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Understanding Technology Diffusion and Spatial Accessibility in the Home Healthcare Industry

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Understanding Technology Diffusion and Spatial Accessibility in the Home Healthcare Industry

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Abstract

Home healthcare is becoming an important alternative to institutionalized care. It not only reduces costs but also increases health outcomes and patient satisfaction. However, the availability and efficiency of home healthcare services need to be improved as the aging population increases in the US. Hence, understanding home healthcare utilization and access are the essential steps to develop strategies ensuring effective and sustainable services to patients.

This research aims to study two main issues in the US home healthcare system: diffusion and long-term impacts of home telehealth and potential spatial accessibility of home healthcare services. Home telehealth is a promising technology that can increase efficiency and health outcomes. However, the diffusion of this technology has been slow basically due to lack of reimbursement and lack of evidence on its impacts. In the first part of this dissertation, we study the innovation characteristics affecting home telehealth diffusion among agencies and develop a system dynamics model to demonstrate the impacts of home telehealth on healthcare utilization and overall healthcare cost. Next, we study the potential spatial access to home healthcare services. Potential spatial accessibility refers to the availability of a service in a given area based on geographical factors, such as distance and location. In this part of the dissertation, a new measure that simultaneously considers both staffing levels and eligible populations is developed and used in a case study to highlight the spatial disparities in access in Arkansas. To the best of our knowledge, no previous measure has been proposed to quantify the potential spatial accessibility of home healthcare services within a geographic region. Then, we examine the factors that are associated with accessibility across the study region by space-varying coefficient models. The results of this part of the dissertation can inform policies that positively impact access to home healthcare services.

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Finally, and most importantly, I would like to thank my family back home in Turkey for their love and support.

Dedication

This dissertation is dedicated to my parents, Gülcan and Ali Kılınç.

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1. Introduction

By 2050, the population over the age of 65 is projected to surpass 85 million in 2050 (a growth of nearly 87 percent) and one in five people will be 65 and older (Figure 1). The main driver of this trend is that 10,000 baby boomers will reach age 65 per day for the next 20 years. Due to the growth of the aging population, the demand for long-term care services is expected to increase dramatically. Aging comes with increased risk of health issues. Approximately 85 percent of those over 65 years of age have at least one chronic condition such as heart failure, cardiovascular disease, and diabetes (AARP, 2009). In addition, over two-thirds of Medicare beneficiaries over 65 years old have multiple (2 or more) chronic conditions (CMS, 2012). Chronic illnesses are the primary reason for rising healthcare utilization and they account for 75 percent of all healthcare expenditures (IOM, 2012). Hence, it is essential to ensure the national availability of affordable quality long-term care services (Hutchison, Hawes, & Williams, 2010).

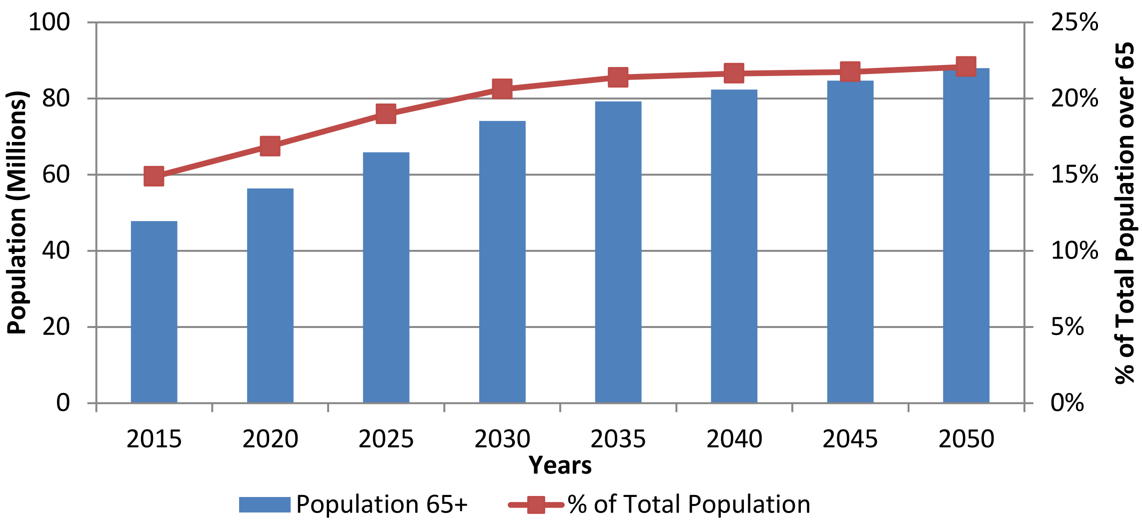

Figure 1. Total and share of population 65 and over: 2015 to 2050 (U.S. Census Bureau, 2014)

Home healthcare, which refers to patients being treated in their home environments, is an important long-term care delivery option for the US health system. It is a cost-effective alternative to institutionalized care. The average cost of a home healthcare visit is $154 per day whereas the same care in a hospital costs $1,889/day and in a nursing home $220/day (AHRQ, 2007; CMS, 2013; Genworth, 2015). In addition to lowering healthcare costs, home healthcare can improve patient satisfaction by promoting independence and avoiding discomfort of hospitalization (Hutchison et al., 2010; