographics	Cross-sectional study of data with ordinary least squares regression	Counties with higher availability of primary care resources saw 2-3% lower mortality than counties with less primary care
Shi, Macinko, Starfield, Xu, & Politzer, 2003	Whether availability of primary care reduces the effect of income equality on stroke mortality	Stroke mortality standardized for age (DV) Gini coefficient MD supply Education levels Unemployment Race/Ethnicity % urban	Pooled time-series cross-sectional analysis 1985-1995 (n=549) using contemporaneous and lagged models	PCP supply negatively associated with stroke mortality. Impact of income inequality reduced with greater MD supply but disappears with control variables.

Author, Year	Study Focus	Variables	Design	Results
Shi, Macinko, Starfield, Xu, Regan, Politzer & Wulu, 2004	How PCP supply (office-based PCPs per 10,000 population) moderates the association between social inequalities and infant mortality and low birth weight	Low birth weight Infant mortality per 1000 live births Gini coefficient Primary care supply % African-American % of metro population % unemployed population % Population >25 years and completed 12 years of education	Pooled cross-sectional, time series analysis of secondary data for 50 U.S. states 1985–1995	Primary care was negatively associated with infant mortality and low birth weight in all models and association was consistent in contemporaneous and time lagged models. Income inequality was positively associated with low birth weight and infant mortality (p,0.0001), but the relationship with infant mortality not present with the addition of sociodemographic covariate
Shi & Starfield, 2001	The difference in effect of income inequality and PCP supply on mortality among Blacks compared with Whites.	Total mortality, White/Black (DV) Gini coefficient , PCP-to-population ratio Per capita income % Population without elementary education %Workforce population unemployed % Population urban % Population below poverty	Multivariate ecologic analysis of 1990 data from 273 U.S. metropolitan areas	Both income inequality and PCP supply were significantly associated with White mortality with inclusion of the socioeconomic status covariates, the effect of income inequality on Black mortality remained significant, but the effect of PCP supply was no longer significant, especially in areas with high income inequality.
<u>Specialist Supply</u>				
Shi, 1994	Relationship between primary and specialty	Total mortality (DV) Cardiovascular and cancer mortality (DV)	Multiple regression models	Primary care significantly related to better health status, correlating with lower overall

Author, Year	Study Focus	Variables	Design	Results
	care and population health outcomes	Life expectancy (DV) Infant mortality (DV) Low birth weight (DV) Socioeconomic environment: education, income, urbanization and pollution Lifestyle index: seat belt usage, obesity, smoking %elderly, % minority Medical care: specialists, PCP, hospital beds		mortality, lower cancer and cardiovascular mortality, longer life expectancy, lower neonatal death rate, and lower low birth weight. Specialty physicians are related to higher total mortality, deaths due to heart diseases and cancer, shorter life expectancy, higher neonatal mortality, and higher low birth weight.
Shi, Macinko, Starfield, Wulu, Regan & Politzer, 2003	Strength of relationships between primary care, income inequality, and population health in 50 states	Age-standardized all-cause mortality (DV) Mortality Income inequality (Gini & Robin Hood indices) Total aggregate income Median income PCP Supply Specialist MD Supply	Ecological cross-sectional design for 1980, 1985, 1990,1995 including 5-year time lagged IVs in weighted multivariate regression models	In all four time periods, both contemporaneous and time lagged income inequality measures significantly associated with all-cause mortality; contemporaneous and time lagged PCP supply associated with lower all-cause mortality; specialist supply associated with higher all-cause mortality
Starfield, Shi, Grover & Macinko, 2005	Relationship between specialist physician supply, PCP supply, and mortality rates	PCP supply Specialist supply Age-adjusted standardized mortality rates Heart disease mortality Cancer mortality per capita income, % high school education,	Pooled cross-sectional multivariate analyses at the county level	Lower mortality rates where there are more PCPs, but not for specialists

Author, Year	Study Focus	Variables	Design	Results
		% unemployment, % elderly, % black, % below poverty, % in MSA		
Ricketts & Holmes, 2007	Examination of MD supply amd mortality for a consistent relationship across regions (repeats Starfield, Shi, Grover & Macinko, (2005) with new statistical method)	age-adjusted all-cause mortality (DV) age-adjusted disease-specific mortality (DV) MD supply Specialist MD supply Per capita income Percent high school education Unemployment rate Percent elderly Percent African American Percent in poverty Percent in MSA	OLS and geographically weighted regression models with were specified using pooled data from 1996 to 2000 The residuals from the OLS models were mapped and examined for potential clustering. A series of geographically weighted regression models run for all 3,070 counties and the z-scores and significance of the models mapped.	With geographic weight the relationship between primary care and specialist physician supply and mortality is mixed and show strong regional patterns. Evidence of regionally focused association between physician supply and mortality, holding constant population characteristics that reflect socio-economic characteristics but not consistent across the U.S.

Demographics and Socio-economic Factors

In population health research, determinants of health include various socio-economic factors such as physical environment and health behaviors. “Socio-economic factors are not only important health determinants themselves, but can also buffer or enhance the impact of ecosystems on human health.” (Oosterbroek, de Kraker, Huynen, & Martens, 2016) p.238. The following section discusses the demographic and socio-economic factors and their suitability for inclusion as controls in the study.

Education and Income

Education, or the level of educational attainment, is a well-documented control variable in studies of populations. Education, measured by years of school completed or degree(s) earned, is positively correlated with income, employment, social support, and community safety. It is reasonable to extrapolate level of education as associated with health literacy, ability to navigate the healthcare system, and, by extension, population health (Ross & Mirowsky, 1999; Shi & Starfield, 2001; Winkleby, Fortmann, & Barrett, 1990). Education, too, is positively correlated with factors including physical environment and health behavior that affect health status (Cutler, Lleras-Muney, & Center, 2006; Susan Egerter et al., 2011; Ross & Mirowsky, 1999). More education prepares individuals to hold jobs with higher incomes. Higher income jobs are more likely to offer health insurance coverage, paid time off, and a safer work environment (Cutler et al., 2006).

Income is also a predictor of healthcare access and affordability of services. Higher incomes allow individuals greater choice of physical environment such as more options for place of residence, mode of transit and transit time to work, as well as control of leisure time (Egerter et al., 2011; Ross & Mirowsky, 1999).

Conversely, individuals in relative poverty are likely to practice poor health behaviors that lead to chronic health conditions, stress, and risk of increased mortality (Geronimus, Hicken, Keene, & Bound, 2006b; Lantz et al., 1998; Williams, 2002). Also, income inequality is linked to lung cancer in female patients, and causal relationship between lung cancer and smoking is well known (Lynch et al., 2004). Increased mortality, particularly from cardiovascular disease and poor health, can be linked to income inequality. Community-level income equality or concentrated poverty serves as a source of stress, with an associated decrease in social support.

The choice of where to live and work influences health indirectly through social support or social network. A vast literature clearly demonstrates the role of neighborhood in individual health outcomes (Acevedo-Garcia, Lochner, Osypuk, & Subramanian, 2003; DeGuzman & Kulbok, 2012; Liu, Wilson, Qi, & Ying, 2007; Lovasi et al., 2012; Winkleby et al., 1990), on social support and safety (Aday, 1993; Haughton & Stang, 2012; Sampson, Raudenbush, & Earls, 1997) and on air quality (Chen, Goldberg, & Villeneuve, 2008).

In addition to social support, family, friends, and neighbors provide peer pressure that may affect health behaviors such as smoking, exercise, use of alcohol, and diet. A longitudinal study examining the association between income and life expectancy suggested a link between life expectancy and income that varied with U.S. geographic location. Further, the variation in life expectancy was strongly related to health behaviors such as smoking, diet, and exercise (Chetty et al., 2016).

Age

It is common to include age in population health research since age predicts healthcare utilization. This is supported by Centers for Medicare & Medicaid Services (CMS) statistics that the 65 and older per capita healthcare spending is five times more than healthcare spending per child and three times that for adults of working age (Centers for Medicare & Medicaid Services, 2016).

As a variable, the role of age on health outcomes is ambiguous in the literature, varying with the phenomena under study. Due to ambiguities in the literature, this study includes age as a controlling factor. Age will be measured as the percentage of the population in the county older than 65.

Race

Prior research has confirmed disparities in health outcomes for Blacks/ African Americans, even more so when their race is separated from socioeconomic status (Braveman, Cubbin, Egerter, Williams, & Pamuk, 2010; Buys et al., 2015; Geronimus et al., 2006; LaVeist, 2005; Ramaswamy & Kelly, 2015; Thorpe et al., 2012; Wallace et al., 2013). Differences in health outcomes for a Black population persist regardless of educational levels when compared with those for a White population with otherwise similar characteristics (Braveman et al., 2010).

Other structural factors affecting predominantly Black population are racial stigmatization and disadvantage. In addition, Blacks or African-Americans are genetically predisposed to certain chronic conditions or diseases. Geronimus et al (2006) introduced another stress factor faced by this population that would increase their unmet health needs. His hypothesis of "weathering" is proposed as the potential for Blacks to have health deterioration earlier in their lifetimes than expected, due to the aggregate consequences of social and or economic hardship and political ostracism. The study, which was based on review of National Health and Nutrition Examination Survey data for black and white individuals, confirmed that “[t]he stress of living in a race conscious society … may cause disproportionate physiological deterioration such that a Black individual may exhibit the morbidity and mortality of a White individual who is significantly older” and these differences were not attributable to poverty (Geronimus, Hicken, Keene, & Bound, 2006a, p. 826). Another study of death records and 2000 census data for seven poverty-stricken areas for the period indicates excessive rates of early onset chronic disease in concentrated poverty areas among working age residents. Higher rates were observed for the Black residents (Geronimus et al, 2011).

To account for these disparities, the percent of Black population in the county is included in this study.

Insurance Coverage

In addition to income, health insurance coverage may contribute to health outcomes. Insurance allows access to care for treatment of chronic conditions, and visits for prevention (Thorpe et al., 2012). Communities with higher rates of insurance coverage have higher rates of utilization of health care services (Kullgren, McLaughlin, Mitra, & Armstrong, 2012).

Studies that explore an association between insurance coverage and healthcare access or healthcare utilization show mixed results. Anderson, Dobkin, and Gross, (2010) examine this relationship in private health insurance[4] using the “age-out” of eighteen year olds from parental plans during the period 1997-2007 using the National Health Interview Survey and administrative records of emergency department (ED) visits and inpatient admissions. They compared healthcare usage of teenagers just before and after their eighteenth birthday and found robust evidence that without health insurance, ED visits decrease. This is contrary to the supposition that the uninsured seek care in the expensive setting of the ED as the healthcare access point of last resort (Hunold et al., 2014; Kwack et al., 2004). However,

[4] As opposed to public insurance programs. These researchers contend that Medicare or Medicaid population are at low risk of waiving insurance coverage.

because the population is so specific, generalizability is limited. Further, with the advent of the federal Affordable Care Act and the attendant state Medicaid eligibility expansions it was predicted that ED utilization was expected to increase (Glied & Ma, 2015)

Given the ambiguity regarding the influence of insurance on health, the percent insured in a county is included in this study as a proxy for access to healthcare.

Obesity

The population health outcomes in this study can be the result of multiple conditions and the sequelae of poor health behaviors. Various lifestyle factors – diet, lack of physical activity, smoking, illicit drug and alcohol abuse — impact chronic disease incidence, and ultimately the adult population health outcomes selected for inclusion in this study. Obesity is known to be associated with some of the chronic illness outcomes in this study (cerebrovascular, cardiovascular, and ischemic heart disease), multiple co-morbidities, as well as type II diabetes and asthma (Guh et al., 2009; Patterson et al., 2004; Yang et al., 2015). Given this association, obesity is included as a control variable.

Control Variable -Structure

Urbanicity

The U.S. Office of Management and Budget classifies counties as metropolitan or non-metropolitan. Metropolitan counties include a central city or cities of 50,000 residents, or more. Non-metropolitan counties are those counties with fewer residents (Ricketts, Johnson-Webb, & Taylor, 1998). In the literature, county population size and proximity to metropolitan area are used for comparative and classification purposes. The measure assures that there is consideration of the structural factors that lead to health and healthcare access inequality between urban and rural counties. The effect of place - the presence or absence of neighborhood characteristics such as crime, food deserts or a lack of green spaces - can contribute to unmet needs in populations, potentially leading to greater incidence of chronic disease, higher mortality, and lower life expectancy (Singh & Siahpush, 2014). Having less but needing more results in health disparities that is not just the effect of age, race, or individual health behavior.

Since the counties in the region being studied vary widely, urbanicity will be included as a modifier of the relationship between provider-to-population ratios and county-level population health measures. Using the U.S. Department of Agriculture Economic Research Service's 2013 Rural-Urban Continuum Codes (RUCC), counties will be classified as metropolitan or large, medium or small nonmetropolitan. The RUCC include nine classes: three define different-size metropolitan counties, and six distinguish nonmetropolitan or rural counties based on degree of urbanization and adjacency to metropolitan areas (Fields et al., 2015).

Literature Summary

Much previous research has documented a relationship between physician supply and population health outcomes while a very small amount has found a relationship between RN supply and population health. The research has been cross-sectional and has focused on PCP supply. Some studies have found that greater numbers of PCPs are associated with fewer hospitalizations for ambulatory-sensitive conditions (an indication of better primary care access leading to improved population health outcomes) and lower mortality, however geographical clusters are indicated. It is notable that cross-sectional studies might be subject to omitted variable bias (direction not known) if provider supply is correlated with factors not observed in the model. A summary of these studies is presented in Table 1. In addition, this literature review examined studies that explore other factors related to population health. These factors will be control variables in the analysis.

Gaps in Existing Literature

Much is known about the impact of primary care and specialist physician supply on population access and health outcomes (Chang et al., 2015; Macinko et al., 2007; Shi & Starfield, 2001; Shi et al., 2003; Shi et al., 2004; Shi, 1994; Shi et al., 2005, 2003). However, there are still several crucial unanswered questions about the role of RNs in population health outcomes despite the extensive role of RNs in care delivery, patient education, and treatment follow-up in a variety of settings.

Research to date on the population health impacts of RN supply has used self-assessed health status, county health ranking, and gender-specific interventions as the selected population health outcome measures. Few RN supply studies use regression analysis with disease specific or total mortality rates as outcome measures as was done in physician supply research. No previous RN supply study has used a lagged model to test the potentially delayed impact of RN supply on population health outcomes. This study will compensate for the limitations of previous research by using objective population health outcome measures and using a distributed lag model.

Contribution of the Study and Research Question

This study identifies the effect of RN supply on specific population health measures in the U.S. It builds on prior studies examining relationships between nurse staffing and patient outcomes at facility levels. It adds to the evidence regarding the effects of RN supply on the micro level (e.g., hospital/health facility level), and informs the field about RN supply on the macro level (e.g., population health, and healthcare delivery by using more robust measures of population health outcomes. The results inform policies to help ensure RN workforce adequacy as suggested by the IOM report, *The Future of Nursing.*

This study fills a void in the literature and answers the research question: What is the impact of RN supply on population health outcomes?

Chapter Summary

This chapter reviews the model for population health outcomes that is the framework for this research and discusses relevant literature concerning population health and RN supply. The framework section discusses Kindig, PHI, eco-epidemiological, and Donabedian SPO frameworks and integrates them into a model showing the relationship between RN supply and population health, with demographic, socio-economic and environmental controls. The literature review section summarizes previous research about clinician-to-population ratios including RN supply and health outcomes. Special attention is given to research on physician supply (both PCPs and specialist physicians) and population health for two reasons: first, the link between physician supply (PCP supply) and population health has been explored much more than between RN supply and population health and thus provides significant insight on the current research; second, PCP supply is an essential independent variable in the research design that is discussed in Chapter Three. Finally, as guided by the Kindig and PHI frameworks for determinants of population health the literature is examined for control variables that affect the relationship between RN supply and population health outcomes.

CHAPTER THREE: METHODOLOGY

This chapter discusses the hypotheses, research design, measures, data sources, procedures, and the statistical analyses used to answer the research question: What is the relationship between RN supply and population health?

The hypotheses of this study and their alternatives are:

$H1_o$: *There is no relationship between RN to population ratio and the rate of low birth weight infants in a county.*

$H1_a$: *Higher county-level RN to population ratios are related to lower rates of low birth weight infants in that county.*

$H2_o$: *There is no relationship between RN to population ratio and infant mortality rates.*

$H2_a$: *Higher county-level RN to population ratios are related to lower infant mortality rates in that county.*

$H3_o$: *There is no relationship between RN to population ratio and total mortality rates.*

$H3_a$: *Higher county-level RN to population ratios are related to lower total mortality rates in that county.*

$H4_o$: *There is no relationship between RN to population ratio and the cerebrovascular mortality rates.*

$H4_a$: *Higher county-level RN to population ratios are related to lower rates of mortality due to cerebrovascular disease in that county.*

$H5_o$: *There is no relationship between RN to population ratio and the ischemic heart disease mortality rate.*

$H5_a$: Higher county-level RN to population ratios are related to lower rates of mortality due to ischemic heart disease in that county.

$H6_o$: There is no relationship between RN to population ratio and cardiovascular disease rates.

$H6_a$: Higher county-level RN to population ratios are related to lower rates of mortality due to cardiovascular disease in that county.

$H7_o$: There is no relationship between RN to population ratio and chronic lower respiratory disease.

$H7_a$: Higher county-level RN to population ratios are related to lower rates of mortality due to chronic lower respiratory disease in that county.

Described in the sections that follow, the research examines the relationship between RN supply and population health outcomes based on the conceptual framework and literature review presented in Chapter Two. National data were analyzed using descriptive statistics, and regression models.

Research Design

As guided by eco-epidemiological theory, this study is an unmixed and ecological cross-sectional study. The analyses compared population- level characteristics to draw inferences only about the population as a group. The unit of analysis was the 3,108 counties and county equivalents in the 48 contiguous states and the District of Columbia and is a cross-sectional analysis using national data.

A cross-sectional study design of secondary data is generally robust in external validity because it allows simultaneous examination of all elements of the population of interest. The generalizability of this design is bolstered by having a large dataset and replication. However, this study was restricted to variables already collected in AHRF, the unit of measurement, and the variable definitions used at collection by the various agencies. Because the study is non-experimental, internal validity is weak. However, the large data set strengthened the internal validity of the study. No causal relationships can be inferred from this analysis; only associations can be identified for future research. Cross-sectional research typically rules out threats of testing, instrumentation, history, maturation, attrition, and selection interactions to internal validity (Babbie, 2013; Campbell & Stanley, 1963).

A special aspect of this study's design is that the predictor variable, RN supply, and control variables such as PCP supply and insurance coverage, are anticipated to have an asynchronous effect on the outcome variables in the hypothesized relationships. That is to say, a population health outcome manifests not only in the same time period, but also after an encounter with clinicians (the variables “RN supply” and “PCP supply”) and both during and after health insurance or lack of it affects the decision to seek care. This scenario is well suited to distributed lag regression modeling (Baltagi, 2008; Verma, Clark, Leider, & Bishai, 2016).

Due to these long-term relationships – those between health workforce and population health outcomes and those between insurance status and health outcomes – the outcome variables in this analysis (population health measures) are associated with the supply and insurance variables in the same time period as well as a period lagged by three to four years compared to the RN and PCP supply variables (Shi et al., 2003; Shi et al., 2004). A sensitivity analysis was conducted to compare the results of this distributed lag model with a contemporaneous model, in which the lagged variables are replaced with variables from the same time frame.

The threat of history describes changes to a study that occur in the interval between outcome measurements and uncontrollable environmental effects. In a cross-sectional study, history is normally not a concern since measurements are a snapshot at a single point in time.

However, this study compares outcome variables to lagged predictor variables, which raises a concern such that the mortality observed in 2014 may be due to factors other than predictors measured years earlier. This threat is mitigated since population health outcome measures are proximal as well as distal, and the selected measures were operationalized as moving averages over three or five years. Measures are discussed in the following section.

Measures

As part of the literature review in Chapter 2, the population health outcome measures were identified in prior research. This section lists operational definitions. These are based on AHRF definitions for these variables (AHRF 2015-2016 Release) using county of residence. All outcome variables use a three (2012 - 2014) or five (2010 -2014) -year moving average. For example, the three-year moving average is defined as:

$$\frac{\textit{(2012 outcome rate + 2013 outcome rate + 2014 outcome rate)}}{3}$$

Total Mortality Rate.

This measure is the moving average of deaths from all causes in the county per 100,000 population for the years 2012 to 2014.

Mortality - Cerebrovascular Disease

Using the AHRF definition, this variable is the three-year moving average of deaths due to cerebrovascular disease (ICD-10[5] codes 160-169) in the county per 100,000 population for the years 2012, 2013, and 2014.

Mortality - Ischemic Heart Disease

This variable is the three-year moving average of deaths from ischemic heart disease (ICD-10 codes 120-125) in the county per 100,000 population for the years 2012, 2013, and 2014.

Mortality - Other Cardio-Vascular Disease

This variable is the three-year moving average of deaths from other cardio-vascular disease – such as rheumatic heart disease, hypertensive heart disease, atherosclerosis – in the county per 100,000 population for the years 2012, 2013, and 2014.

Mortality - Chronic Lower Respiratory Disease.

This variable is the three-year moving average of deaths due to chronic lower respiratory disease (ICD-10 codes J40- J47) in the county per 100,000 population for the years 2012, 2013 and 2014.

[5] The 10th iteration of the International Statistical Classification of Diseases and Related Health Problems (ICD), a medical classification list by the World Health Organization (WHO).

Infant Mortality

This variable is the five-year moving average for deaths of infants less than one year of age in the county per 1,000 live births for the years 2010 – 2014. It is calculated from the formula shown in equation 1:

$$\textit{Infant mortality (5 Year)} = \frac{\textit{(5-Year Infant Deaths} < \textit{1 Year x 1000)}}{\textit{5-Year Live Births}} \tag{1}$$

Low Infant Birth Weight

This measure is the moving average rates of infants who weigh less than 2500 grams at birth per 1,000 live births for the years 2012, 2013 and 2014 (as shown in equation 2).

$$\textit{Low infant birth weight} = \frac{\textit{(3-Year Infants Born} < \textit{2500 grams x 1000)}}{\textit{3-Year Live Births}} \tag{2}$$

Predictor (Independent) Variables

Clinician-to-population ratios are a comparative index of provider supply - as an estimation of healthcare workforce requirements- and are a proxy for the adequacy of access to healthcare. The ratio is calculated as the number of clinicians available to serve a specific number of patients in a given area (Bärnighausen & Bloom, 2009; Chen & Lowenstein, 1985).

RN Supply

For this study, RN supply is a ratio of the number of licensed RNs per 100,000 population (both part and full time) (Fields et al., 2015). Location of nurses within the professional registry data is listed as residential address. This definition excludes licensed practical nurses (LPNs), licensed vocational nurses (LVNs), and certified nursing assistants (CNAs).

It is calculated from the following formula:

$$\frac{\text{Total number of RNs X 100,000}}{\text{Total population}}$$

Control Variables

The models will be adjusted for variables based on other researchers' experience with population characteristics associated with higher mortality and other population health outcomes (Starfield, Shi, Grover, et al., 2005). These control variables include: PCP supply, county classification as either rural or urban and proximity to metro area, county level percentages of the population with health insurance coverage, median county income, percentages of people in the country age 65 or older, percentage of the population in different racial groups, and percentages of the population with a higher educational level. Specifically:

PCP Supply

PCP supply, another clinician to population ratio, is the number of licensed primary care physicians (those in general family medicine, general practice, internal medicine, and pediatrics) per 100,000 population in active patient care.

Health Insurance Coverage

Estimates of individuals with health insurance coverage are derived in AHRF from the American Community Survey (ACS). The data sum responses to survey questions about current health insurance coverage. The survey data, population estimates, aggregate federal tax returns, and social welfare program participation informs a U.S. Census predictive model (AHRF 2015-2016 Release). Data are reported as percentages of the population in the county.

Urbanicity

Using the U.S. Department of Agriculture Economic Research Service's 2013 Rural Urban Continuum Codes (RUCC), counties will be classified as metropolitan or large, medium or small nonmetropolitan (Fields et al., 2015). These nine classes will be obtained from the AHRF data and will be merged into four categories for the analysis using degree of urbanization as listed in Table 3.

Table 3 Urbanicity Classifications

Urbanicity	Urban-rural continuum— Nine levels of classification based on size of population and relation to metropolitan (metro) area	
	Original Classes	New Classes
1	1—1 million or more in metro area 2—250,000 – 1million in metro area 3—<250,000 in metro area	Metropolitan
2	4—>= 20,000, adjacent to metro area 5—>= 20,000, not adjacent to metro area	Large Non-Metro
3	6—2,500 – 19,999, adjacent to metro area 7—2,500 – 19,999, not adjacent to metro	Medium Non-Metro
4	8—< 2,500 adjacent to metro area 9—< 2,500 not adjacent to metro area	Small Non-Metro

Income

Median family income in the AHRF is obtained from the ACS Summary File, U.S. Census Bureau. A family is defined as all persons living at the same address related by birth, marriage, or adoption. The ACS continuously samples by questionnaire the population to obtain self-reported family income data. Paper, telephone, and online responses are compiled. Income is gross pay (in U.S. dollars) on a regular basis and does not include voucher payments families receive such as food stamps, housing subsidies, and Medicaid. Income data for the preceding 12 months are calculated from persons aged 15 years and older. The median is the mid-point of income distribution of the total families in the county, and includes families that do not earn income (AHRF 2015-2016 Release).

Age

This study will use the percentage of the estimated population in the county who are age 65, or older as at April 1, 2013 (AHRF 2015-2016 Release).

Race

Obtained from 2013 population estimate data in AHRF, this study will use the percentage of the population in each county who are Black or African-American (AHRF 2015-2016 Release).

Education

The study operationalizes education as the percentage of the population in each county older than age 25 with four or more years of college from 2013 data (AHRF 2015-2016 Release.

Obesity

The study operationalizes obesity as the percentage of the population in each county older than age 20 that have reported a body mass index of greater than, or equal to, 30 kg/m^2 (BRFSS, 2013).

Table 4 summarizes these variables and describes their use as outcome (dependent), predictor (independent), or control (other independent) variables, as well as the source of the data and measurement type. The most recent year of available health outcome data for total mortality, disease-specific mortalities, and low infant birth weight are the three-year moving averages from 2012 - 2014. The most recent data for the five-year average of infant mortality are from 2010-2014. In order to lag these dependent variables in relation to the predictor variable, RN supply, and two of the control variables, PCP supply and insurance coverage, the data for these variables will be from 2010. The rest of the control variables will all be from the midpoint of the three-year moving average outcome data - 2013.

Table 4 Variables, Definition, and Data Sources

Measure	Definition/Description	Measurement Type	Data Source	Year
Outcome (Dependent) Variables				
Total mortality	All cause death 2012-2014/100,000 population 3-year average	ratio	AHRF	2012-2014
Mortality - cerebrovascular disease	Mortality due to cerebrovascular disease in the county/100,000 population, 3-year average	ratio	AHRF	2012-2014
Mortality - ischemic heart disease	Mortality due to ischemic heart disease in the county/ 100,000 population, 3-year average	ratio	AHRF	2012-2014
Mortality - other cardio-vascular disease	Mortality due to other cardio-vascular disease in the county/100,000 population, 3-year average	ratio	AHRF	2012-2014
Mortality - chronic lower respiratory disease	Mortality due to chronic lower resp. disease in the county/100,000 population, 3-year average	ratio	AHRF	2012-2014
Infant mortality	Mortality of infants under 1 year of age in county/ 1,000 live births, 5-year average	ratio	AHRF	2010-2014
Low infant birth weight	Infants born weighing < 2500 grams/1,000 live birth, 3-year average	ratio	AHRF	2012-2014
Predictor (Independent)Variable				
RN Supply	Licensed RNs/100,000 population in the county	ratio	SBN	2010 (dlm, lm) 2013 (cm & dlm)

Measure	Definition/Description	Measurement Type	Data Source	Year
Control (Independent) Variables				
PCP Supply	Licensed PCPs/100,000 population in the county	ratio	AHRF	2010 (dlm, lm) 2013 (cm & dlm)
Urbanicity	See Table 3	ordinal	AHRF	2013
Health insurance coverage	Percentage of persons < 65 with health insurance in county	ratio	AHRF	2010 (dlm, lm) 2013 (cm & dlm)
Income	Median family income in county	ratio	AHRF	2013
Population age	% Population 65 + years of age in county	ratio	AHRF	2013
Population race/ ethnicity	% Black, non-Hispanic in county	ratio	AHRF	2013
Education	% Persons > 25 with 4+ years of college in county	ratio	AHRF	2013
Obesity	% Persons > 20 reporting a body mass index (BMI) $\geq$ 30 kg/m^2 in county	ratio	BRFSS	2013

AHRF- Area health resource file
BRFSS – Behavioral risk factor surveillance system
SBN –State boards of nursing or equivalent (for each State)
cm – in contemporaneous model
lm – in three-year lagged model
dlm – in distributed lag model

Data Sources

As shown in Table 4, the data were obtained from several secondary sources: the state boards of nursing (SBN), the area health resources file (AHRF), and the behavioral risk factor surveillance system (BRFSS). RNs per 100,000 population - “RN supply”- the predictor variable, was obtained from the nurse licensure statistics or annual reports of 48 state nurse licensing boards. Data for all outcome and control variables were obtained from the area health resources file (AHRF). AHRF is publicly available and provided all county-level data such as census data, population demographics, county urbanicity, PCP supply, and the selected population health outcome measures. The BRFSS is publicly available from the CDC and included county level data on obesity prevalence.

IRB and Ethics

This research relies on secondary analysis of publicly available county-level data (AHRF and BRFSS), matched to county aggregate data requested from the SBN. Personal identification information that would violate the confidentiality and anonymity was not requested, or used in the analysis, or disseminated. The data linkage via county of residence used common identifiers - FIPS codes. Only county-level results was reported. Institutional review board (IRB) approval was sought to substantiate data requests from individual SBN. On review, the IRB deemed the study not human subject research – ID SBE-17-12934 (see Appendix for IRB determination).

Procedures

Data Acquisition

After IRB review of the study protocol and adjudication on February 15, 2017, requests for the RN supply data were submitted by email to the executive directors (or equivalents) of SBNs for each of the 48 contiguous states and the District of Columbia on February 17 and 20, 2017. Data were requested for 2010 and 2013 licensed RNs by county to include APRN/ARNPs and exclude LVNs/LPNs. Second request emails were sent, and follow-up phone calls were made during the period to March 2 to April 6, 2017.

From the email inquiry, 18 SBNs stated data were not available. The reasons included: county of residence was updated in the SBN database with the current RN residential address on license renewal; county of residence was not captured historically; the years of interest for the study, 2010 and 2013, were not available; or the agency lacked the manpower to provide the data. See Table 5 for details.

Four SBNs indicated the data were available for a fee. Appeals for a fee waiver were fruitless.

Eight SBNs did not respond to the request for data despite several contacts.

Table 5 Summary of State Board of Nursing Responses to Data Request

State Board of Nursing Response	States	Number of counties or county equivalents
RN data included	AR, CA, FL, IA, KS, LA, MN, MO, NV, NM, NY, NC, ND, OK, SC, SD, TX, WA, WV	1472
Fee payment required	DE, UT, WI, WY	127
RN data not available		1166
• Current address only/not associated by county, no historical data	AZ, CO, DC, GA, ID, IL, IN, MA, MI, MT, NH, NJ, OH, PA, VT	
• Not available for 2010 and/or 2013	OR, MS, VA, TN	
• No manpower	NH	
No response	AL, CT, KY, MD, ME, NE, NH, RI	343

Description of the Sample

Thus, not every county or county equivalent could be included in the study as planned. The final data set included 19 states with data for 1,472 counties representing 47% of the total target population of 3,108 U.S. counties and county equivalents. Regions of the U.S. represented are:

Midwest – IA, KS, MN, MO, ND, SD

Northeast – NY

Southeast – AR, FL, LA, NC, OK, SC, TX, WV

Southwest – CA, NM, NV

Northwest – WA

This resulted in a convenience sample, although appropriate for exploratory research, is limited in generalizability (Babbie, 2013).

Data Preparation

Using the U.S. Department of Agriculture Economic Research Service 2013 Rural Urban Continuum Codes (RUCC), counties were classified as metropolitan or large, medium, or small nonmetropolitan. These nine classes were obtained from the AHRF and were aggregated into four categories for the analysis based on degree of urbanization as specified in Table 3.

Data from AHRF was retrieved from the U.S. Department of Health and Human Services, Bureau of Health Professions website. Data for the states included in the study were downloaded for the years 2010-2014 for the selected variables at the county level. Obesity prevalence data from BRFSS for 2013 were downloaded from the CDC and were merged based on county FIPS code.

To form the sample for the hypotheses, the county-level RN supply data were match-merged with the county-level data from AHRF using county FIPS code for the 19 states. The data in the merged data set were cleaned and inspected for missing elements using IBM SPSS Statistics 23.

Next, the data were recoded to create the final variables in the study. RN to population ratios for 2010 and 2013 were calculated from the counts for licensed RNs in each county per 100,000 population in the county from the AHRF county population data from the U.S. Census for the corresponding year. This calculation created the predictor variable "RN Supply." A similar calculation was conducted to create the variable PCP Supply from the AHRF data.

A variable was created from AHRF population data "Age" – percentage of population aged 65 and older – using the formula:

$$\frac{\text{Estimated female + male population (aged 65 and over) x 100}}{\text{Total population estimates for 2013}}$$

Using Stat/Transfer® version 13 (Circle Systems, Seattle, WA) the complete data file was converted from SPSS® to Stata ® format for regression analysis[6]. All regression models were generated using Stata Statistical Software: Release 14. (StataCorp LP, College Station, TX):

[6] This was expedient. The research began at University of Central Florida where the SPSS® was the widely available tool until the candidate relocated and Stata® was available in the new environment.

Data Analysis

Using the model derived from the Donabedian framework of structure, process, outcome (Donabedian, 1978) and guided by eco-epidemiological theory (March & Susser, 2006; Susser, 2004; Susser & Susser, 1996) this study controls for factors that influence population health by examining *only* ecological-level variables and uses regression models to control the effects of confounding variables.

Linear regression is appropriate when the following conditions are satisfied: The outcome variable Y has a linear relationship to the predictor variable X. For each value of X, the probability distribution of Y has the same standard deviation σ. When this condition is satisfied, the variability of the residuals is relatively constant across all values of X, which is easily checked in a residual plot. For any given value of X, the Y values are independent, as indicated by a random pattern on the residual plot. The Y values are roughly normally distributed (i.e., symmetric and unimodal). A histogram or a dot plot shows the shape of the distribution (Fox, 1991; Kileinbaum & Kupper, 1988). The data were assessed for these conditions, as described in the paragraphs below.

Each variable in the model was summarized with descriptive statistics for central tendency and variability, i.e. mean, median, range, and standard deviation. The distributions are described and presented in table format. Normality tests were conducted to determine skew, kurtosis, and the presence or absence of outliers. Outliers were examined for influence (leverage and discrepancy)(Fox, 1991). Problematic predictor outliers were investigated for errors, or conditions specific to that county. If indeed problematic, these outliers could have been replaced with mean values, or the minimum or maximum value within the dataset and the results compared. No replacements were made in the data after these investigations.

The dependent variables obtained from AHRF were left-censored. Mortality data in AHRF is not reported in counties with fewer than ten mortalities per annum (U S Department of Health and Human Services, 2013). Values appearing in the data as zero could take on any value between zero and nine. Tobit models are deemed to be appropriate for censored data (Breen, 1996; Burke, 2009; Carson & Sun, 2007; Muddasar Jamil Shera & Sajjad Dar, 2014)

Bivariate analyses were conducted to determine if the variables in the model satisfied the assumption of no collinearity for linear regression. Pearson's bivariate correlations were explored among the predictor variables. Variance inflation factors were examined for evidence of multicollinearity for values higher than 10 (Fox, 1991). Where multicollinearity was evident, an exploratory factor analysis (Cronbach's) was conducted to explore the suitability of combining predictors into a scale, and assure that non-normality of errors was met. Then the results from preliminary least squares regression models were examined.

After these procedures, quadratic terms for RN supply and PCP supply (RN supply squared and PCP supply squared) were created and added to the dataset. A quadratic term is indicated when a curvilinear relationship is observed (Ganzach, 1998; Gianino et al., 2017). This non-linear association was found on scatterplots and could be supported by the hypothesized relationship between RN supply and the health outcome.

For each hypothesis, a model was estimated using Stata® version 14.1 (Stata Corp LP, College Station, TX). Tobit regression models were used to derive beta weights and coefficients (β) for each hypothesis (each population health outcomes measure), using the RN-to-population ratios (RN supply) as the primary predictor variable. For each model, standard errors that are robust to heteroscedasticity was computed. Alpha < .05 was considered statistically significant. The regression equation for the contemporaneous models is represented by equation 3:

$$\textit{Population health outcome (each of the 7 measures, in individual models)}^{7} = \textit{Constant} + f(b_1 \textit{RN Supply} + b_2 \textit{RN Supply}^2 + b_3 \textit{PCP Supply} + b_4 \textit{PCP Supply}^2 + b_5 \textit{Urbanicity} + b_6 \textit{Health insurance coverage} + b_7 \textit{Income} + b_8 \textit{Population age} + b_9 \textit{Population race/ ethnicity} + b_{10} \textit{Education} + b_{11} \textit{Obesity})$$

where $b_{1\text{-}11}$ *is the beta coefficient for the predictor variable* (3)

Equation 4 is the regression equation for the distributed lag models:

$$\textit{Population health outcome (each of the 7 measures, in individual models)} = \textit{Constant} + f(b_1 \textit{RN Supply} + b_2 \textit{RN Supply}^2 + b_3 \textit{RN Supply}_{t-3} + b_4 \textit{RN Supply}^2_{t-3} + b_5 \textit{PCP Supply} + b_6 \textit{PCP Supply}^2 + b_7 \textit{PCP Supply}_{t-3} + b_8 \textit{PCP Supply}^2_{t-3} + b_9 \textit{Health insurance coverage} + b_{10} \textit{Health insurance coverage}_{t-3} + b_{11} \textit{Urbanicity} + b_{12} \textit{Income} + b_{13} \textit{Population age} + b_{14} \textit{Population race/ ethnicity} + b_{15} \textit{Education} + b_{16} \textit{Obesity})$$

where $b_{1\text{-}15}$ *is the beta coefficient for the predictor variable, t-3 denotes the lagged variables, and t is 2013* (4)

Equation 5 is the regression equation for the three year lagged models:

$$\textit{Population health outcome (each of the 7 measures, in individual models)} = \textit{Constant} + f(b_1 \textit{RN Supply}_{t-3} + b_2 \textit{RN Supply}^2_{t-3} + b_3 \textit{PCP Supply}_{t-3} + b_4 \textit{PCP Supply}^2_{t-3} + b_5 \textit{Health insurance coverage}_{t-3} + b_6 \textit{Urbanicity} + b_7 \textit{Income} + b_8 \textit{Population age} + b_9 \textit{Population race/ ethnicity} + b_{10} \textit{Education} + b_{11} \textit{Obesity})$$

where $b_{1\text{-}11}$ *is the beta coefficient for the predictor variable, t-3 denotes the lagged variables, and t is 2013* (5)

Chapter Summary

This chapter presented the research question and the seven hypotheses to be tested. Also described are the research design and the procedures used to acquire and prepare the data for analysis. Data analysis included descriptive statistics to explore the normality of the data, and bivariate analyses to examine the direction and strength of relationships between variables. Linear regression models were used to test the hypothetical relationship between

[7] Models for infant mortality measure were compared with and without the control variable "obesity."

total mortality, disease specific mortalities, and RN supply. The products of these analyses are presented in Chapter 4.

CHAPTER FOUR: FINDINGS

This chapter presents the statistical analyses for this dissertation. It includes descriptive statistics and statistical results for the research question: What is the relationship between RN supply and population health?

Description of the Variables

Table 6 includes the descriptive statistics of outcome variables for the study, which included 1,472 counties. Mean rates of negative population outcomes ranged from 1 infant death per 1000 live births to a 1,052 total deaths per 100,000 population. Among the disease specific mortalities studied, the mean rates of ischemic heart disease mortality and other cardio-vascular disease mortality were 134 deaths per 100,000 population and 91 deaths per 100,000 population, respectively. The mean rates of infant mortality showed positive skew, which was attributed to the values left censored at 10.

Table 7 includes the descriptive statistics for the independent and control variables, including the mean, minimum, and standard deviation. RN supply mean values of 1,859 RNs per 100,000 population from the 2013 data, and 1,679 RNs per 100,000 population in 2010 were observed. These data were also positively skewed. A wealth of literature confirms that the presence of non-normal data in social science research is not atypical (Bono, Blanca, Arnau, & Gómez-Benito, 2017; Micceri, 1989). Given that the underlying data included counties that reported zero RNs per 100,000 population, and some low population counties with proximity to major hospitals with outlier values, these data were not transformed. Other variables showing positive skew include education (percent of population aged 25 and older with four years of college) with a mean of 0.18 and standard deviation of 0.42; and race (% of population identified as Black) with a mean of 8.10 and standard deviation of 12.53.

Table 6 Descriptive Statistics for the Outcome Variables (N = 1472)

Variable	Mean	SD	Min	Max	Skewness
Low infant birth weight/ 1000 live births	5.51	4.13	0.00	16.57	-0.26
Infant mortality rate/1000 live births	0.97	2.37	0.00	13.30	2.32
Total mortality rate/100k population	1052.26	283.43	0.00	2091.26	-0.25
Cerebrovascular mortality rate/100k pop.	29.42	29.75	0.00	154.88	0.53
Ischemic heart disease mortality rate/ 100k pop.	134.23	81.51	0.00	488.40	0.15
Chronic lower respiratory disease mortality rate/ 100k pop.	42.99	39.80	0.00	207.40	0.47
Other cardiovascular disease mortality rate/100k pop.	91.11	64.40	0.00	597.93	0.68

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Table 7 Descriptive Statistics of the Predictor (Independent) Variables (N = 1472)

Variable	Mean	Std. Dev.	Min	Max	Skewness
RN supply 2013: #RNs/100k pop.	1859.35	12559.29	0.00	430828.80	28.62
RN supply 2010: #RNs/100k pop.	1679.18	10668.31	0.00	368265.50	28.82
PCP supply 2013: #PCPs/100k pop.	50.67	32.87	0.00	423.73	1.72
PCP supply 2010: #PCPs/100k pop.	50.22	31.81	0.00	426.80	1.77
Insurance 2013: % < 65 with insurance	64.97	6.68	33.19	83.85	-0.56
Insurance 2010: % < 65 with insurance	64.54	6.44	33.68	81.28	-0.56
Median Household Income 2013	45,511	10,536	21,572	110,930	1.23
Median Household Income 2010	42,337	9,301	20,577	105,987	1.36
Population Age: % aged >65	17.54	4.61	6.70	51.60	0.72
Education: % >25 with college	0.18	0.42	0.00	7.86	8.32
Obesity: % >20 with BMI >=30 kg/m^2	31.16	4.36	13.70	45.50	-0.11
Race: % population Black	8.10	12.53	0.00	72.91	2.29

Table 8 describes the urbanicity of the counties included in the study. Fifty five percent of the counties (817 counties) were considered rural with populations of less than 20,000.

Table 8 Frequency of Urbanicity Classes

	Urbanicity Classes	Frequency	Percent
1	Metropolitan	514	34.92
2	Large Non-Metro	141	9.58
3	Medium Non-Metro	494	33.56
4	Small Non Metro	323	21.94

Tobit Analysis

Since the dependent variables of interest are left-censored and include zero values with non-zero probability, Tobit regression models were run with three distinct specifications. Specification one regressed the variable of interest on contemporaneous RN supply together with contemporaneous control variables. Specification two was a distributed lagged model where RN supply was included both with its 2013, as well as its 2010 value. Similarly, a set of controls was also included with both their contemporary and lagged value: PCP supply, health insurance, and income. Specification three only included the lagged value regarding RN supply and the set of control variables for the same year noted above. In all three specifications a set of controls (urbanicity dummies, variables capturing population age, obesity, and race) were included with their contemporary values. Note that in the case of urbanicity, the lowest category was omitted. Therefore, other dummy coefficients should be interpreted as partial associations relative to this lowest category

The Tobit regression models of the three different specifications derived beta coefficients (β) and tests of significance using the RN-to-population ratios as the primary predictor variable. Tests of significance included the likelihood ratio and Akaike information criterion (AIC). The likelihood ratio chi-square is the indication that the model as a whole fits significantly better than a model with no predictors. AIC is the indication of the quality of model relative to other models using the same the data. The lowest value for AIC indicates the model with the best fit for the data (Akaike, 1974; Sawa, 2015).

Quadratic Term Interpretation

Since each of the models includes a quadratic term, a discussion of the interpretation of these results is appropriate. The relationship between the variable and the squared term indicates the shape of the non-linear relationship with the outcome variable in keeping with the standard quadratic equation $y = Ax^2 + Bx + C$. Coefficient A determines the width of the parabola and its shape. A positive value for coefficient A indicates a convex shape (vertex closer to the x-axis), and a negative value indicates a concave shape, the opposite. Coefficient B is an aid to showing where the curve is located relative to the origin of the x and y-axes. For positive values of coefficient B, the vertex is left of the origin for values of coefficient A greater than zero, and to the right of the origin when coefficient A is less than zero. For negative values of coefficient B, the opposite is true – to the right of origin for values of coefficient A greater than zero, and left of origin if coefficient A is less than zero. C, the constant, is the y-intercept. The x coordinate of the vertex is determined from the calculation of $-B/2A$ (Cohen, Cohen, West, Aiken, & Rutherford, 2003; UCLA Institute for Digital Research and Education, n.d.). In the interpretation of the interaction, the coefficient for linear term (coefficient B) suggests the direction of the relationship. The coefficient for the quadratic term (coefficient A) suggests the rate of change.

When combined these values suggest six different types of parabolas and interpretations. These types are summarized in the table 9 below.

Table 9 Guide to Interpretation of Quadratic Term

	Conditions			
Interpretation of result	Coefficient A	x-coordinate of vertex (-B/2A)	y-intercept	Description of parabola
Positive with an increasingly positive slope	Greater than zero	Close to zero	Positive, Close to zero	Convex (opens upward), right arm of parabola
Positive with an increasingly positive slope	Greater than zero	Close/Not close to zero	Negative	Convex, right arm of parabola only
Negative with an increasingly positive slope	Greater than zero	Not close to zero	Positive, Not close to zero	Convex, left arm of parabola (and possibly remainder, needs more analysis)
Negative with an increasingly negative slope	Less than zero	Close to zero	Positive, Not close to zero	Concave (opens downward) right arm of parabola
Positive with an increasingly negative slope	Less than zero	Not close to zero	Positive, Close to zero	Concave, left arm of parabola (and possibly remainder, needs more analysis)
Positive with an increasingly negative slope	Less than zero	Close/Not close to zero	Negative	Concave, left arm of parabola (and possibly remainder, needs more analysis)

Adapted from (UCLA Stat Consulting Group, 2014)

The following sections discuss the results of the seven hypotheses tested.

Results for Hypothesis 1 – Rate of Low Birth Weight Infants

Hypothesis 1 tested the research question by assessing the relationship between RN-to-population ratio and the rate of low birth weight infants in a county. The null and alternate hypotheses were:

$H1_o$: There is no relationship between RN to population ratio and the rate of low birth weight infants in a county.

$H1_a$: Higher county-level RN to population ratios are related to lower rates of low birth weight infants in that county.

The results for Hypothesis 1 are shown in table 10. There were 472 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 1124.86 (df =13), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 1130.28 (df =18), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 1108.47 (df =13), $p < .001$. According to the AIC, the contemporaneous model fits best, with a related AIC of 6162.05 (compared with 6184.47, and 6166.6 for the three-year lagged and the distributed lag models respectively).

RN supply was not significantly associated with the rate of low birth weight infants in any model specification. Thus, the null hypothesis of no relationship between RN supply and rate of low birth weight infants in a county was not rejected.

PCP supply was not significant in the distributed lag model; however, the variable was significant in the other model specifications. In the contemporaneous model, PCP supply was positively related to the rate of low infant birth weight in the county (β 0.04769, $p < .001$), and PCP supply squared, was negatively related to the outcome variable (β -0.00023, $p < .01$). The result is shown in equation 7:

$$y = -0.00023 PCP\ supply\ squared + 0.04769 PCP\ supply + 10.58 \quad (6)$$

The x coordinate for the vertex (- (0.04769/2*-0.00023) = 103.67, which is not close to 0.

Similarly, in the lagged model PCP supply was positively related to the outcome variable (β 0.04786, $p < .001$), and PCP supply squared was negatively related to the outcome variable (β -0.00023, $p < .01$). The result is shown in equation 7:

$$y = -0.00023 PCP\ supply\ squared + 0.04786\ PCP\ supply + 9.67 \quad (7)$$

The x coordinate for the vertex (- (0.04786/2*-0.00023) = 104.04, which is not close to 0. These calculations indicate a positive relationship with increasingly negative slope, but could reach a maximum and become negative.

Altogether this indicates a positive relationship between PCP supply and the rate of low birth weight infants with increasingly negative slope. However, more analysis is required to discover the remainder of the parabola.

Median household income was negatively related to the rate of low infant birth weight in the three model specifications: contemporaneous (β -0.00008, $p < .001$); distributed lag (β -0.00007, $p < .001$); and three-year lagged (β -0.00006, $p < .001$).

Population age was also negatively related to the rate of low infant birth weight in the three model specifications: contemporaneous (β -0.15597, $p < .001$); distributed lag (β -0.16945, $p < .001$); and three-year lagged (β -0.14856, $p < .001$).

Conversely, race - defined in the study as the percent of Black population - was consistently positively related to the rate of low infant birth weight in each specification: contemporaneous model (β 0.12787, $p < .001$); distributed lag (β 0.12743, $p < .001$); and three-year lagged (β 0.13430, $p < .001$).

The predicted rate of low birth weight infants in medium and small non-metropolitan areas[8] were consistently lower (medium non-metro = 1.7 times and small non-metro = 8 times) when compared to the reference group major metropolitan area in each model specification.

[8] The reference group, metropolitan, includes counties with populations > 250,000 in a metropolitan area.
Large non-metro category includes those counties with populations < 250,000 but > 20,000 either adjacent or not adjacent to metro area. Medium non-metro includes counties with populations >2,500, but <20,000 either adjacent or not adjacent to metro area. Small non-metro includes counties with populations < 2,500 either adjacent or not adjacent to metro area.

Table 10 Summary of Tobit Regression Analyses Rate of Low Birth Weight Infants

Predictors	Low Birth Rate (O) Contemporaneous Model	Low Birth Rate (O) Distributed Lag Model	Low Birth Rate (O) Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	-0.00015 (0.00013)	-0.00059 (0.00030)	
RN Supply 2013 squared	-0.00000 (0.00000)	-0.00000 (0.00000)	
RN Supply 2010		0.00051 (0.00030	-0.00003 (0.00013)
RN Supply 2010 squared		-0.00000 (0.00000)	-0.00000 (0.00000)
PCP Supply 2013	0.04769*** (0.01025)	0.03769 (0.02055)	
PCP Supply 2013 squared	-0.00023** (0.00007)	-0.00018 (0.00015)	
PCP Supply 2010		0.01280 (0.02087)	0.04786*** (0.01041)
PCP Supply 2010 squared		-0.00006 (0.00016)	-0.00023** (0.00007)
Urbanicity: Large Non-Metro[a]	0.21268 (0.37858)	0.19116 (0.37864)	0.27669 (0.38424)
Urbanicity: Medium Non-Metro	-1.72194*** (0.28412)	-1.74524*** (0.28489)	-1.77542*** (0.28993)
Urbanicity: Small Non-Metro	-8.05120*** (0.41176)	-8.05955*** (0.41608)	-8.18300*** (0.41911)
Insurance 2013: % < 65 with insurance	0.01866	-0.03173	

Predictors	Low Birth Rate (O) Contemporaneous Model	Low Birth Rate (O) Distributed Lag Model	Low Birth Rate (O) Lag Model
	(0.02335)	(0.05808)	
Insurance 2010 % < 65 with insurance		0.04616	0.01775
		(0.05067)	(0.02101)
Median Household Income 2013	-0.00008***	-0.00007***	
	(0.00002)	(0.00002)	
Median Household Income 2010			-0.00006***
			(0.00002)
Population Age % aged >65	-0.15597***	-0.16945***	-0.14856***
	(0.03014)	(0.03351)	(0.02854)
Race % Black	0.12787***	0.12743***	0.13430***
	(0.00978)	(0.0984)	(0.00965)
Education % >25 with college	-0.02826	-0.02956	-0.02323
	(0.02337)	(0.02357)	(0.01810)
Obesity % >20 c BMI >=30 kg/m2	-0.02152	-0.01901	-0.01810
	(0.03411)	(0.03415)	(0.03384)
Constant	10.57712***	10.70706***	9.66890***
	(1.77482)	(1.77961)	(1.71574)
R^2	.16	.16	.15
df_r	1452	1447	1454
AIC	6162.04551	6166.62814	6184.46984

[a] Reference group for Urbanicity is large metropolitan areas
$*p < .05$, $**p < .01$, $***p < .001$

Results for Hypothesis 2 – Infant Mortality Rate

Hypothesis 2 tested the research question by assessing the relationship between RN to population ratio and infant mortality rates. The null and alternate hypotheses were:

$H2_o$: There is no relationship between RN to population ratio and infant mortality rates.

$H2_a$: Higher county-level RN to population ratios are related to lower infant mortality rates in that county.

The results for Hypothesis 2 are shown in Table 11. There were 1,238 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 754.42 (df =11), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 794.00 (df =16), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 758.94 (df =11), $p < .001$. According to AIC, the distributed lag model fits best, with a related AIC of 1756.13 (compared with 1785.72, and 1781.91 for the contemporaneous and three-year lagged models respectively).

RN supply was not significantly associated with the dependent variable in any model specification. Thus, the null hypothesis of no relationship between RN supply and infant mortality rates in a county was not rejected.

PCP supply was significant in each model specification. In the contemporaneous model, PCP supply was positively related to the infant mortality rate in the county (β 0.23960, $p < .001$), and PCP supply squared, was negatively related to the outcome variable (β -0.00105, $p < .001$). In the three-year lagged model PCP supply was positively related to the outcome variable (β 0.24699, $p < .001$), and PCP supply squared was negatively related to the outcome variable (β -0.00102, $p < .001$). In the distributed lag model with 2010 and

2013 values for PCP supply and the quadratic version, only the 2013 values were significant. PCP supply was positively related to the infant mortality rate (β 0.22070, $p < .01$); and PCP supply squared was negatively related (β -0.00050, $p < .01$). The resulting equation (equation 8) is:

$$y = -0.00050 \text{ PCP supply squared} + 0.22070 \text{ PCP supply} + 3.14 \tag{8}$$

The x coordinate for the vertex (- (0.22070/2*-0.00050) = 220.7, which is not close to 0. These results indicate a positive relationship between PCP supply and infant mortality rate with increasingly negative slope, but could reach a maximum and become negative (opens downward, concave, left arm of parabola plus possibly the remainder of the parabola). This relationship would require further additional data analysis to pinpoint the remainder of the parabola.

Median household income was negatively related to infant mortality rate in two of the three model specifications: contemporaneous (β -0.00008, $p < .05$); distributed lag (β -0.00010, $p < .001$). Median household income from 2010 was not significant in the three-year lagged model.

Health insurance, defined in this study as percent of population under age 65 with insurance was negatively associated to infant mortality in the three-year lagged model (β -0.14551, $p < .05$). However, in the distributed lagged model which included insurance variables for 2010 and 2013, the 2010 variable was negatively associated (β -0.78548, | $p < .05$), but the 2013 variable was positively associated (β 0.85332, $p < .001$).

Population age was also negatively related to infant mortality rate in the three model specifications: contemporaneous (β -0.49272, $p < .001$); distributed lag (β -0.27044, $p < .01$); and three-year lagged (β -0.52231, $p < .001$).

Race was positively related to infant mortality rate in only two models: contemporaneous model (β 0.14410, $p < .001$); and three-year lagged (β 0.13890, $p < .001$). Race, defined in the study as percent of population identified as Black, was not significant in the distributed lag model.

Obesity, defined in the study as percent of population aged over 20 with a self-reported body mass index (BMI) greater than 30 kg/m^2 was also negatively related to infant mortality rate in the three model specifications: contemporaneous (β -0.30693, $p < .01$); distributed lag (β -0.31575, $p < .001$); and three-year lagged (β -0.21416, $p < .05$).

The predicted infant mortality rate in large non-metro areas were consistently 7.25-7.5 times lower when compared to the reference group major metropolitan area in each model specification. The results from medium and small non-metro groups were not significant.

Table 11 Summary of Tobit Regression Analyses Infant Mortality Rate

Predictors	Infant Mortality (O) Contemporaneous Model	Infant Mortality (O) Distributed Lag Model	Infant Mortality (O) Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	0.00041 (0.00067)	0.00275 (0.00213)	
RN Supply 2013 squared	-0.00000 (0.00000)	-0.00000 (0.00000)	
RN Supply 2010		-0.00266 (0.00224)	0.00020 (0.00072)
RN Supply 2010 squared		0.00000 (0.00000)	-0.00000 (0.00000)
PCP Supply 2013	0.23960*** (0.03022)	0.22070** (0.07901)	
PCP Supply 2013 squared	-0.00105*** (0.00016)	-0.00050** (0.00000)	
PCP Supply 2010		0.03260 (0.07718)	0.24699*** (0.03052)
PCP Supply 2010 squared		0.00037 (0.00049)	-0.00102*** (0.00016)
Urbanicity: Large Non-Metro[a]	-7.56397*** (0.98591)	-7.24924*** (0.94100)	-7.56791*** (0.97900)
Urbanicity: Medium Non-Metro	-40.41586 (--)	-46.09463 (--)	-42.18869 (--)
Urbanicity: Small Non-Metro	-35.68305 (--)	-44.12596 (--)	-36.21558 (--)

Predictors	Infant Mortality (O) Contemporaneous Model	Infant Mortality (O) Distributed Lag Model	Infant Mortality (O) Lag Model
Insurance 2013: % < 65 with insurance	-0.00626 (0.06926)	0.85332*** (0.17210)	
Insurance 2010 % < 65 with insurance		-0.78548*** (0.14687)	-0.14551* (0.06116)
Median Household Income 2013	-0.00008* (0.00004)	-0.00010** (0.00004)	
Median Household Income 2010			-0.00003 (0.00004)
Population Age % aged >65	-0.49272*** (0.09065)	-0.27044** (0.9574)	-0.52231*** (0.08170)
Race %Black	0.14410*** (0.02535)	0.14969 (0.02474)	0.13890*** (0.02497)
Education % >25 with college	-0.04497 (0.05835)	-0.12169* (0.05804)	-0.05289 (0.05634)
Obesity % >20 c BMI >=30 kg/m2	-0.30693** (0.09547)	-0.31575*** (0.09310)	-0.21416* (0.09432)
_cons	10.21623 (5.32912)	3.13986 (5.36879)	14.69173** (4.90970)
R^2	.30	.32	.30
df_r	1454	1449	1456
AIC	1785.72174	1756.13651	1781.91306

[a]Reference group for Urbanicity is large metropolitan areas
*$p < .05$, **$p < .01$, ***$p < .001$

Results for Hypothesis 3 – Total Mortality Rate

Hypothesis 3 tested the research question by assessing the relationship between RN to population ratio and total mortality rates. The null and alternate hypotheses were:

$H3_o$: There is no relationship between RN to population ratio and total mortality rates.

$H3_a$: Higher county-level RN to population ratios are related to lower total mortality rates in that county.

The results for Hypothesis 3 are presented in table 12. There were 12 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 1555.27 (df =13), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 1571.81 (df =18), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 1556.57 (df =13), $p < .001$. According to AIC, the distributed lag model fits best, with a related AIC of 19048.05 (compared with 19054.59, and 19084.68 for the contemporaneous and three-year lagged models respectively).

RN supply was significantly associated with the total mortality in two of three models. In the distributed lag model with 2010 and 2013 values for RN supply and the quadratic version, none of the coefficients were significant. In the contemporaneous model, RN supply was positively related to the total mortality (β 0.01113, $p < .05$), and the quadratic variable, RN supply squared, was negatively related to the outcome variable (β -0.00000, $p < .05$). The resulting equation is shown in equation 9 below:

$$y = -0.000001 \textit{ RN supply squared} + 0.01113 \textit{ RN supply} + 28.20 \qquad (9)$$

The x coordinate for the vertex (- (0.01113/2*-0.000001) = 5565. These results indicate a positive relationship between RN supply and total mortality rate with increasingly negative slope, but it could reach a maximum and become negative. Further analysis is required to explore this relationship

Similarly, RN supply was positively related to the outcome variable in the three-year lagged model (β 0.01550, $p < .001$), and RN supply squared was negatively related to the outcome variable (β -0.00000, $p < .001$). The resulting equation (equation 10) is:

$$y = -0.000001 \textit{ RN supply squared} + 0.01550 \textit{ RN supply} + 74.35 \tag{10}$$

The x coordinate for the vertex (- (0.01550/2*-0.00001) = 7750. These results appear to indicate a positive relationship between RN supply and total mortality rate with increasingly negative slope, but it could reach a maximum and become negative. Further analysis is required to explore this relationship.

Therefore, the null hypothesis that there would be no relationship between RN supply and total mortality rates in a county was rejected.

PCP supply was not significant in the distributed lag model; however, the variable was significant in the other model specifications. In the contemporaneous model PCP supply was positively related to total mortality rate in the county (β 1.85953, $p < .001$), and the quadratic variable, PCP supply squared, was negatively related to the outcome variable (β -0.00386, $p < .01$). The resulting equation is shown in equation 11:

$$y = -0.00386 \textit{ PCP supply squared} + 1.85953 \textit{ PCP supply} + 28.22 \tag{11}$$

The x coordinate for the vertex (- (1.85953/2*-0.00386) = 240.87, which is not close to 0.

Similarly, PCP supply was positively related to the outcome variable in the three-year lagged model (β 2.03088, $p < .001$), and PCP supply squared was negatively related to the outcome variable (β -0.00411, $p < .001$). The resulting equation is shown in equation 12:

$$y = -0.00411 \textit{ PCP supply squared} + 2.03088 \textit{ PCP supply} + 74.35 \qquad (12)$$

The x coordinate for the vertex (- (2.03088/2*-0.00411) = 247.07, which is not close to 0.

These results indicate a positive relationship between PCP supply and total mortality rate with increasingly negative slope, but could reach a maximum and become negative (opens downward, concave, left arm of parabola plus possibly the rest of the parabola). Further analysis is required to explore this relationship.

Median household income was negatively related to total mortality rate in the three model specifications: contemporaneous (β -0.00455, $p < .001$); distributed lag (β -0.00458, $p < .001$); and three-year lagged (β -0.00469, $p < .001$).

Health insurance was positively associated to total mortality in each model: contemporaneous (β 3.96802, $p < .001$); distributed lag (β 6.27277, $p < .001$); and three-year lagged (β 3.06926, $p < .001$).

Population age was positively related to total mortality in the three model specifications: contemporaneous (β 40.30617, $p < .001$); distributed lag (β 40.76323, $p < .001$); and three-year lagged (β 39.36743, $p < .001$).

Education, defined for this study as percent of population aged over 25 with a college education, was negatively related to total mortality rate in each specification:

contemporaneous model (β -8.28599, $p < .001$); distributed lag (β -8.69864, $p < .001$); and three-year lagged (β -8.14308, $p < .001$).

Obesity was positively related to total mortality in the three model specifications: contemporaneous (β 10.18570, $p < .001$); distributed lag (β 10.00327, $p < .001$); and three-year lagged (β 10.62199, $p < .001$).

The predicted total mortality rate in medium non-metro areas were consistently higher when compared to the reference group major metropolitan area in each model specification: contemporaneous model – 34 times higher; distributed lag model – 31 times higher; three-year lagged model – 26 times higher. The results from medium and large non-metro groups were not significant.

Table 12 Summary of Tobit Regression Analyses Total Mortality Rate

Predictors	Total Deaths Contemporaneous Model	Total Deaths Distributed Lag Model	Total Deaths Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	0.01113* (0.00477)	-0.00453 (0.01035)	
RN Supply 2013 squared	-0.00000* (0.00000)	0.00000 (0.00000)	
RN Supply 2010		0.01777 (0.01024)	0.01550*** (0.00447)
RN Supply 2010 squared		-0.00000 (0.00000)	-0.00000*** (0.00000)
PCP Supply 2013	1.85953*** (0.27226)	1.16386 (0.70474)	
PCP Supply 2013 squared	-0.00386** (0.00124)	-0.00566 (0.00517)	
PCP Supply 2010		0.92190 (0.68908)	2.03088*** (0.26936)
PCP Supply 2010 squared		0.00137 (0.00510)	-0.00411*** (0.00123)
Urbanicity: Large Non-Metro[a]	-3.87277 (16.29628)	-6.53063 (16.21694)	-9.11624 (16.47183)
Urbanicity: Medium Non-Metro	34.27659** (11.97304)	30.73379* (11.94858)	25.75498* (12.16310)
Urbanicity: Small Non-Metro	26.11256 (14.47055)	22.86915 (14.60066)	13.00405 (14.74185)

Predictors	Total Deaths Contemporaneous Model	Total Deaths Distributed Lag Model	Total Deaths Lag Model
Insurance 2013: % < 65 with insurance	3.96802***	6.27277**	
	(0.93269)	(2.14622)	
Insurance 2010 % < 65 with insurance		-2.32914	3.06926***
		(1.86664)	(0.83548)
Median Household Income 2013	-0.00455***	-0.00458***	
	(0.00064)	(0.00065)	
Median Household Income 2010			-0.00469***
			(0.00073)
Population Age % aged >65	40.30617***	40.76323***	39.36743***
	(1.20196)	(1.31080)	(1.13692)
Race %Black	0.21375	0.30714	0.28076
	(0.41336)	(0.41324)	(0.40617)
Education % >25 with college	-8.28599***	-8.69864***	-8.14308***
	(0.92559)	(0.92950)	(0.91502)
Obesity % >20 c BMI >=30 kg/m2	10.18570***	10.00327***	10.62199***
	(1.38511)	(1.38150)	(1.36490)
Constant	28.22615	27.08634	74.35160
	(70.87250)	(70.55095)	(68.80603)
R^2	.08	.08	.08
df_r	1452	1447	1454
AIC	19054.59144	19048.04942	19084.68015

[a]Reference group for Urbanicity is large metropolitan areas
*p < .05, **p < .01, ***p < .001 .

Results for Hypothesis 4 – Cerebrovascular Mortality Rates

Hypothesis 4 tested the research question by assessing the relationship between RN to population ratio and cerebrovascular mortality rates. The null and alternate hypotheses were:

$H4_o$: There is no relationship between RN to population ratio and the cerebrovascular mortality rates.

$H4_a$: Higher county-level RN to population ratios are related to lower rates of mortality due to cerebrovascular disease in that county.

The results for hypothesis 4 are presented in table 13. There were 645 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 725.92 (df =13), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 731.48 (df =18), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 718.04 (df =13), $p < .001$. According to AIC, the contemporaneous model fits best, with a related AIC of 9050.97 (compared to 9062.69 and 9055.42 for the distributed lag and three-year lagged models respectively).

RN supply was not significantly associated with the dependent variable in any model specification. Thus, the null hypothesis of no relationship between RN supply and cerebrovascular mortality rates in a county was not rejected.

PCP supply was not significant in the distributed lag model; however, the variable was significant in the other model specifications. In the contemporaneous model PCP supply was positively related to cerebrovascular mortality rate in the county (β 0.54952, $p < .001$). However, the quadratic variable, PCP supply squared, was negatively related to the outcome variable (β -0.00249, $p < .01$). The resulting equation (equation 13) is:

$$y = -0.00249 \text{ PCP supply squared} + 0.54952 \text{ PCP supply} - 53.80 \tag{13}$$

The x coordinate for the vertex (- (0.54952/2*-0.00249) = 110.35, which is not close to 0. The y intercept, the constant in the equation, is negative.

Similarly, PCP supply was positively related to the outcome variable in the three-year lagged model (β 0.60622, $p < .001$), and PCP supply squared was negatively related to the outcome variable (β -0.11348, $p < .001$). The resulting equation (equation 14) is:

$$y = -0.11348 \text{ PCP supply squared} + 0.60622 \text{ PCP supply} - 50.14 \tag{14}$$

The x coordinate for the vertex (- (0.60622/2*-0.11348) = 2.67, which is close to 0. The y intercept, the constant in the equation, is negative.

These results indicate a positive relationship between PCP supply and cerebrovascular mortality rate with increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Median household income was negatively related to cerebrovascular mortality rate in the three model specifications: contemporaneous (β -0.00065, $p < .001$); distributed lag (β -0.00065, $p < .001$); and three-year lagged (β -0.00045, $p < .05$).

Health insurance was positively related to cerebrovascular mortality rate in two of the three models: contemporaneous (β 0.74200, $p < .01$); and three-year lagged (β 0.46609, $p < .05$).

Population age was positively related to cerebrovascular mortality in the three model specifications: contemporaneous (β 1.88724, $p < .001$); distributed lag (β 1.99385, $p < .001$); and three-year lagged (β 1.73737, $p < .001$).

Race was positively related to total mortality rate in only two of the three models: contemporaneous model (β 0.49568, $p < .001$); and three-year lagged (β 0.52277, $p < .001$).

The predicted cerebrovascular mortality rate in large non-metro areas were consistently about 12 times higher when compared to the reference group in each model. However, the predicted cerebrovascular mortality rate was lower in medium and small non-metro areas (~19 times lower, and ~85 times lower respectively).

Table 13 Summary of Tobit Regression Analyses Cerebrovascular Mortality Rate

Predictors	CV Deaths Contemporaneous Model	CV Deaths Distributed Lag Model	CV Deaths Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	-0.00091	-0.00441	
	(0.00150)	(0.00334)	
RN Supply 2013 squared	-0.00000	0.00000	
	(0.00000)	(0.00000)	
RN Supply 2010		0.00412	0.00016
		(0.00325)	(0.00155)
RN Supply 2010 squared		-0.00000	-0.00000
		(0.00000)	(0.00000)
PCP Supply 2013	0.54952***	0.26372	
	(0.11130)	(0.23002)	
PCP Supply 2013 squared	-0.00249***	-0.00089	
	(0.00072)	(0.00163)	
PCP Supply 2010		0.33297	0.60622***
		(0.23486)	(0.11348)
PCP Supply 2010 squared		-0.00187	-0.00285***
		(0.00170)	(0.00075)
Urbanicity: Large Non-Metro[a]	11.89749**	11.63924**	12.06999*
	(3.82244)	(3.82219)	(3.86816)
Urbanicity: Medium Non-Metro	-19.08219***	-19.49680***	-19.86183***
	(2.97591)	(2.98344)	(3.02577)
Urbanicity: Small Non-Metro	-85.18380***	-86.15969***	-86.33554***
	(5.02938)	(5.10034)	(5.09933)
Insurance 2013: % < 65 with insurance	0.74200**	1.10590	

Predictors	CV Deaths Contemporaneous Model	CV Deaths Distributed Lag Model	CV Deaths Lag Model
	(0.25457)	(0.64013)	
Insurance 2010 % < 65 with insurance		-0.37800	0.46609*
		(0.55327)	(0.22625)
Median Household Income 2013	-0.00065***	-0.00065***	
	(0.00017)	(0.00017)	
Median Household Income 2010			-0.00045*
			(0.00019)
Population Age % aged >65	1.88724***	1.99385***	1.73737***
	(0.32532)	(0.36047)	(0.30428)
Race %Black	0.49568***	0.51222	0.52277***
	(0.10239)	(0.10306)	(0.10077)
Education % >25 with college	0.29199	0.22853	0.23777
	(0.24643)	(0.24854)	(0.24360)
Obesity % >20 c BMI >=30 kg/m2	0.31098	0.29887	0.46940
	(0.36183)	(0.36240)	(0.35816)
Constant	-53.79449**	-55.10116**	-50.13616**
	(19.33594)	(19.41001)	(18.49406)
R^2	.08	.08	.07
df_r	1452.00000	1447.00000	1454.00000
AIC	9050.97487	9055.41684	9062.69399

[a]Reference group for Urbanicity is large metropolitan areas
$*p < .05$, $**p < .01$, $***p < .001$.

Results for Hypothesis 5 – Ischemic Heart Disease Mortality Rates

Hypothesis 5 tested the research question by assessing the relationship between RN to population ratio and ischemic heart disease mortality rates. The null and alternate hypotheses were:

$H5_o$: There is no relationship between RN to population supply ratio and the ischemic heart disease mortality rate.

$H5_a$: Higher county-level RN to population ratios are related to lower rates of mortality due to ischemic heart disease in that county.

The results for Hypothesis 5 are presented in table 14. There were 225 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 582.72 (df =13), p < .001. The distributed lag model, specification two, produced a likelihood ratio chi-square of 596.33 (df =18), p < .001. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 575.00 (df =13), p < .001. According to the Akaike information criterion (AIC), the distributed lag model fits best, with a related AIC of 14774.54 (compared to 14778.15 and 14801.88 for the contemporaneous and three-year lagged model respectively).

RN supply was significantly associated with ischemic heart disease mortality in one of the model specifications. In the distributed lag model, RN supply 2013 was negatively related to the outcome variable (β -0.01512, p < .05). The quadratic term, RN supply 2013 squared, was positively related to the outcome variable (β 0.0000, p < .05). The resulting equation is shown below in equation 15:

$$y = 0.00001 \text{ RN supply squared} - 0.01512 \text{ RN supply} - 116.85 \tag{15}$$

The x coordinate for the vertex (- (-0.01512/2*-0.00001) = -756. The y-intercept, the constant in the equation, is negative, - 116.85. Most of this parabola is below the positive y-axis, therefore not part of the study. The part of it in the positive x and y quadrant (feasible for the study) appears to be the left arm of the parabola, which means it has a positive relationship with an increasingly positive slope. Further analysis is required to explore this relationship.

The null hypothesis that there would be no relationship between RN supply and ishemic heart disease rates in a county was rejected.

PCP supply was significant in each model specification. In the contemporaneous model PCP supply was positively related to ischemic heart disease mortality rates in the county (β 1.02208, $p < .001$), and PCP supply squared, was negatively related to the outcome variable (β -0.00579, $p < .001$). Similarly, PCP supply was positively related to the outcome variable in the three-year lagged model (β 0.96715, $p < .01$), and PCP supply squared was negatively related to the outcome variable (β -0.00496, $p < .001$). In the distributed lag model with 2010 and 2013 values for PCP supply and the quadratic version, only the 2013 values were significant. PCP supply 2013 was positively related to ischemic heart disease mortality rates (β 1.02249, $p < .01$); and PCP supply squared was negatively related (β -0.00792, $p < .01$). The resulting equation is shown in equation 16:

$$y = -0.00792 \text{ PCP supply squared} + 1.02249 \text{ PCP supply} - 116.85 \quad (16)$$

The x coordinate for the vertex (- (1.02249/2*-0.00792) = 64.55, which is not close to 0. The y-intercept is negative, - 116.85. These results indicate a positive relationship between PCP supply and ischemic heart disease mortality rate with an increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Median household income was negatively related to ischemic heart disease mortality rates in two model specifications: contemporaneous (β -0.00123, $p < .001$); and three-year lagged (β -0.00098, $p < .01$).

Health insurance was positively related to ischemic heart disease mortality rates in two of the three models: contemporaneous (β 2.26608, $p < .001$); and three-year lagged (β 0.195483, $p < .001$). Population age was positively related to cerebrovascular mortality in the three model specifications: contemporaneous (β 7.48812, $p < .001$); distributed lag (β 7.11470, $p < .001$); and three-year lagged (β 6.92068, $p < .001$).

Education was negatively related to ischemic heart disease mortality rates in each specification: contemporaneous model (β -1.94507, $p < .001$); distributed lag (β -2.03095, $p < .001$); and three-year lagged (β -2.09916, $p < .001$).

Obesity was positively related to ischemic heart disease mortality rates in the three model specifications: contemporaneous (β 1.84820, $p < .01$); distributed lag (β 1.89911, $p < .01$); and three-year lagged (β 2.06063, $p < .05$).

The predicted ischemic heart disease mortality rates in small non-metro areas were consistently ~100 times lower when compared to the reference group major metropolitan area in each model specification. In the other urbanicity classes, the difference was not significant.

Table 14 Summary of Tobit Regression Analyses Ischemic Heart Disease Mortality Rate

Predictors	Ischemic Deaths Contemporaneous Model	Ischemic Deaths Distributed Lag Model	Ischemic Deaths Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	-0.00179 (0.00237)	-0.01512* (0.00587)	
RN Supply 2013 squared	-0.00000 (0.00000)	0.00000* (0.00000)	
RN Supply 2010		0.01626* (0.00701)	-0.00069 (0.00222)
RN Supply 2010 squared		-0.00000* (0.00000)	-0.00000 (0.00000)
PCP Supply 2013	1.02208*** (0.18748)	1.02249** (0.35361)	
PCP Supply 2013 squared	-0.00579*** (0.00129)	-0.00792** (0.00262)	
PCP Supply 2010		0.00841 (0.35778)	0.96715** (0.18926)
PCP Supply 2010 squared		0.00245 (0.00270)	-0.00496*** (0.00134)
Urbanicity: Large Non-Metro[a]	1.36187 (7.60218)	0.81190 (7.58321)	1.67490 (7.67878)
Urbanicity: Medium Non-Metro	5.73503 (5.60874)	4.63614 (5.60982)	4.62152 (5.69490)
Urbanicity: Small Non-Metro	-99.91976*** (7.10817)	-99.70679*** (7.19035)	-100.84316*** (7.23050)
Insurance 2013: % < 65 with insurance	2.26608***	1.01706	

Predictors	Ischemic Deaths Contemporaneous Model	Ischemic Deaths Distributed Lag Model	Ischemic Deaths Lag Model
	(0.44826)	(1.04680)	
Insurance 2010 % < 65 with insurance		1.11055	1.95483***
		(0.90459)	(0.39885)
Median Household Income 2013	-0.00123***	-0.00108	
	(0.00031)	(0.00031)	
Median Household Income 2010		--	-0.00098**
			(0.00035)
Population Age % aged >65	7.48812***	7.11470***	6.92068***
	(0.57633)	(0.63144)	(0.54317)
Race %Black	0.00050	-0.00674	0.01400
	(0.19395)	(0.19453)	(0.19039)
Education % >25 with college	-1.94507***	-2.03095***	-2.09916***
	(0.44575)	(0.44858)	(0.43995)
Obesity % >20 c BMI >=30 kg/m2	1.84820**	1.89911**	2.06063**
	(0.65615)	(0.65574)	(0.64644)
Constant	-123.30567	-116.84647***	-111.61290
	(34.05751)	(34.06498)	(32.87297)
R^2	.04	.04	.04
df_r	1452	1447	1454
AIC	14778.14684	14774.53550	14801.87565

[a]Reference group for Urbanicity is large metropolitan areas
*$p < .05$, **$p < .01$, ***$p < .001$

Results for Hypothesis 6 – Chronic Lower Respiratory Disease Mortality Rates

Hypothesis 6 tested the research question by assessing the relationship between RN to population ratio and chronic lower respiratory disease mortality rates. The null and alternate hypotheses were:

$H6_o$: There is no relationship between RN to population supply ratio and the chronic lower respiratory disease in a county.

$H6_a$: Higher county-level RN to population ratios are related to rates of chronic lower respiratory disease.

The results for hypothesis 6 are presented in table 15. There were 541 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 635.70 (df =13), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 648.57 (df =18), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 616.56 (df =13), $p < .001$. According to the Akaike information criterion (AIC), the distributed lag model fits best, with a related AIC of 10506.50 (compared to 10509.37 and 10533.19 for the contemporaneous and three-year lagged models respectively).

RN supply was significantly associated with chronic lower respiratory disease mortality rates in one of the model specifications. In the distributed lag model, RN supply 2013 was negatively related to the outcome variable (β -0.01013, $p < .01$). The quadratic term, RN supply 2013 squared, was positively related to the outcome variable (β 0.0000, $p < .05$). The resulting equation is shown in equation 17:

$$y = 0.000001 \text{ RN supply squared} - 0.01013 \text{ RN supply} + 8.49 \qquad (17)$$

The x coordinate for the vertex (- (-0.01013/2*-0.000001) = -5065, which is not at all close to 0. These results indicate a positive relationship between RN supply and chronic lower respiratory disease mortality rates with an increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship. The null hypothesis that there would be no relationship between RN supply and chronic lower respiratory disease mortality rates in a county was rejected.

PCP supply was not significant in the distributed lag model; however, the variable was significant in the other model specifications. In the contemporaneous model PCP supply was positively related to chronic lower respiratory disease mortality rates (β 0.67534, $p < .001$), and the quadratic variable, PCP supply squared, was negatively related to the outcome variable (β -0.00337, $p < .001$). The resulting equation is shown in equation 18:

$$y = -0.00337 \text{ PCP supply squared} + 0.67534 \text{ PCP supply} + 4.50 \tag{18}$$

The x coordinate for the vertex (- (0.67534/2*-0.00337) = 100.20, which is not close to zero. These results indicate a positive relationship between PCP supply and ischemic heart disease mortality rate with an increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Similarly, PCP supply was positively related to the outcome variable in the three-year lagged model (β 0.67731, $p < .001$), and PCP supply squared was negatively related to the outcome variable (β -0.00370, $p < .001$). The resulting equation (equation 19) is:

$$y = -0.00370 \text{ PCP supply squared} + 0.67731 \text{ PCP supply} - 9.38 \tag{19}$$

The x coordinate for the vertex (- (0.67731/2*-0.00370) = 91.53, which is not close to 0. The y-intercept is negative, - 9.38.

These results indicate a positive relationship between PCP supply and ischemic heart disease mortality rate with an increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Median household income was negatively related to chronic lower respiratory disease mortality rates in all models: contemporaneous (β -0.00120, $p < .001$); distributed lag ((β -0.000108, $p < .001$) and three-year lagged (β -0.00104, $p < .001$).

Health insurance was positively related to chronic lower respiratory disease mortality rate in two of the three models: contemporaneous (β 0.60088, $p < .001$); and three-year lagged (β 0.65836, $p < .05$).

Population age was positively related to chronic lower respiratory disease mortality rate in the three model specifications: contemporaneous (β 2.50680, $p < .001$); distributed lag (β 2.15909, $p < .001$); and three-year lagged (β 2.53327, $p < .001$).

Education was only negatively related chronic lower respiratory disease mortality rate in the three-year lagged model (β -0.62447, $p < .05$).

The predicted chronic lower respiratory disease mortality rate in small non-metro areas were consistently lower when compared to the reference group major metropolitan area in each model specification: contemporaneous model – 103 times; distributed lag model – 103 times; three-year lagged model – 105 times. In medium non-metro areas, the predicted chronic lower respiratory disease mortality rate was lower than the reference group of large metropolitan areas in only the contemporaneous and distributed lag model (28.8 times lower, and 29 times lower respectively).

Table 15 Summary of Tobit Regression Analyses Chronic Lower Respiratory Disease (CLRD) Mortality Rate

Predictors	CLRD Death s Contemporaneous Model	CLRD Deaths Distributed Lag Model	CLRD Deaths Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	-0.00223 (0.00162)	-0.01013** (0.00369)	
RN Supply 2013 squared	0.00000 (0.00000)	0.00000* (0.00000)	
RN Supply 2010		0.00907* (0.00401)	0.00000 (0.00159)
RN Supply 2010 squared		-0.00000 (0.00000)	-0.00000 (0.00000)
PCP Supply 2013	0.67534*** (0.13062)	0.48850 (0.25788)	
PCP Supply 2013 squared	-0.00337*** (0.00087)	-0.00152 (0.00188)	
PCP Supply 2010		0.23153 (0.26169)	0.67731*** (0.13242)
PCP Supply 2010 squared		-0.00225 (0.00195)	-0.00370*** (0.00091)
Urbanicity: Large Non-Metro[a]	2.07118 (4.74202)	1.83292 (4.72848)	2.90713 (4.81738)
Urbanicity: Medium Non-Metro	-28.83775*** (3.63338)	-29.08075*** (3.62946)	-29.35774 (3.70894)
Urbanicity: Small Non-Metro	-103.28203*** (5.35891)	-102.71942*** (5.39698)	-105.32570*** (5.46518)
Insurance 2013: % < 65 with insurance	0.60088* (0.30125)	-0.84033 (0.75745)	
Insurance 2010 % < 65 with insurance		1.32277*	0.65836*

Predictors	CLRD Death s Contemporaneous Model	CLRD Deaths Distributed Lag Model	CLRD Deaths Lag Model
		(0.65858)	(0.26956)
Median Household Income 2013	-0.00120***	-0.00108***	
	(0.00020)	(0.00021)	
Median Household Income 2010			-0.00104***
			(0.00023)
Population Age % aged >65	2.50680***	2.15909***	2.53327***
	(0.38638)	(0.42655)	(0.36465)
Race %Black	-0.20494	-0.22761	-0.11363
	(0.12568)	(0.12601)	(0.12410)
Education % >25 with college	-0.54563	-0.51359	-0.62447*
	(0.29689)	(0.29892)	(0.29427)
Obesity % >20 c BMI >=30 kg/m2	0.59780	0.68566	0.58196
	(0.43242)	(0.43203)	(0.42905)
Constant	4.49568	8.48789	-9.37690
	(22.91102)	(22.91069)	(22.19070)
R^2	.06	.06	.06
df_r	1452	1447	1454
AIC	10509.36571	10506.49871	10533.19445

[a]Reference group for Urbanicity is large metropolitan areas

**p* < .05, ***p* < .01, ****p* < .001

Results for Hypothesis 7 – Other Cardiovascular Disease Mortality Rates

Hypothesis 7 tested the research question by assessing the relationship between RN to population ratio and mortality rates from other cardiovascular disease in a county. The corresponding hypotheses were:

$H7_o$: There is no relationship between RN to population supply ratio and the other cardiovascular disease mortality rate in a county.

$H7_a$: Higher county-level RN to population ratios are related to other cardiovascular disease mortality rate.

The results for hypothesis 7 are presented in table 16. There were 323 left-censored observations in these models. The contemporaneous model, specification one, produced a likelihood ratio chi-square of 585.29 (df =13), $p < .001$. The distributed lag model, specification two, produced a likelihood ratio chi-square of 616.01 (df =18), $p < .001$. The three-year lagged model, specification three, resulted in a likelihood ratio chi-square of 594.64 (df =13), $p < .001$. According to AIC, the distributed lag model contemporaneous model fits best, with a related AIC of 13371.13 (compared to 13391.85 and 13390.07 for the contemporaneous and three-year lagged models respectively).

RN supply was significantly associated with other cardiovascular disease mortality rates in one of the model specifications. In the distributed lag model, RN supply 2013 was negatively related to the outcome variable (β -0.01870, $p < .01$). The quadratic term, RN supply 2013 squared, was positively related to the outcome variable (β 0.0000), and was not significant. The resulting equation is shown in equation 20:

$$y = 0.000001 \text{ RN supply squared} - 0.01870 \text{ RN supply} - 90.33 \tag{20}$$

The x coordinate for the vertex (- (-0.01870/2*-0.000001) = 9350, which is not close to 0. The y-intercept is negative, - 90.33. These results indicate a positive relationship between RN supply and other cardiovascular disease mortality rate with an increasingly positive slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Also in the distributed lag model, RN supply 2010 was positively related to the outcome variable (β 0.01970, $p < .01$), and the quadratic term, RN supply 2010 squared, was negatively related to the outcome variable (β -0.0000, $p < .05$). The resulting equation is shown in equation 21:

$$y = -0.000001\ RN\ supply\ squared + 0.01970\ RN\ supply - 90.33 \qquad (21)$$

The x coordinate for the vertex -0.01970/2*-0.000001) = 9850, which is not close to 0. The y-intercept, the constant in the equation, is negative, - 90.33. Most of this parabola is below the positive y-axis, therefore not part of the study. The part of it in the positive x and y quadrant (feasible for the study) appears to be the left arm of the parabola, which means it has a positive relationship with an increasingly negative slope. Further analysis is required to explore this relationship.

The null hypothesis that there would be no relationship between RN supply and other cardiovascular disease mortality rates in a county was rejected.

PCP supply was not significant in the distributed lag model; however, the variable was significant in the other model specifications. In the contemporaneous model PCP supply was positively related to other cardiovascular disease mortality rates (β 0.57554, $p < .001$), and the quadratic variable, PCP supply squared, was negatively related to the outcome variable (β -0.00313, $p < .01$). The resulting equation is shown in equation 22;

$$y = -0.00313 \; PCP\ supply\ squared + 0.57554 \; PCP\ supply - 102.48 \qquad (22)$$

The x coordinate for the vertex (- (0.57554/2*-0.00313) = 91.94, which is not close to zero. The y-intercept is negative, - 102.48.

PCP supply was positively related to the outcome variable in the three-year lagged model (β 0.65979, $p < .001$), and PCP supply squared was also positively related to the outcome variable (β 0.00380, $p < .01$). The resulting equation is shown in equation 23:

$$y = -0.00380 \; PCP\ supply\ squared + 0.65979 \; PCP\ supply - 121.58 \qquad (23)$$

The x coordinate for the vertex (- (0.65979/2*-0.00380) = 86.81, which is not close to zero. The y-intercept is negative, - 121.58

These results indicate a positive relationship between PCP supply and other cardiovascular disease mortality rate with an increasingly negative slope, but could reach a maximum and become negative. Further analysis is required to explore this relationship.

Median household income was negatively related to other cardiovascular disease mortality rates in all models: contemporaneous (β -0.00113 $p < .001$); distributed lag (β -0.00084, $p < .01$) and three-year lagged (β -0.00081, $p < .01$).

In the contemporaneous model the three-year lagged model, health insurance was positively related to other cardiovascular disease mortality rates (β 1.80208 $p < .001$ and β 1.90124 $p < .001$ respectively). In the distributed lag model which included insurance variables for 2010 and 2013, the 2010 variable was negatively associated (β -1.92413, $p < .05$), but the 2013 variable was positively associated (β 3.43529, $p < .001$).

Population age was positively related to other cardiovascular disease mortality rates in the three model specifications: contemporaneous (β 4.96130, $p < .001$); distributed lag (β 3.99195, $p < .001$); and three-year lagged (β 4.66169, $p < .001$).

Race was consistently positively related to other cardiovascular disease mortality rates in each specification: contemporaneous model (β 1.12959, $p < .001$); distributed lag (β 1.06849, $p < .001$); and three-year lagged (β 1.21353, $p < .001$).

Education was only negatively related to other cardiovascular disease mortality rates in the three-year lagged model (β -0.89933, $p < .05$).

Obesity was positively related other cardiovascular disease mortality rates in the three model specifications: contemporaneous (β 1.39849, $p < .05$); distributed lag (β 1.58470, $p < .01$); and three-year lagged (β 1.37989, $p < .05$).

The predicted other cardiovascular disease mortality rates in small non-metro areas were consistently lower when compared to the reference group major metropolitan area in each model specification: contemporaneous model – 97 times; distributed lag model – 94 times; three-year lagged model – 96 times.

Table 16 Summary of Tobit Regression Analyses Other Cardiovascular Disease Mortality Rates

Predictors	CV Deaths Contemporaneous Model	CV Deaths Distributed Lag Model	CV Deaths Lag Model
	β (*SE*)	β (*SE*)	β (*SE*)
RN Supply 2013	-0.00323	-0.01870**	
	(0.00210)	(0.00579)	
RN Supply 2013 squared	0.00000	0.00000	
	(0.00000)	(0.00000)	
RN Supply 2010		0.01970**	0.00013
		(0.00713)	(0.00212)
RN Supply 2010 squared		-0.00000*	-0.00000
		(0.00000)	(0.00000)
PCP Supply 2013	0.57554***	0.25543	
	(0.16541)	(0.31533)	
PCP Supply 2013 squared	-0.00313**	-0.00102	
	(0.00113)	(0.00232)	
PCP Supply 2010		0.40525	0.65979***
		(0.32001)	(0.16656)
PCP Supply 2010 squared		0.40525	0.00380**
		(0.32001)	(0.00117)
Urbanicity: Large Non-Metro[a]	-0.28549	-0.84961	0.63147
	(6.52745)	(6.47581)	(6.56477)
Urbanicity: Medium Non-Metro	-3.25146	-3.80688	-3.38060
	(4.84751)	(4.82063)	(4.90048)
Urbanicity: Small Non-Metro	-97.02058***	-94.35355***	-96.05575***
	(6.39844)	(6.41554)	(6.47267)
Insurance 2013: % < 65 with insurance	1.80208***	-1.92413*	
	(0.39344)	(0.95530)	

Predictors	CV Deaths Contemporaneous Model	CV Deaths Distributed Lag Model	CV Deaths Lag Model
Insurance 2010 % < 65 with insurance		3.43529***	1.90124***
		(0.83244)	(0.35060)
Median Household Income 2013	-0.00113***	-0.00084**	
	(0.00027)	(0.00027)	
Median Household Income 2010			-0.00081**
			(0.00030)
Population Age % aged >65	4.96130***	3.99195***	4.66169***
	(0.50695)	(0.55365)	(0.47621)
Race %Black	1.12959***	1.06849***	1.21353***
	(0.16719)	(0.16695)	(0.16352)
Education % >25 with college	-0.69173	-0.62723	-0.89933*
	(0.39008)	(0.39118)	(0.38366)
Obesity % >20 c BMI >=30 kg/m2	1.39849*	1.58470**	1.37989*
	(0.57235)	(0.56886)	(0.56202)
Constant	-102.47709***	-90.33109**	-121.58182***
	(29.88010)	(29.77390)	(28.75468)
R^2	.04	.04	.04
df_r	1452	1447	1454
AIC	13391.85377	13371.13320	13390.06647

[a]Reference group for Urbanicity is large metropolitan areas
**p* < .05, ***p* < .01, ****p* < .001

Chapter Summary

This chapter presented the results of the statistical analyses to support this research. The analyses show mixed results. The alternative hypotheses could be rejected for three of the seven hypotheses since there was no association to RN supply in any of the three associated model specifications. However, we can conclude that RN supply shows a positive relationship to total mortality rates, ischemic heart disease mortality rates, chronic lower respiratory disease mortality and other cardiovascular disease mortality. Chapter 5 discusses these findings and the implications for policy and research.

CHAPTER FIVE: CONCLUSION

The purpose of this research study was to examine the effect of RN supply on selected population health outcome measures. This is a retrospective, cross-sectional study of U.S. counties and county-equivalents using national data. Seven population health outcomes (total and disease specific mortalities and low infant birth-weight rate) were the response variables. RN supply was the predictor variable. The predictor variable, RN supply, and certain control variables were thought to have an asynchronous effect on the seven outcome variables in the hypothesized relationship. Therefore, these variables were examined using three different models: contemporaneous; a three-year lagged; and a distributed lag (both contemporaneous and lagged variables). Quadratic terms for RN and physician supply variables were included. Because the AHRF outcome variables were skewed toward zero and left censored, Tobit regression analyses were used.

The results of the data analyses were presented in Chapter Four. These analyses included descriptive statistics, and twenty-one Tobit regression models (three for every hypothesis) in the three model specifications. This chapter presents a discussion of the results for testing each hypothesis, a discussion of how the results collectively inform the research question, and the strengths and limitations of this study. Finally, this chapter includes the policy implications and recommendations for future research in this area.

Hypothesis Testing Results

In this section, an analysis of the statistical results for the seven hypotheses that inform the research question follows.

> Hypothesis 1 - Higher county-level RN to population ratios are related to lower rates of low birth weight infants in that county.

The analyses did not support this hypothesis in any model specification. The null hypothesis was not rejected.

> Hypothesis 2 - Higher county-level RN to population ratios are related to lower infant mortality rates in that county.

The analyses did not support this hypothesis in any model specification. The null hypothesis was not rejected.

The results for Hypotheses 1 and 2 were unexpected given RNs' role in patient education and prenatal care and the negative association found in previous studies between low birth-weight infants and PCP supply (Macinko, Starfield, & Shi, 2007; Shi et al., 2004). Attempting to explain the difference in relationship to low birth weight infants between PCP supply and RN supply is only conjecture. Further research is needed.

> Hypothesis 3 - Higher county-level RN to population ratios are related to lower total mortality rates in that county.

The analyses revealed a strong relationship between RN supply and total mortality rates. The same relationship was consistently observed in two of the three models examined: the contemporaneous model, and the three-year lagged model. A curvilinear relationship was identified. The direction of the relationship suggests that the total mortality rate in the county increases as RN supply increases, but that the positive relationship increasingly becomes less so and transitions to a negative relationship.

The results suggest there is an underlying relationship although the direction of the relationship is unexpected. It is possible that the relationship between RN supply and total mortality is dependent on the effects of a variable not part of this study (more later). It is also possible that RN supply has a different effect on some causes of mortality than on others (Bigbee, 2008). Further research, including moderation analysis, is needed.

Hypothesis 4 - Higher county-level RN to population ratios are related to lower rates of mortality due to cerebrovascular disease in that county.

The analyses did not support this hypothesis in any model specification. The null hypothesis was not rejected.

Hypothesis 5 - Higher county-level RN to population ratios are related to lower rates of mortality due to ischemic heart disease in that county.

The analyses revealed a relationship between RN supply and ischemic heart disease mortality rates in the distributed lag model. A curvilinear relationship was identified. The direction of the relationship suggests that the ischemic heart disease mortality rate in the county increases as RN supply increases, and the positive relationship becomes increasingly more positive. These results suggest there is an underlying relationship even though the direction and strength of the relationship is unexpected. It is possible the relationship between RN supply and ischemic heart disease mortality is dependent on the effects of a variable not included in this study. For example, prior research established an association between air quality and ischemic heart disease mortality for which urbanicity may not have provided an adequate control (Thurston et al., 2016). Alternatively, the role of suboptimal diets in ischemic heart disease incidence and mortality might not have been controlled by income, race, obesity, or urbanicity (Micha et al., 2017). These data did not provide enough information and attempting to explain this relationship without further analysis is only speculation. Further research, including moderation analysis, is needed.

Hypothesis 6 - Higher county-level RN to population ratios are related to lower rates of mortality due to chronic lower respiratory disease in that county.

The analyses revealed a relationship between RN supply and chronic lower respiratory disease mortality rates in the distributed lag model. A curvilinear relationship was identified. The direction of the relationship suggests that the mortality rate due to chronic lower respiratory disease in the county increases as RN supply increases, but that the positive relationship increasingly becomes less so and transitions to a negative relationship. The results suggest an underlying relationship even though the direction of that relationship is unexpected. It is possible that the relationship between RN supply and mortality due to chronic lower respiratory disease is dependent on the effects of a variable not included in this study. For example, a wealth of literature documents the association between air quality and chronic lower respiratory disease (Chen et al., 2008; Cohen et al., 2017; Hao et al., 2015) It is possible that the controls of urbanicity, income, age, and race proved inadequate to control for health behaviors or the effect of place in these models. These data did not provide enough information and attempting to explain this relationship without further analysis is only speculation. Further research, including moderation analysis, is needed.

Hypothesis 7 - Higher county-level RN to population ratios are related to lower rates of mortality due to other cardiovascular disease in that county.

The analyses revealed a relationship between RN supply and other cardiovascular disease mortality in the distributed lag model. A curvilinear relationship was identified. The direction of the relationship suggests that the mortality rate due to other cardiovascular disease in the county increases as RN supply increases, but that the positive relationship increasingly becomes less so and transitions to a negative relationship. The results suggest an underlying relationship although its direction is unexpected. It is possible the relationship between RN supply and other cardiovascular disease mortality is dependent on the effects of a variable not included in this study. Obesity was included as a control for other chronic diseases and lifestyle factors and is a known risk factor (Hubert, Feinleib, McNamara, & Castelli, 1983; Micha et al., 2017). However, these data were self-reported and thus obesity may be underreported. Further analysis is required to explore this relationship.

RN Supply

In summary, there were mixed results for the effect of RN supply on the selected health outcomes. Greater RN supply was significantly (positively) related to higher mortality due to ischemic heart disease, other cardiovascular disease, and chronic lower respiratory disease in the distributed lag model. Higher RN supply was not significantly related to rates of low infant birth weight, infant mortality, or mortality from cerebrovascular disease in any model. Higher RN supply was positively related to total deaths in the contemporaneous and lagged models.

The significant results showing that greater RN supply was positively related to negative population outcomes, is counter-intuitive. It is possible that despite the role RNs play in patient education and care, their effectiveness is largely connected with their institutional roles. Thus, the hypothesized effect of RN supply on population health outcomes might be observed in a compound measure of outcomes that are amenable to healthcare, or outcomes that are RN sensitive (Gianino et al., 2017; Schoenbaum, Schoen, Nicholson, & Cantor, 2011). The results may be due partly to including all RNs as the predictor variable and the specific population health outcomes that were selected.

One counterargument for these findings is that RN supply and PCP supply are strongly correlated, and therefore the results are biased. While it would be logical to make this assumption given that similar factors influence RN and PCP location, analysis of these data found almost no correlation between them.

The choice of APRNs might be more appropriate for the population health measures chosen. Increasingly, APRNs practice at the top of their licenses and serve as independent primary care providers (Gutchell, Idzik, & Lazear, 2014; Oliver, Pennington, Revelle, & Rantz, 2014; Romanowski, 2015). Also, APRNs are significantly more likely to increase access to primary care (Neff et al., 2018). Thus, this subset of RNs is more likely to be involved in direct patient care. Research using only APRNs and other population health outcomes is needed.

At the outset, this study deliberately avoided gender-specific (e.g. breast health screenings, pre-natal care) or subjective health outcome measures (self-reported health status) to compensate for the limitations in extant literature. However, the technical outcomes selected from the AHRF are now left-censored which potentially introduced bias. This limitation is discussed later. It is possible that objective measures for population health outcomes are inadequate to support research in this area.

The hypothesized relationship may have been observed more clearly in a population health outcome measure that combined population level as well as individual risk or captured the role of RNs in patient education as shown by the reduction of individual health risk. Cardiovascular health risk index (CVHI) is one potential measure. CVHI is a composite measure developed by the American Heart Association that was conceived by combining individual and population level concepts of disease prevention (Lloyd-Jones et al., 2010; Pilkerton, Singh, Bias, & Frisbee, 2017). CVHI proffers an amalgam of evidenced based biological measures (cholesterol, blood pressure and glucose, as well as body mass index) and health behaviors (smoking, diet, and exercise) to score cardiovascular health. However, this is the challenge that Susser's eco-epidemiology theory which guided this study served as an effective guard: a heightened awareness that all determinants in the model have relationships to other factors; and that inferences about the population must be made from population comparisons (Diez-Roux, 1998; March & Susser, 2006; Mervyn Susser, 1973; Mervyn Susser & Susser, 1996).

Another relationship is endogeneity affecting RN supply. The social and economic environment that influence healthcare facility location and demand for healthcare providers, also influence RN and PCP supply in that geographic area. The statistical association of interest here was the relationship between RN supply and population health, which is affected by health facility location and demand for RNs and PCPs. Healthcare facility location and demand for RNs is, in turn, affected by RN supply. These endogenous loops present analytical challenges to isolating the statistical association of interest, and determining the strength and/or direction of relationships (Mark, 2006; Phillips et al., 1998; Zhang et al., 2014). In this study, urbanicity was a proxy for this endogenous relationship.

Although the study controlled for PCPs – and those results are discussed in the next section – physician assistants were not included, which could have biased the results. Physician assistants, like APRNs, are part of a typical primary care team and have a similar role in treatment and patient education (Bodenheimer & Pham, 2010; Chang, O'Malley, & Goodman, 2017; Cooper, 2015; Davis, Guo, Titler, & Friese, 2017; Henry & Lisa, 2015; Intrator et al., 2005). Also, the counts of RNs could potentially overestimate the number of nurses. This limitation is discussed subsequently.

Control Variable Results

A discussion of the results from the analysis for the control variables included in the study is presented in the sections that follow:

PCP Supply

PCP supply (primary care physician supply) consistently demonstrated a strong positive relationship with each of the seven health outcome measures selected for the study. The result is inconsistent with previous research that finds a negative relationship (Macinko et al., 2007; Shi et al., 2004; Shi et al., 2005; Shi, Macinko, Starfield, Xu, & Politzer, 2003). However, a later study found a pattern of geographic variation and a mixed result (Ricketts & Holmes, 2007). These researchers (Ricketts and Holmes) also found a positive relationship between PCP supply and health outcomes, but concentrated in southern states. Their finding is consistent with these data where 11 of the 19 states included in the study were in the South.

Similar counterarguments could be made for PCP supply as discussed above for RN supply. One theoretical explanation was that PCP supply was highly correlated with RN supply. However, empirical analysis found almost no correlation between these variables. The dependency of PCP supply on health facility location and the endogeneity that results, is the same as for RN supply. Isolating the individual effects of PCP supply and RN supply may only become more challenging in the future as the scope of practice debate continues. Reconsidering healthcare supply as a composite measure of healthcare workforce supply and health facility concentration is one potential solution. Another is structural equation modelling. The latter is discussed later.

Education and Income

Higher median household income was negatively associated with all seven health outcome measures. However, higher education (measured as per cent of the population over age 25 with four years of college) was associated with lower infant, total, ischemic heart disease, chronic lower respiratory, and other cardiovascular disease mortality. College education was not significant for the rate of low infant birth-weight and cerebrovascular disease mortality. Nonetheless, this confirms the role of these socio-demographic indicators in health outcomes as proxies for health literacy, health behavior, and access to healthcare.

Age

In keeping with the ambiguity of the role of age in health outcome research, the effect of age in the hypotheses was mixed—as predicted—and also varied by dependent variable measure. Maternal health outcomes, low infant birth weight and infant mortality were negatively associated with age (measured here as per cent of population age 65 and older). This is logical, and suggests that this definition of age is not appropriate for maternal health outcomes, since it excludes women of childbearing age. Conversely, total and four disease specific mortalities (cerebrovascular, ischemic heart disease, chronic lower respiratory disease, and other cardiovascular disease) were positively associated with population age 65 and older.

Race

Race, measured in the study as the percent of Black/African American population, was significant in four of the seven outcome measures: populations with a higher percentage of Blacks/African Americans had higher rates of low infant birth weight, and higher rates of infant mortality, cerebrovascular mortality, and other cardiovascular disease mortality. There is evidence of a positive relationship between race and infant mortality rates, and between race and rates of low infant birth weight in the literature (Shi et al., 2004). This has been attributed to lower utilization rates for prenatal care and the quality of care available even when income and insurance coverage are controlled. The literature confirms race as an important factor in health outcomes and for a predisposition to chronic conditions (Braveman, Cubbin, Egerter, Williams, & Pamuk, 2010; Buys et al., 2015; Geronimus et al., 2006; LaVeist, 2005; Ramaswamy & Kelly, 2015; Thorpe et al., 2012; Wallace et al., 2013).

Insurance Coverage

Insurance coverage, measured as per cent of the population in the county under age 65 with health insurance, was consistently positively related to six of the seven health outcomes. The relationship was not significant, however, for rates of low infant birth weights. This is expected, given the wide availability of coverage for maternity care and childbirth from the Children's Health Insurance Program and Medicaid. But, insurance coverage was negatively associated with infant mortality rates, which is perplexing when compared with the results for low infant birth weight. This suggests the presence of factors not discerned by this study.

Similarly, insurance coverage was positively related to total mortality, cerebrovascular mortality, ischemic heart disease mortality, chronic lower respiratory heart disease mortality, and other cardiovascular disease mortality. Insurance coverage was included to account for access to healthcare for treatment of chronic illness and preventive measures (Thorpe et al., 2012). Extant research shows that higher rates of insurance coverage result in higher use rates of healthcare services (Kullgren et al., 2012). The positive relationship between higher rates of insurance coverage and higher mortality rates suggests a corollary: greater utilization of health care causes worse health outcomes. This is counterintuitive. Another explanation is that worse health outcomes are an artefact of the quality or the availability of care in non-metropolitan areas. Yet another explanation is that insurance coverage alone does not surmount other healthcare access challenges such as convenient hours, transportation, or time off from work. Moderation analysis is required to examine this relationship.

Obesity

Obesity was a control variable— a proxy for poor health behaviors, which are associated with the chronic illnesses studied here, e.g., cerebrovascular, cardiovascular, and ischemic heart disease, and multiple co-morbidities (Guh et al., 2009; Patterson et al., 2004; Yang et al., 2015). However, the results of this study are mixed. Obesity, measured as a self-reported BMI greater than 30kg/m^2, was not significantly related to low infant birth weight, cerebrovascular disease, or chronic lower respiratory disease mortality. It was negatively associated with infant mortality, but consistent with prior research, it was positively related to total mortality, ischemic heart disease mortality, and mortality from other cardiovascular disease.

Urbanicity

Urbanicity controlled for county population and proximity to a metropolitan area. It assured attention to structural factors manifest as inequity in healthcare access and higher incidence of chronic disease (Singh & Siahpush, 2014), and as a proxy for health facility concentration. Four categories were created based on the U.S. Department of Agriculture Economic Research Service's 2013 Rural-Urban Continuum Codes (RUCC) and classified as metropolitan or large, medium, or small nonmetropolitan. The more rural categories - large, medium, and small non-metro areas - were considered in reference to the metropolitan areas. Urbanicity was significant in all tests, but the effect of urbanicity varied among the hypotheses.

The predicted rates of low infant birth weight, ischemic heart disease mortality, chronic lower respiratory disease mortality, and other cardiovascular disease mortality was significantly lower in small non-metro areas than in metropolitan areas. This result suggests a higher prevalence of healthy behaviors such as nonsmoking, lower BMI, and greater physical activity in more rural areas than in metropolitan areas. This is supported by recent analysis of the Behavioral Risk Factor Surveillance System results (Matthews et al., 2017). The predicted infant mortality rate in large non-metro areas was consistently lower when compared to the reference group major metropolitan area. It is known that availability and quality of prenatal care are vital to maternal health outcomes, however other neighborhood effects play an essential role. The availability of prenatal care and services in major metropolitan areas may not surmount the stresses of life in depressed inner city areas, and those at lower income levels may not have the choice to live in the suburbs (Egerter et al., 2011; Pickett & Pearl, 2001; Wilkinson & Pickett, 2006).

In contrast, the predicted total mortality rate in medium non-metro areas was consistently higher when compared with the reference group major metropolitan area. Further, the predicted cerebrovascular mortality rate in large non-metro areas was higher than the reference group, but lower than the reference group in medium and small non-metro areas. These geographic disparities might reflect the combination of differences in behavioral risk, socioeconomic status, and unequal access to healthcare (Singh, Azuine, & Siahpush, 2015).

Implications for Research Question

This study examined seven hypotheses to answer the research question: What is the relationship between RN supply and population health? In sum, the study found that greater RN supply is significantly related to higher mortality rates from ischemic heart disease, other cardiovascular disease, and chronic lower respiratory disease in the distributed lag models. Higher RN supply is not significantly related to rates of low infant birth weight, infant mortality, or mortality from cerebrovascular disease in any model. Higher RN supply is positively related to total deaths in the contemporaneous and lagged model. With few exceptions, prior research found that physician supply is non-significant or positively related to these negative outcomes. Health insurance and obesity tended to be positively related to poor health outcomes at the county level, while income and education were negatively related with better health outcomes.

The results suggest a counter-intuitive relationship between RN supply and health outcomes. Because of its curvilinearity, the relationship is unclear. The results here provide evidence of a possible relationship. More research is needed to understand these relationships.

Strengths, Limitations, & Future Research

This exploratory study provides the first findings on the relationship between RN supply and population health. A strength of this study is that the lagged models used introduced temporal order to observe the effect of RN supply on population health outcomes that manifest after the opportunity to receive healthcare services, and addressed the potential for simultaneity bias. Another strength of the study is the inclusion of a quadratic term in the statistical model for a more accurate examination of the non-linear relationship between healthcare outcomes and healthcare workforce supply. Additionally, Tobit regression models facilitated the analyses of left censored health outcome data. However, since the research is cross-sectional, only associations and not causal relationships can be inferred.

This study had some limitations. The health outcomes selected for the study addressed the limitations of previous health research in which health status outcomes were self-reported, were gender specific, or were health screenings. However, by using mortality data, other sources of bias may have been introduced and health-seeking behavior may not be adequately captured. Poor self-reported health status may lead persons to seek medical attention sooner or more frequently, which results in reduced health risks. The control variables selected - education, median income, ethnicity, and insurance coverage – partially address this inadequacy. A strong positive association between low income and educational attainment and poor self-rated health has been identified (Kawachi et al., 1999).

One important consideration is that sequelae from other chronic diseases contribute to the health outcome measures selected for this study, thus biasing results. For example, lupus may cause patients to suffer a cardiovascular event. Lupus disproportionately affects women and people of color (Bernatsky et al., 2006; Manzi et al., 1997). Although the variable, race, (per cent of Black population) modifies this relationship, its direction is unknown. Future research should examine the relationship between RN supply and the mortality that is amenable to healthcare.

The main limitation of the research was the data missing from secondary datasets, particularly as these data affected the outcome variables for mortality. To prevent identification of individual patients, the National Center for Health Statistics does not report mortality and low infant birth weight data for counties with fewer than 10 instances annually. Consequently, low or no mortality in a county underreports population health outcomes particularly in low population counties; this introduced a selection bias. The Tobit regression models used in this study compensate for these left censored mortality data, however these models can also introduce another source of bias. Even though the data are reported as zero in counties in which mortality is 10 or less, the bias results from instances of numbers closer to nine (Breen, 1996; Burke, 2009; Carson & Sun, 2007; Comber, Brunsdon, & Radburn, 2011; Grogger & Carson, 1991; Lin & Cheng, 2011; Muddasar Jamil Shera & Sajjad Dar, 2014).

Another limitation of analyzing secondary datasets is that the study is restricted to definitions used by the primary data collector. RN supply - defined in the dataset as the number of licensed RNs - includes all RNs with a license whether or not they are currently working, and, in particular, whether or not they are working in direct patient care. Thus, this study potentially over counts the number of RNs contributing directly to population health outcomes. Additionally, when data are collected, the address in the dataset is the RN's residence. The practice address could be a different county (Wing, Armstrong, Forte, & Moore, 2016). Thus, there may be geographic interdependencies such that the health outcomes in one county are affected by RN supply in another county. Spatial regression should be used in future research to deconstruct these dependencies using data that include a workforce participation adjustment for RN supply.

The fallacy in any clinician to population ratio is the assumption that patients do not travel outside the area of measurement for care (Chen & Lowenstein, 1985; Petersdorf, 1975; Rosenblatt & Hart, 2000; Rosenthal et al., 2005). For example, patients may travel into neighboring counties or cross state lines to seek care (Basu & Mobley, 2007). Alternatively, patients may not travel in straight lines between points of origin and destination because of geography or road networks. . The metric also assumes that use rates are exactly the same, and that health facility concentrations in the market are similar; this may not be the case (Glied & Ma, 2015).

Further, the data were not a random sample or a purposive or strongly representative sample of the counties in the U.S. Since RN supply data was unevenly available only counties from 19 states were included. Due to these limitations, the generalizability of this study is somewhat limited.

Last, the analytical challenge presented by endogenous loops between RN supply, health facility location and population health outcomes (discussed earlier). Future research should continue exploring and parse the relationship between RN supply and population health outcomes using structural equation modeling to isolate and address the moderating variable(s) and the endogenous relationships with healthcare facility location. Although this analysis addressed the variation between metropolitan and non-metropolitan areas and population size, other ecological effects on population health should be considered in future research. Factors that measure healthcare utilization, health facility concentration, quality of life, environmental quality, community or neighborhood cohesion, health behaviors, and health risk should be considered for comprehensive study.

Future studies should consider other snapshot health outcome measures that assess population health across the lifespan and include other healthcare professionals such as physician assistants for comparative purposes. Analyses should address spatial effects. In addition, retrospective longitudinal studies that track RN and APRN supply over time in relation to population health trends are recommended.

Implications for Policy and Practice

Future demand for services will increase as Baby Boomers seek healthcare. (Dall et al., 2013). The debate over expanded roles for APRNs complicates determining the extent of the pending healthcare workforce shortage of primary care providers. Attention must be paid to RN supply; policies must be devised to reduce the current and growing future RN shortage (Center to Champion Nursing in America (CCNA), n.d.; Skillman, Palazzo, Hart, & Keepnews, 2010). Knowing the relationship between RN/APRN supply and population health or aggregate health outcomes can influence healthcare workforce policies. At this point, that knowledge is limited.

Healthcare workforce research is essential for effective health policy development and policy evaluation. This study highlights the significance of an adequate RN workforce. However, a limitation on this type of research is the paucity of national historical data on RN supply. This illustrates the importance of a data collection and sharing strategy to support research to assure the adequacy of RN supply and understand its geographic maldistribution. Maldistribution affects parity of access to healthcare, particularly in rural areas and depressed urban areas. While it is unreasonable to expect an RN supply evenly distributed by population, there are many disparities that are influenced by location. It is known that health disparities and the etiology of disease transcend boundaries imposed by administrative divisions at the local level of government (Clark & Williams, 2016; Murray et al., 2006). Therefore, robust historical and longitudinal RN supply data must be available to inform strategic decision making, workforce planning, and program effectiveness evaluation.

APPENDIX A: IRB DETERMINATION

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2012 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To : **Carla J. Sampson**

Date : **February 15, 2017**

Dear Researcher:

On 02/15/2017 the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

Type of Review:	Not Human Research Determination
Project Title:	The Effect of Registered Nurse Supply on Population Health Outcomes: A Distributed Lag Model Approach
Investigator:	Carla J. Sampson
IRB ID:	SBE-17-12934
Funding Agency:	
Grant Title:	
Research ID:	N/A

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Kamille Chap

Signature applied by Kamille Chaparro on 02/15/2017 10:33:10 AM EST

IRB Coordinator

APPENDIX B: POPULATION HEALTH INSTITUTE PERMISSION

From: Website CHRR
Sent: Friday, February 9, 2018 11:00 AM
To: Carla Jackie Sampson
Subject: RE: County Health Rankings Model Use Permission

Hi Carla,

You are welcome to use the model graphic in your dissertation. We request that the following citation be used in any publication:

University of Wisconsin Population Health Institute. County Health Rankings & Roadmaps 2017. www.countyhealthrankings.org.

If you have any additional questions, please feel free to let us know.

Thanks,
Lindsay

-----Original Message-----
From: noreply@countyhealthrankings.org [mailto:noreply@countyhealthrankings.org]
Sent: Friday, February 9, 2018 9:00 AM
To: info@countyhealthrankings.org
Subject: County Health Rankings Model Use Permission

Submitted on Friday, February 9, 2018 - 10:00 Submitted by anonymous user: 155.247.197.49 Submitted values are:

Your Name: Carla Jackie Sampson
Your Email Address: carla.sampson@temple.edu
State: Pennsylvania
Subject: County Health Rankings Model Use Permission
Message:
Team:
I write to seek permission to include a reproduction of the the County Health Rankings Model in my dissertation at the University of Central Florida, College of Health and Public Affairs. The exploratory research seeks to find a relationship between nurse supply and county health population outcomes. The model serves as the perfect organizing framework for the selection of control variables.
Please let me know if you require any additional information.
Regards,
Carla Jackie Sampson
Phone: 2152047293
County: Montgomery

The results of this submission may be viewed at:
http://www.countyhealthrankings.org/node/19393/submission/785584

REFERENCES

Abraham, J., Jerome-D'Emilia, B., & Begun, J. W. (2011). The diffusion of Magnet hospital recognition. *Health Care Management Review*, *36*(4), 306–14. https://doi.org/10.1097/HMR.0b013e318219cd27

Acevedo-Garcia, D., Lochner, K. A., Osypuk, T. L., & Subramanian, S. V. (2003). Future directions in residential segregation and health research: a multilevel approach. *American Journal of Public Health*, *93*(2), 215–21. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1447719&tool=pmcentrez&rendertype=abstract

Aday, L. A. (1993). Indicators and Predictors of Health Services Utilization. In S. J. Williams & P. R. Torrens (Eds.), *Introduction to Health Services* (pp. 46–70).

Akaike, H. (1974). A New Look at the Statistical Model Identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

An, J., Braveman, P., Dekker, M., Egerter, S., & Grossman-Kahn, R. (2011). *Changes in Work and in the Workforce: Implications for Health*. Princeton.

Anderson, M., Dobkin, C., & Gross, T. (2010). The Effect of Health Insurance Coverage on the Use of Medical Services. *American Economic Journal : Economic Policy*, *4*(1), 1–27. https://doi.org/10.3386/w15823

Association of American Medical Colleges (AAMC). (2015). New Physician Workforce Projections Show the Doctor Shortage Remains Significant - News Releases - Newsroom - AAMC. Retrieved November 30, 2015, from https://www.aamc.org/newsroom/newsreleases/426166/20150303.html

Auerbach, D. I., Buerhaus, P. I., & Staiger, D. O. (2015). Will the RN Workforce Weather the Retirement of the Baby Boomers? *Medical Care*, 1. https://doi.org/10.1097/MLR.0000000000000415

Auerbach, D. I., Buerhaus, P. I, & Staiger, D. O. (2017). How fast will the registered nurse workforce grow through 2030? Projections in nine regions of the country. *Nursing Outlook*, *65*(1), 116–122. https://doi.org/10.1016/j.outlook.2016.07.004

Babbie, E. R. (2013). *The basics of social research*. Cengage Learning.

Bailey, B. A., & Byrom, A. R. (2007). Factors predicting birth weight in a low-risk sample: The role of modifiable pregnancy health behaviors. *Maternal and Child Health Journal*, *11*(2), 173–179. https://doi.org/10.1007/s10995-006-0150-7

Bain, L. E., & Awah, P. K. (2014). Eco-epidemiology: challenges and opportunities for tomorrow's epidemiologists. *The Pan African Medical Journal*, *17*, 317. https://doi.org/10.11604/pamj.2014.17.317.4080

Baltagi, B. (2008). Distributed Lags and Dynamic Models 6.1. In *Econometrics* (Fourth, pp. 129–145). Berlin: Springer-Verlag Berlin Heiderlberg. https://doi.org/10.1007/978-3-642-20059-5

Basu, J., & Mobley, L. R. (2007). Illness severity and propensity to travel along the urban-rural continuum. *Health and Place*, *13*(2), 381–399. https://doi.org/10.1016/j.healthplace.2006.03.002

Bauer, J. C. (2010). Nurse practitioners as an underutilized resource for health reform: Evidence-based demonstrations of cost-effectiveness. *Journal of the American Academy of Nurse Practitioners*, *22*(4), 228–231. https://doi.org/10.1111/j.1745-7599.2010.00498.x

Beckmann, M. J. (1971). Market share, distance and potential. *Regional and Urban Economics*, *1*(1), 3–18. https://doi.org/10.1016/0034-3331(71)90015-7

Bernatsky, S., Boivin, J. F., Joseph, L., Manzi, S., Ginzler, E., Gladman, D. D., … Ramsey-Goldman, R. (2006). Mortality in systemic lupus erythematosus. *Arthritis and Rheumatism*, *54*(8), 2550–2557. https://doi.org/10.1002/art.21955

Berwick, D., & Fox, D. M. (2016). "Evaluating the Quality of Medical Care": Donabedian's Classic Article 50 Years Later. *The Milbank Quarterly*, *94*(2), 237–41. https://doi.org/10.1111/1468-0009.12189

Berwick, D. M., Nolan, T. W., & Whittington, J. (2008). The triple aim: care, health, and cost. *Health Affairs (Project Hope)*, *27*(3), 759–69. https://doi.org/10.1377/hlthaff.27.3.759

Bigbee, J. L. (2003). The relationship between nurse to population ratio and county health indices...proceedings of the Communicating Nursing Research Conference and WIN Assembly, "Responding to Societal Imperatives Through Discovery and Innovation", held April 10-12, 2003, Sc. In *Communicating Nursing Research* (Vol. 36, p. 385–385 1p). Orvis Endowed Professor, Orvis School of Nursing, University of Nevada, Reno, Reno, NV: Western Interstate Commission for Higher Education. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=rzh&AN=106660014&site=eds-live&scope=site

Bigbee, J. L. (2008). Relationships between nurse- and physician-to-population ratios and state health rankings. *Public Health Nursing*, *25*(3), 244–252. https://doi.org/10.1111/j.1525-1446.2008.00701.x

Bigbee, J. L., Evans, S., Lind, B., Perez, S., Jacobo, L., & Geraghty, E. M. (2014). RN-to-Population Ratio and Population Health: A Multifactorial Study. *Journal of Nursing Regulation*, *5*(1), 11–17. https://doi.org/10.1016/S2155-8256(15)30094-6

Blegen, M. A., Vaughn, T., & Vojir, C. P. (2008). Nurse staffing levels: Impact of organizational characteristics and registered nurse supply. *Health Services Research*, *43*(1, part 1), 154–173. https://doi.org/10.1111/j.1475-6773.2007.00749.x

Bodenheimer, T., & Pham, H. H. (2010, May 1). Primary care: Current problems and proposed solutions. *Health Affairs*. https://doi.org/10.1377/hlthaff.2010.0026

Bodenheimer, T., & Sinsky, C. (2014). From triple to quadruple aim: care of the patient requires care of the provider. *Annals of Family Medicine*, *12*(6), 573–6. https://doi.org/10.1370/afm.1713

Bono, R., Blanca, M. J., Arnau, J., & Gómez-Benito, J. (2017). Non-normal distributions commonly used in health, education, and social sciences: A systematic review. *Frontiers in Psychology*. Frontiers Media SA. https://doi.org/10.3389/fpsyg.2017.01602

Brailsford, S. C., Silverman, E., Rossiter, S., Bijak, J., Shaw, R. J., Viana, J., … Vlachantoni, A. (2011). Complex systems modeling for supply and demand in health and social care. In *Proceedings of the Winter Simulation Conference* (pp. 1125–1136). Winter Simulation Conference.

Braveman, P. A., Cubbin, C., Egerter, S., Williams, D. R., & Pamuk, E. (2010). Socioeconomic disparities in health in the united States: What the patterns tell us. *American Journal of Public Health*, *100*(SUPPL. 1). https://doi.org/10.2105/AJPH.2009.166082

Braveman, P., Dekker, M., Egerter, S., Sadegh-Nobari, T., & Pollack, C. (2011). *EXPLORING THE SOCIAL DETERMINANTS OF HEALTH Issue Brief 7: Housing and Health*.

Breen, R. (1996). *Regression models : censored, sample selected or truncated data*. Sage Publications. Retrieved from https://books.google.com/books?id=btrvKnZSqIIC&dq=lower+limit+censored+data+and+r

egression+models&lr=&source=gbs_navlinks_s

Brennan, T. A., & Berwick, D. M. (1996). New rules: regulation, markets and the quality of American health care. *BMJ*, *312*, 1108.

Brooten, D., Youngblut, J. M., Kutcher, J., & Bobo, C. (2004). Quality and the nursing workforce: APNs, patient outcomes and health care costs. *Nursing Outlook*, *52*(1), 45–52. https://doi.org/10.1016/j.outlook.2003.10.009

Burke, W. J. (2009). Fitting and interpreting Cragg's tobit alternative using Stata. *Stata Journal*, *9*(4), 584–592. https://doi.org/The Stata Journal

Buys david.buys@msstate.edu, D. R., Howard, V. J. ., McClure, L. A. ., Buys, K. C., Sawyer, P., Allman, R. M., & Levitan, E. B. . (2015). Association Between Neighborhood Disadvantage and Hypertension Prevalence, Awareness, Treatment, and Control in Older Adults: Results From the University of Alabama at Birmingham Study of Aging. *American Journal of Public Health*, *105*(6), 1181–1188. Retrieved from 10.2105/AJPH.2014.302048

Campbell, D., & Stanley, J. (1963). *Experimental and quasi-experimental designs for research*. Boston: Houghton Mifflin Company. https://doi.org/10.1016/0306-4573(84)90053-0

Carpiano, R. M. (2006). Toward a neighborhood resource-based theory of social capital for health: Can Bourdieu and sociology help? *Social Science & Medicine*, *62*(1), 165–175. https://doi.org/10.1016/j.socscimed.2005.05.020

Carpiano, R. M., & Daley, D. M. (2006). A guide and glossary on post-positivist theory building for population health. *Journal of Epidemiology and Community Health*, *60*(7), 564–70. https://doi.org/10.1136/jech.2004.031534

Carr-Hill, R., & Currie, E. (2013). What explains the distribution of doctors and nurses in different countries, and does it matter for health outcomes? *Journal of Advanced Nursing*, *69*(11), 2525–2537 13p. https://doi.org/10.1111/jan.12138

Carson, R. T., & Sun, Y. (2007). The Tobit model with a non-zero threshold. *Econometrics Journal*, *10*(3), 488–502. https://doi.org/10.1111/j.1368-423X.2007.00218.x

Carter, A. J. E., & Chochinov, A. H. (2007). A systematic review of the impact of nurse practitioners on cost, quality of care, satisfaction and wait times in the emergency department. *Cjem*, *9*(4), 286–95.

Center for Workforce Studies. (2013). 2013 State Physician Workforce Data Book. *Association of American Medical Colleges*, (November). Retrieved from https://members.aamc.org/eweb/upload/State Physician Workforce Data Book 2013 (PDF).pdf

Center to Champion Nursing in America (CCNA). (n.d.). CCNA Fact Sheet: Providers of Nursing Care: Numbers, Preparation/Training and Roles | Future of Nursing. Retrieved November 29, 2015, from http://campaignforaction.org/providers-care-nurses

Centers for Disease Control and Prevention. (2015). Diabetes | At A Glance Reports | Publications | Chronic Disease Prevention and Health Promotion | CDC. Retrieved October 18, 2016, from https://www.cdc.gov/chronicdisease/resources/publications/aag/diabetes.htm%0Ahttps://www.cdc.gov/chronicdisease/resources/publications/aag/diabetes.htm%5Cnhttp://www.cdc.gov/chronicdisease/resources/publications/aag/healthy-aging.htm

Centers for Medicare & Medicaid Services. (2016). NHE-Fact-Sheet. Retrieved September 16, 2016, from https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html

Chang, C.-H., Stukel, T. A., Flood, A. B., & Goodman, D. C. (2011). Primary Care Physician

Workforce and Medicare Beneficiaries' Health Outcomes. *JAMA (Journal of the American Medical Association)*, *305*(20), 2096–2105. https://doi.org/10.1001/jama.2011.665

Chang, C. H., O'Malley, A. J., & Goodman, D. C. (2017). Association between Temporal Changes in Primary CareWorkforce and Patient Outcomes. *Health Services Research*, *52*(2), 634–655. https://doi.org/10.1111/1475-6773.12513

Chang, C., Stukel, T. A., Flood, A. B., & Goodman, D. C. (2015). Primary Care Physician Workforce. *JAMA*, *305*(20), 2096–2105.

Chen, H., Goldberg, M. S., & Villeneuve, P. J. (2008). A systematic review of the relation between long-term exposure to ambient air pollution and chronic diseases. *Reviews on Environmental Health*, *23*(4), 243–297. https://doi.org/10.1515/reveh.2008.23.4.24

Chen, M. K., & Lowenstein, F. (1985). The physician/population ratio as a proxy measure of the adequacy of health care. *International Journal of Epidemiology*, *14*(2), 300–303.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., … Cutler, D. (2016). The Association Between Income and Life Expectancy in the United States, 2001-2014. *Jama*, *315*(16), 1750–1766. https://doi.org/10.1001/jama.2016.4226

Cho, S.-H., Ketefian, S., Barkauskas, V. H., & Smith, D. G. (2015). The effects of nurse staffing on adverse events, morbidity, mortality, and medical costs. *Nursing Research*, *52*(3000), 71–79. https://doi.org/10.1097/00006199-200303000-00003

Clark, C. R., & Williams, D. R. (2016, December 13). Understanding county-level, cause-specific mortality: The great value-and limitations-of small area data. *JAMA - Journal of the American Medical Association*. American Medical Association. https://doi.org/10.1001/jama.2016.12818

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., … Forouzanfar, M.

H. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, *389*(10082), 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6

Cohen, J., Cohen, P., West, S. G., Aiken, L. S., & Rutherford, A. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. *British Journal of Mathematical & Statistical Psychology* (Vol. 56). Routledge.

Comber, A. J., Brunsdon, C., & Radburn, R. (2011). A spatial analysis of variations in health access: linking geography, socio-economic status and access perceptions. *International Journal of Health Geographics*, *10*(1), 44. https://doi.org/10.1186/1476-072X-10-44

Cooper, R. (Buz). (2015). What does it mean to have a physician shortage? *Journal of the American Academy of Physician Assistants*, *28*(3), 17–18. https://doi.org/10.1097/01.JAA.0000460925.13380.92

Cooper, R. A. (2004). Weighing the evidence for expanding physician supply. *Annals of Internal Medicine*, *141*, 705–714. https://doi.org/10.1177/153100350501700318

Cunningham, P. J. (2011). State variation in primary care physician supply: implications for health reform Medicaid expansions. *Research Briefs Center for Studying Health System Change*, (19), 1–11. Retrieved from https://folio.iupui.edu/handle/10244/1004

Cutler, D. M., Lleras-Muney, A., & Center, N. P. (2006). *Education and Health: Evaluating Theories and Evidence. National Poverty Center Working Paper Series #06-19*. *National Poverty Center, University of Michigan*. National Poverty Center, University of Michigan. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED539500&site=eds-live&scope=site

Dall, Tim Managing Director, LIfe Sciences, West, Terry, Director, Chakrabarti, Ritashree, Consultant, Iacobucci, Will, A. I. I. for A. (2015). The Complexities of Physician Supply and Demand: Projections from 2013 to 2025 Final Report Association of American Medical Colleges, (March), 68 p.

Dall, T. M., Gallo, P. D., Chakrabarti, R., West, T., Semilla, A. P., & Storm, M. V. (2013). An Aging Population And Growing Disease Burden Will Require ALarge And Specialized Health Care Workforce By 2025. *Health Affairs*, *32*(11), 2013–2020. https://doi.org/10.1377/hlthaff.2013.0714

Davis, M. A., Guo, C., Titler, M. G., & Friese, C. R. (2017). Advanced practice clinicians as a usual source of care for adults in the United States. *Nursing Outlook*, *65*(1), 41–49. https://doi.org/10.1016/j.outlook.2016.07.006

De Snyder, V. N. S., Friel, S., Fotso, J. C., Khadr, Z., Meresman, S., Monge, P., & Patil-Deshmukh, A. (2011). Social conditions and urban health inequities: Realities, challenges and opportunities to transform the urban landscape through research and action. *Journal of Urban Health*, *88*(6), 1183–1193. https://doi.org/10.1007/s11524-011-9609-y

DeGuzman, P. B., & Kulbok, P. A. (2012). Changing Health Outcomes of Vulnerable Populations Through Nursing's Influence on Neighborhood Built Environment: A Framework for Nursing Research. *Journal of Nursing Scholarship*, *44*(4), 341–348 8p. https://doi.org/10.1111/j.1547-5069.2012.01470.x

Dierick-Van Daele, A. T. M., Steuten, L. M. G., Metsemakers, J. F. M., Derckx, E. W. C. C., Spreeuwenberg, C., & Vrijhoef, H. J. M. (2010). Economic evaluation of nurse practitioners versus GPs in treating common conditions. *British Journal of General Practice*, *60*(570), 28–33. https://doi.org/10.3399/bjgp10X482077

Diez-Roux, A. V. (1998). Bringing Context Back into Epidemiology: Variables and Fallacies in Multilevel Analysis. *J Public Health*, *88*, 216–222.

Diez-Roux, A. V. (2000). Multilevel Analysis in Public Health Research. *Annual Review of Public Health*, *21*, 171–192. https://doi.org/10.1146/annurev.publhealth.21.1.171

Diez Roux, A. V. (2007). Integrating Social and Biologic Factors in Health Research: A Systems View. *Ann Epidemiol*, *17*, 569–574. https://doi.org/10.1016/j.annepidem.2007.03.001

Donabedian, A. (1966). Evaluating the quality of medical care. *The Milbank Memorial Fund Quarterly*, *44*(3), 166–206.

Donabedian, A. (1978). The quality of medical care. *The Milbank Memorial Fund Quarterly*, *44*(3), 166–206. Retrieved from http://www.jstor.org/stable/3348969?seq=1#page_scan_tab_contents

Duff, P. (1992). Structure, process and outcome. *Nursing Standard*, *7*(11), 4–5.

Dunn, J. R., & Hayes, M. V. (n.d.). Toward a lexicon of population health. *Canadian Journal of Public Health*, *90*.

Dussault, G., & Franceschini, M. C. (2006). Not enough there, too many here: understanding geographical imbalances in the distribution of the health workforce. *Human Resources for Health*, *4*(1), 12. https://doi.org/10.1186/1478-4491-4-12

Egerter, S., Barclay, C., Grossman-Kahn, R., & Braveman, P. (2011). *Violence , Social Disadvantage and Health*. *Robert Wood Johnson Foundation*. Princeton: Robert Wood Johnson Foundation (RWJF). Retrieved from www.rwjf.org/content/dam/farm/reports/issue_briefs/2011/rwjf70452

Egerter, S., Braveman, P., Sadegh-Nobari, T., Grossman-Kahn, R., & Dekker, M. (2011). *Exploring the Social Determinants of Health Issue Brief #5*. Retrieved from http://www.rwjf.org/content/dam/farm/reports/issue_briefs/2011/rwjf70447

Fields, B. E., Bigbee, J. L., & Bell, J. F. (2015). Associations of Provider-to-Population Ratios and Population Health by County-Level Rurality. *The Journal of Rural Health*, *32*(3), n/a-n/a. https://doi.org/10.1111/jrh.12143

Fink, D. S., Keyes, K. M., & Cerdá, M. (2016). Social Determinants of Population Health: A Systems Sciences Approach. *Current Epidemiology Reports*, *3*(1), 98–105. https://doi.org/10.1007/s40471-016-0066-8

Fox, J. (1991). Regression diagnostics: quantitative applications in the social sciences. *Sage Univ Paper*, *7*, 1–92.

Ganzach, Y. (1998). Nonlinearity, multicollinearity and the probability of type II error in detecting interaction. *Journal of Management*, *24*(5), 615–622. https://doi.org/10.1177/014920639802400503

Geronimus, A. T., Hicken, M., Keene, D., & Bound, J. (2006a). "Weathering" and age patterns of allostatic load scores among blacks and whites in the United States. *American Journal of Public Health*, *96*(5), 826–833. https://doi.org/10.2105/AJPH.2004.060749

Geronimus, A. T., Hicken, M., Keene, D., & Bound, J. (2006b). "Weathering" and Age Patterns of Allostatic Load Scores Among Blacks and Whites in the United States. *American Journal of Public Health*, *96*(5), 826–833. https://doi.org/10.2105/AJPH.2004.060749

Gianino, M. M., Lenzi, J., Muça, A., Fantini, M. P., Siliquini, R., Ricciardi, W., & Damiani, G. (2017). Declining Amenable Mortality: Time Trend (2000–2013) and Geographic Area Analysis. *Health Services Research*, *52*(5), 1908–1927. https://doi.org/10.1111/1475-6773.12563

Glied, S., & Ma, S. (2015). How will the Affordable Care Act affect the use of health care services? *Issue Brief (Commonwealth Fund)*, *4*, 1–15. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=cmedm&AN=25898418&site=eds-live&scope=site

Grogger, J. T., & Carson, R. T. (1991). Models for truncated counts. *Journal of Applied Econometrics*, *6*(3), 225–238. https://doi.org/10.1002/jae.3950060302

Guh, D. P., Zhang, W., Bansback, N., Amarsi, Z., Birmingham, C. L., Anis, A. H., … Ardern, C. (2009). The incidence of co-morbidities related to obesity and overweight: A systematic review and meta-analysis. *BMC Public Health*, *9*(1), 88. https://doi.org/10.1186/1471-2458-9-88

Gustafson, D. H., & Hundt, A. S. (1995). Findings of innovation research applied to quality management principles for health care. *Health Care Management Review VO - 20*, (2), 16. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edsgao&AN=edsgcl.16877183&site=eds-live&scope=site

Gutchell, V., Idzik, S., & Lazear, J. (2014). An Evidence-based Path to Removing APRN Practice Barriers. *Journal for Nurse Practitioners*, *10*(4). https://doi.org/10.1016/j.nurpra.2014.02.005

Hao, Y., Balluz, L., Strosnider, H., Wen, X. J., Li, C., & Qualters, J. R. (2015). Ozone, fine particulate matter, and chronic lower respiratory disease mortality in the United States. *American Journal of Respiratory and Critical Care Medicine*, *192*(3), 337–341. https://doi.org/10.1164/rccm.201410-1852OC

Haughton, B., & Stang, J. (2012). Population Risk Factors and Trends in Health Care and Public Policy. *Journal of the Academy of Nutrition & Dietetics*, *112*(March Supplement), S35–

S46. https://doi.org/0.1016/j.jand.2011.12.011

Health, I. of M. (US) C. on U. P. M. to I. C., Durch, J. S., Bailey, L. A., & Stoto, M. A. (1997). Understanding Health and Its Determinants. National Academies Press (US). Retrieved from http://www.ncbi.nlm.nih.gov/books/NBK233009/

Henry, & Lisa. (2015). Physician Assistants, Nurse Practitioners, and Community Health Centers under the Affordable Care Ac. *Human Organization; Spring*, *74*(1).

Huang, E. S., & Finegold, K. (2013). Seven Million Americans Live In Areas Where Demand For Primary Care May Exceed Supply By More Than 10 Percent. *HEALTH AFFAIRS*. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000316557900022&site=eds-live&scope=site

Hubert, H. B., Feinleib, M., McNamara, P. M., & Castelli, W. P. (1983). Obesity as an independent risk factor for cardiovascular disease: A 26-year follow-up of participants in the Framingham Heart Study. *Circulation*, *67*(5), 968–977. https://doi.org/10.1161/01.CIR.67.5.968

Hunold, K. M., Richmond, N. L., Waller, A. E., Cutchin, M. P., Voss, P. R., & Platts-Mills, T. F. (2014). Primary care availability and emergency department use by older adults: A population-based analysis. *Journal of the American Geriatrics Society*, *62*(9), 1699–1706. https://doi.org/10.1111/jgs.12984

Institute of Medicine (US). Committee on the Robert Wood Johnson Foundation Initiative on the Future of Nursing. (2011). *The future of nursing: Leading change, advancing health*. National Academies Press.

Intrator, O., Feng, Z., Mor, V., Gifford, D., Bourbonniere, M., & Zinn, J. (2005). The employment of nurse practitioners and physician assistants in U.S. nursing homes. *The Gerontologist*, *45*(4), 486–95. https://doi.org/10.1093/geront/45.4.486

Irving, R. J., Belton, N. R., Elton, R. A., & Walker, B. R. (2000). Adult cardiovascular risk factors in premature babies Birth size and arterial compliance in young adults For personal use only . Not to be reproduced without permission of The Lancet . *The Lancet*, *355*, 2135–2136.

Kawachi, I., Kennedy, B. P., & Glass, R. (1999). Social capital and self-rated health: a contextual analysis. *American Journal of Public Health*, *89*(8), 1187–1193. https://doi.org/10.2105/AJPH.89.8.1187

Kileinbaum, D. G., & Kupper, L. L. (1988). Applied regression analysis and other multivariate methods. *Boston, PWS-Kent Publishing Company*.

Kindig, D. A. (2007). Understanding population health terminology. *The Milbank Quarterly*, *85*(1), 139–61. https://doi.org/10.1111/j.1468-0009.2007.00479.x

Kindig, D. A., Asada, Y., Booske, B., DA, K., G, S., H, G., … DM, C. (2008). A Population Health Framework for Setting National and State Health Goals. *JAMA*, *299*(17), 2081. https://doi.org/10.1001/jama.299.17.2081

Kindig, D., & Stoddart, G. (2003). What Is Population Health? *Am J Public Health*, *93*, 380–383.

Kleiner, M. M., Marier, A., Park, kyoung W., & Wing, C. (2014). Relaxing Occupational Licensing Requirements :

Konetzka, R. T., Stearns, S. C., & Park, J. (2008). The staffing-outcomes relationship in nursing homes. *Health Services Research*, *43*(3), 1025–1042. https://doi.org/10.1111/j.1475-6773.2007.00803.x

Kotecha, S. J., Dunstan, F. D., & Kotecha, S. (2012). Long term respiratory outcomes of late preterm-born infants. *Seminars in Fetal and Neonatal Medicine*, *17*(2), 77–81. https://doi.org/10.1016/j.siny.2012.01.004

Kullgren, J. T., McLaughlin, C. G., Mitra, N., & Armstrong, K. (2012). Nonfinancial barriers and access to care for U.S. adults. *Health Services Research*, *47*(1 PART 2), 462–485. https://doi.org/10.1111/j.1475-6773.2011.01308.x

Kuo, Y.-F. Y.-F., Loresto, F. L., Rounds, L. R., & Goodwin, J. S. (2013). States With The Least Restrictive Regulations Experienced The Largest Increase In Patients Seen By Nurse Practitioners. *Health Affairs*, *32*(7), 1236–1243. https://doi.org/10.1377/hlthaff.2013.0072

Kwack, H., Sklar, D., Skipper, B., Kaufman, A., Fingado, E., & Hauswald, M. (2004). Effect of Managed Care on Emergency Department Use in an Uninsured Population. *Annals of Emergency Medicine*, *43*(2), 166–173. https://doi.org/10.1016/j.annemergmed.2003.09.010

Laditka, J. N. (2004). Physician supply, physician diversity, and outcomes of primary health care for older persons in the United States. *Health & Place*, *10*(3), 231–44. https://doi.org/10.1016/j.healthplace.2003.09.004

Lantz, P. M., House, J. S., Lepkowski, J. M., Williams, D. R., Mero, R. P., & Chen, J. (1998). Socioeconomic Factors, Health Behaviors, and Mortality: Results From a Nationally Representative Prospective Study of US Adults. *JAMA*, *279*(21), 1703–1708. https://doi.org/10.1001/jama.279.21.1703

LaVeist, T. A. (2005). Disentangling Race and Socioeconomic Status: A Key to Understanding Health Inequalities. *Journal of Urban Health: Bulletin of the New York Academy of Medicine, 82*(2_suppl_3), iii26-iii34. https://doi.org/10.1093/jurban/jti061

Lin, K. C., & Cheng, S. F. (2011). Tobit model for outcome variable is limited by censoring in nursing research. *Nursing Research*, *60*(5), 354–360.

https://doi.org/10.1097/NNR.0b013e318226a091

Liu, G. C., Wilson, J. S., Qi, R., & Ying, J. (2007). Green neighborhoods, food retail and childhood overweight: Differences by population density. *American Journal of Health Promotion*, *21*(4 SUPPL.), 317–325. https://doi.org/hepr-21-00-06.3d

Lloyd-Jones, D. M., Hong, Y., Labarthe, D., Mozaffarian, D., Appel, L. J., Van Horn, L., … American Heart Association Strategic Planning Task Force and Statistics Committee. (2010). Defining and setting national goals for cardiovascular health promotion and disease reduction: the American Heart Association's strategic Impact Goal through 2020 and beyond. *Circulation*, *121*(4), 586–613. https://doi.org/10.1161/CIRCULATIONAHA.109.192703

Lovasi, G. S., Bader, M. D. M., Quinn, J., Neckerman, K., Weiss, C., & Rundle, A. (2012). Body mass index, safety hazards, and neighborhood attractiveness. *American Journal of Preventive Medicine*, *43*(4), 378–84. https://doi.org/10.1016/j.amepre.2012.06.018

Lynch, J., Smith, G. D., Harper, S., Hillmier, M., Ross, N., Kaplan, G. A., & Wolfson, M. (2004). Is Income Inequality a Determinant of Population Health? Part 1. A Systematic Review. *The Milbank Quarterly*, *82*(1), 5–99. https://doi.org/10.1111/j.0887-378X.2004.00302.x

Macdonald, S. E., Newburn-Cook, C. V, Allen, M., & Reutter, L. (2013). Embracing the population health framework in nursing research. *Nursing Inquiry*, *20*(1), 30–41. Retrieved from 10.1111/nin.12017

Macinko, J., Starfield, B., & Shi, L. (2003). The contribution of primary care systems to health outcomes within Organization for Economic Cooperation and Development (OECD) countries, 1970-1998. *Health Serv Res*, *38*(0017–9124 (Print)), 831–865.

https://doi.org/10.1111/1475-6773.00149

Macinko, J., Starfield, B., & Shi, L. (2007). Quantifying the health benefits of primary care physician supply in the United States. *International Journal of Health Services : Planning, Administration, Evaluation*, *37*(1), 111–126. https://doi.org/10.2190/3431-G6T7-37M8-P224

Manzi, S., Meilahn, E. N., Rairie, J. E., Conte, C. G., Medsger, T. A., Jansen-McWilliams, L., … Kuller, L. H. (1997). Age-specific incidence rates of myocardial infarction and angina in women with systemic lupus erythematosus: Comparison with the Framingham study. *American Journal of Epidemiology*, *145*(5), 408–415. https://doi.org/10.1093/oxfordjournals.aje.a009122

March, D., & Susser, E. (2006). The eco- in eco-epidemiology. *International Journal of Epidemiology*, *35*(6), 1379–1383. https://doi.org/10.1093/ije/dyl249

Mark, B. A. (2006). Methodological issues in nurse staffing research: Search. *Western Journal of Nursing Research*, *28*(6), 694–709. Retrieved from http://eds.a.ebscohost.com/eds/detail/detail?vid=1&sid=4edc0e66-7b0b-4d77-a428-0b9b85625b29%40sessionmgr4002&hid=4110&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3D%3D#AN=106361687&db=rzh

Matthews, K. A., Croft, J. B., Liu, Y., Lu, H., Kanny, D., Wheaton, A. G., … Giles, W. H. (2017). Health-Related Behaviors by Urban-Rural County Classification — United States, 2013. *MMWR. Surveillance Summaries*, *66*(5), 1–8. https://doi.org/10.15585/mmwr.ss6605a1

McHugh, M. D., Kutney-Lee, A., Cimiotti, J. P., Sloane, D. M., & Aiken, L. H. (2011). Nurses' widespread job dissatisfaction, burnout, and frustration with health benefits signal problems for patient care. *Health Affairs*, *30*(2), 202–210. https://doi.org/10.1377/hlthaff.2010.0100

McLaren, L., & Hawe, P. (2005). Ecological perspectives in health research. *Journal of Epidemiology and Community Health*, *59*(1), 6–14. https://doi.org/10.1136/jech.2003.018044

Meara, E. R., Richards, S., & Cutler, D. M. (2008). The gap gets bigger: changes in mortality and life expectancy, by education, 1981-2000. *Health Affairs (Project Hope)*, *27*(2), 350–60. https://doi.org/10.1377/hlthaff.27.2.350

Micceri, T. (1989). The Unicorn, The Normal Curve, and Other Improbable Creatures. *Psychological Bulletin*, *105*(1), 156–166. https://doi.org/10.1037/0033-2909.105.1.156

Micha, R., Peñalvo, J. L., Cudhea, F., Imamura, F., Rehm, C. D., & Mozaffarian, D. (2017). Association between dietary factors and mortality from heart disease, stroke, and type 2 diabetes in the United States. *JAMA - Journal of the American Medical Association*, *317*(9), 912–924. https://doi.org/10.1001/jama.2017.0947

Miller, K. M., & Stokes, C. S. (1978). Health status, health resources, and consolidated structural parameters: implications for public health care policy. *Journal of Health & Social Behavior*, *19*(3), 263–279. https://doi.org/10.2307/2136559

Muddasar Jamil Shera, H. M., & Sajjad Dar, I. (2014). Addressing Corner Solution Effect for Child Mortality Status Measure: An Application of Tobit Model. *International Journal of Academic Research in Business and Social Sciences*, *4*(12), 2222–6990. https://doi.org/10.6007/IJARBSS/v4-i12/1340

Murray, C. J. L., Kulkarni, S. C., Michaud, C., Tomijima, N., Bulzacchelli, M. T., Iandiorio, T. J., & Ezzati, M. (2006). Eight Americas: Investigating mortality disparities across races, counties, and race-counties in the United States. *PLoS Medicine*, *3*(9), 1513–1524.

https://doi.org/10.1371/journal.pmed.0030260

Naylor, M. D., & Kurtzman, E. T. (2010). The role of nurse practitioners in reinventing primary care. *Health Affairs*, *29*(5), 893–899. https://doi.org/10.1377/hlthaff.2010.0440

Neff, D. F., Yoon, S. H., Steiner, R. L., Bejleri, I., Bumbach, M. D., Everhart, D., & Harman, J. S. (2018). The impact of nurse practitioner regulations on population access to care. *Nursing Outlook*. https://doi.org/10.1016/J.OUTLOOK.2018.03.001

Newhouse, J. P., Williams, A. P., Bennett, B. W., & William, B. (1982). Does the geographical distribution of physicians reflect market failure ? *The Bell Journal of Economics*, *13*(2), 493–505. https://doi.org/10.2307/3003469

Newhouse, R. P., Stanik-Hutt, J., White, K. M., Johantgen, M., Bass, E. B., Zangaro, G., … Heindel, L. (2011). Advanced practice nurse outcomes 1990-2008: a systematic review. *Nursing Economics*, *29*(5), 230.

Oliver, G. M., Pennington, L., Revelle, S., & Rantz, M. (2014). Impact of nurse practitioners on health outcomes of Medicare and Medicaid patients. *Nursing Outlook*. https://doi.org/10.1016/j.outlook.2014.07.004

Oosterbroek, B., de Kraker, J., Huynen, M. M. T. E., & Martens, P. (2016). Assessing ecosystem impacts on health: A tool review. *Ecosystem Services*, *17*, 237–254. https://doi.org/10.1016/j.ecoser.2015.12.008

Paneth, N. (1995). The Problem of Low Birth Weight. *The Future of Children*, *5*(1), 19–34. Retrieved from http://www.ncbi.nlm.nih.gov/books/NBK222095/

Park, S. H., Blegen, M. a, Spetz, J., Chapman, S. a, & Groot, H. a De. (2012). Comparison of Nurse Staffing Measurements. *Medical Care*, *53*(1), 1–8. https://doi.org/10.1097/MLR.0b013e318277eb50

Parrish, R. G. (2010). Measuring population health outcomes. *Preventing Chronic Disease*, *7*(4), A71. https://doi.org/10.1377/hlthaff.28.1.42

Patterson, R. E., Frank, L. L., Kristal, A. R., White, E., Flegal, K. M., Carroll, M. D., … Najjar, M. (2004). A comprehensive examination of health conditions associated with obesity in older adults. *American Journal of Preventive Medicine*, *27*(5), 385–390. https://doi.org/10.1016/j.amepre.2004.08.001

Petersdorf, R. G. (1975). Health Manpower: Numbers, Distribution, Quality. *Annals of Internal Medicine*, *82*(5), 694. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=6957873&site=eds-live&scope=site

Phelan, J. C., Link, B. G., Diez-Roux, A., Kawachi, I., & Levin, B. (2004). "Fundamental Causes" of Social Inequalities in Mortality: A Test of the Theory. *Journal of Health and Social Behavior*, *45*(3), 265–285. https://doi.org/10.1177/002214650404500303

Phillips, K. A., Morrison, K. R., Andersen, R., & Aday, L. A. (1998). Understanding the context of healthcare utilization: assessing environmental and provider-related variables in the behavioral model of utilization. *Health Services Research*, *33*(3 Pt 1), 571.

Pickett, K. E., & Pearl, M. (2001). Multilevel analyses of neighbourhood socioeconomic context and health outcomes: a critical review. *Journal of Epidemiology & Community Health*, *55*(2), 111–122. https://doi.org/10.1136/jech.55.2.111

Pilkerton, C. S., Singh, S. S., Bias, T. K., & Frisbee, S. J. (2017). Healthcare resource availability and cardiovascular health in the USA. *BMJ Open*, *7*(12), e016758. https://doi.org/10.1136/BMJOPEN-2017-016758

Pohl, J. M., Hanson, C., Newland, J. A., & Cronenwett, L. (2010). ANALYSIS &

COMMENTARY: Unleashing Nurse Practitioners' Potential To Deliver Primary Care And Lead Teams. *Health Affairs*, *29*(5), 900–905. Retrieved from http://search.proquest.com/docview/304593712?accountid=14732

Ramaswamy, M., & Kelly, P. J. (2015). Institutional racism as a critical social determinant of health. *Public Health Nursing*, *32*(4), 285–286. https://doi.org/10.1111/phn.12212

Reidpath, D. D., & Allotey, P. (2003). Infant mortality rate as an indicator of population health. *Journal of Epidemiology and Community Health*, *57*(5), 344–6. https://doi.org/10.1136/JECH.57.5.344

Remington, P. L., & Booske, B. C. (2011). Measuring the Health of Communities—How and Why? *Public Health Management Practice*, *17*(5), 397–400. https://doi.org/10.1097/PHH.0b013e318222b897

Rice, T. H., & Unruh, L. (2015). *The economics of health reconsidered* (Fourth). Health Administration Press.

Ricketts, T. C., & Fraher, E. P. (2013). Reconfiguring health workforce policy so that education, training, and actual delivery of care are closely connected. *Health Affairs*, *32*(11), 1874–1880. https://doi.org/10.1377/hlthaff.2013.0531

Ricketts, T. C., & Holmes, G. M. (2007). Mortality and Physician Supply: Does Region Hold the Key to the Paradox? *Health Services Research*, *42*(6p1), 2233–2251. https://doi.org/10.1111/j.1475-6773.2007.00728.x

Ricketts, T. C., Johnson-Webb, K. D., & Taylor, P. (1998). *Definitions of rural: A handbook for health policy makers and researchers*. Office of Rural Health Policy.

Romanowski, A. (2015). Increased utilization of APRN ' s in Health Care : GIS review.

Rosenblatt, R. A., & Hart, L. G. (2000). Physicians and rural America. *WESTERN JOURNAL*

OF MEDICINE. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000165244700025&site=eds-live&scope=site

Rosenthal, M. B., Zaslavsky, A., & Newhouse, J. P. (2005). The geographic distribution of physicians revisited. *Health Services Research*, *40*(6p1), 1931–1952.

Ross, C. E., & Mirowsky, J. (1999). Refining the association between education and health: The effects of quantity, credential, and selectivity. *Nov*, *36*(4).

Rosseter, R. J. (2014). Nursing Shortage fact Sheet. Retrieved November 29, 2015, from http://www.aacn.nche.edu/media-relations/fact-sheets/nursing-shortage

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science (New York, N.Y.)*, *277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918

Sawa, T. (2015). Information Criteria for Discriminating Among Alternative Regression Models Author(s): Takamitsu Sawa Source: *Source: Econometrica Econometrica*, *46*(6), 1273–1291. Retrieved from http://www.jstor.org/stable/1913828

Schlesinger, M. (2004). Editor's Note: On Government's Role in the Crossing of Chasms. *Journal of Health Politics, Policy and Law*, *29*(1), 1–10.

Schoenbaum, S. C., Schoen, C., Nicholson, J. L., & Cantor, J. C. (2011). Mortality amenable to health care in the United States: The roles of demographics and health systems performance. *Journal of Public Health Policy*, *32*(4), 407–429. https://doi.org/10.1057/jphp.2011.42

Schreuders, L. W., Bremner, A. P., Geelhoed, E., & Finn, J. (2014). The relationship between nurse staffing and inpatient complications. *Journal of Advanced Nursing*, (October), 1–13.

https://doi.org/10.1111/jan.12572

Seago, J. A., Spetz, J., Ash, M., Herrera, C. N., & Keane, D. (2011). Hospital RN Job Satisfaction and Nurse Unions. *Journal of Nursing Administration*, *41*(3), 109–114. https://doi.org/10.1097/NNA.0b013e31820c726f

Shi, L. (1994). Primary Care, Specialty Care, and Life Chances. *International Journal of Health Services*, *24*(3), 431–458. https://doi.org/10.2190/BDUU-J0JD-BVEX-N90B

Shi, L., Macinko, J., Starfield, B., Politzer, R., Wulu, J., & Xu, J. (2005). Primary Care, Social Inequalities, and All-Cause, Heart Disease, and Cancer Mortality in US Counties, 1990. *American Journal of Public Health*, *95*(4), 674–680. https://doi.org/10.2105/AJPH.2003.031716

Shi, L., Macinko, J., Starfield, B., Xu, J., & Politzer, R. (2003). Primary care, income inequality, and stroke mortality in the United States : A longitudinal analysis, 1985-1995. *Stroke*, *34*(8), 1958–1964. https://doi.org/10.1161/01.STR.0000082380.80444.A9

Shi, L., Macinko, J., Starfield, B., Xu, J., Regan, J., Politzer, R., & Wulu, J. (2004). Primary care, infant mortality, and low birth weight in the states of the USA. *Journal of Epidemiology and Community Health*, *58*(5), 374–380. https://doi.org/10.1136/jech.2003.013078

Shi, L., & Starfield, B. (2001). The effect of primary care physician supply and income inequality on mortality among blacks and whites in US metropolitan areas. *American Journal of Public Health*, *91*(8), 1246–50. https://doi.org/10.2105/AJPH.91.8.1246

Shi, L. Y., Macinko, J., Starfield, B., Wulu, J., Regan, J., & Politzer, R. (2003). The relationship between primary care, income inequality, and mortality in US states, 1980-1995. *JOURNAL OF THE AMERICAN BOARD OF FAMILY PRACTICE*, *16*(5), 412–422. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000186909000007&site=eds-live&scope=site

Singh, G. K., Azuine, R. E., & Siahpush, M. (2015). Widening Geographical Disparities in Cardiovascular Disease Mortality in the United States , 1969-2011. *International Journal of MCH and AIDS*, *3*(2), 134–149.

Singh, G., & Siahpush, M. (2014). Widening Rural-Urban Disparities in All-Cause Mortality and Mortality from Major Causes of Death in the USA, 1969-2009. *Journal of Urban Health*, *91*(2), 272–292. Retrieved from http://10.0.3.239/s11524-013-9847-2

Skillman, S. M., Palazzo, L., Hart, L. G., & Keepnews, D. (2010). The characteristics of registered nurses whose licenses expire: why they leave nursing and implications for retention and re-entry. *Nursing Economic$*, *28*(3), 181–189.

Spetz, J., Harless, D. W., Herrera, C.-N., & Mark, B. A. (2013). Using Minimum Nurse Staffing Regulations to Measure the Relationship Between Nursing and Hospital Quality of Care. *Medical Care Research and Review*, *70*(4), 380–399. https://doi.org/10.1177/1077558713475715

Squires, D. A. (2011). The US health system in perspective: a comparison of twelve industrialized nations. *Issue Brief (Commonwealth Fund)*, *16*, 1–14.

Stange, K. (2014). How does provider supply and regulation influence health care markets? Evidence from nurse practitioners and physician assistants. *Journal of Health Economics*, *33*(1), 1–27. https://doi.org/10.1016/j.jhealeco.2013.10.009

Starfield, B., Shi, L., Grover, A., & Macinko, J. (2005). The effects of specialist supply on populations' health: Assessing the evidence. *HEALTH AFFAIRS*, *24*(3), W97–W107. https://doi.org/10.1377/hlthaff.w5.97

Starfield, B., Shi, L., & Macinko, J. (2005). Contribution of Primary Care to Health Systems and Health. *The Milbank Quarterly VO - 83*, (3), 457. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.30045625&site=eds-live&scope=site

Susser, E. (2004). Eco-epidemiology: thinking outside the black box. *Epidemiology*, *15*(5), 519–520.

Susser, M. (1973). Causal thinking in the health sciences concepts and strategies of epidemiology. In *Causal thinking in the health sciences concepts and strategies of epidemiology*. Oxford University Press.

Susser, M. (1998). Does risk factor epidemiology put epidemiology at risk? Peering into the future*. *J Epidemiol Community Health*, *52*, 608–611.

Susser, M., & Susser, E. (1996). Choosing a future for epidemiology: I. Eras and paradigms. *American Journal of Public Health*, *86*(5), 668–673. https://doi.org/10.2105/AJPH.86.5.668

Susser, M., & Susser, E. (1996). Choosing a future for epidemiology: II. From black box to Chinese boxes and eco-epidemiology. *American Journal of Public Health*, *86*(5), 674–677. https://doi.org/10.2105/AJPH.86.5.674

The Henry J. Kaiser Family Foundation. (2016). Total Number of Professionally Active Nurses |. Retrieved November 29, 2015, from http://kff.org/other/state-indicator/total-registered-nurses/#

Thorpe, R. J., Koster, A., Bosma, H., Harris, T. B., Simonsick, E. M., Van Eijk, J. T. M., … Kritchevsky, S. B. (2012). Racial differences in mortality in older adults: Factors beyond socioeconomic status. *Annals of Behavioral Medicine*, *43*(1), 29–38. https://doi.org/10.1007/s12160-011-9335-4

Thurston, G. D., Burnett, R. T., Turner, M. C., Shi, Y., Krewski, D., Lall, R., … Arden Pope, C. (2016). Ischemic heart disease mortality and long-term exposure to source-related components of U.S. fine particle air pollution. *Environmental Health Perspectives*, *124*(6), 785–794. https://doi.org/10.1289/ehp.1509777

U S Department of Health and Human Services. (2013). *Area Health Resource Files (AHRF). Rockville, MD: Health Resources and Services Administration, Bureau of Health Professions*.

UCLA Stat Consulting Group. (2014). FAQ How do I interpret the sign of the quadratic term in a polynomial regression ? Retrieved January 13, 2018, from https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faqhow-do-i-interpret-the-sign-of-the-quadratic-term-in-a-polynomial-regression/

University of Wisconsin Population Health Institute. (2016). Our Approach | County Health Rankings & Roadmaps. Retrieved October 19, 2016, from http://www.countyhealthrankings.org/our-approach

Unruh, L. (2003). Licensed nurse staffing and adverse events in hospitals. *Medical Care*, *41*(1), 142–152.

Unruh, L. Y. (2005). Employment Conditions at the Bedside. *Journal of Nursing Administration*, *35*(1), 11–14.

Unruh, L., & Zhang, N. J. (2013). The role of work environment in keeping newly licensed RNs in nursing: A questionnaire survey. *International Journal of Nursing Studies*, *50*(12), 1678–1688. https://doi.org/10.1016/j.ijnurstu.2013.04.002

Verma, R., Clark, S., Leider, J., & Bishai, D. (2016). Impact of State Public Health Spending on Disease Incidence in the United States from 1980 to 2009. *Health Services Research*.

https://doi.org/10.1111/1475-6773.12480

Vlahov, D., Freudenberg, N., Proietti, F., Ompad, D., Quinn, A., Nandi, V., & Galea, S. (2007). Urban as a determinant of health. *Journal of Urban Health*, *84*(SUPPL. 1). https://doi.org/10.1007/s11524-007-9169-3

Wallace, M., Harville, E., Theall, K., Webber, L., Chen, W., & Berenson, G. (2013). Neighborhood poverty, allostatic load, and birth outcomes in African American and white women: Findings from the Bogalusa Heart Study. *Health and Place*, *24*, 260–266. https://doi.org/10.1016/j.healthplace.2013.10.002

Wilkinson, R. G., & Pickett, K. E. (2006). Income inequality and population health: a review and explanation of the evidence. *Social Science & Medicine (1982)*, *62*(7), 1768–84. https://doi.org/10.1016/j.socscimed.2005.08.036

Williams, D. R. (2002). Racial/ethnic variations in women's health: The social embeddedness of health. *AMERICAN JOURNAL OF PUBLIC HEALTH*. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000174558800025&site=eds-live&scope=site

Wing, P., Armstrong, D., Forte, G., & Moore, J. (2016). *Health Workforce Analysis Guide, 2016 Edition*. Rensselaer, NY. Retrieved from http://www.healthworkforceta.org/wp-content/uploads/2016/11/Health-Workforce-Analysis-Guide_2016-Edition.pdf

Winkleby, M. A., Fortmann, S. P., & Barrett, D. C. (1990). Social class disparities in risk factors for disease: eight-year prevalence patterns by level of education. *Preventive Medicine*, *19*(1), 1–12. Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=cmedm&AN=2320553&site=eds-live&scope=site

Wyszewianski, L., & Donabedian, A. (1981). Equity in the distribution of quality of care. *Medical Care*, *XIX*(12 supp.), 28–56. Retrieved from http://eds.b.ebscohost.com/eds/detail/detail?vid=15&sid=6364acdd-0b61-4390-a9d9-bb537141432c%40sessionmgr105&hid=104&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3D%3D#AN=113847968&db=edb

Xue, Y., Ye, Z., Brewer, C., & Spetz, J. (2015). Impact of State Nurse Practitioner Scope-of-Practice Regulation on Healthcare Delivery: Systematic Review. *Nursing Outlook*. https://doi.org/10.1016/j.outlook.2015.08.005

Yang, L., Colditz, G. A., TL, V., A, M., YG, D., D, G., & LW, G. (2015). Prevalence of Overweight and Obesity in the United States, 2007-2012. *JAMA Internal Medicine*, *175*(8), 1412. https://doi.org/10.1001/jamainternmed.2015.2405

Zhang, X., Holt, J. B., Lu, H., Wheaton, A. G., Ford, E. S., Greenlund, K. J., & Croft, J. B. (2014). Multilevel regression and poststratification for small-area estimation of population health outcomes: a case study of chronic obstructive pulmonary disease prevalence using the behavioral risk factor surveillance system. *American Journal of Epidemiology*, *179*(8), 1025–33. https://doi.org/10.1093/aje/kwu018

Zinn, J. S., & Mor, V. (1998). Organizational structure and the delivery of primary care to older Americans. *Health Services Research*, *33*(2 Pt Ii), 354–80. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9618675

Zurn, P., Dal Poz, M. R., Stilwell, B., & Adams, O. (2004). Imbalances in the health workforce. *Human Resources for Health*, *2*, 13. https://doi.org/10.1186/1478-4491-2-13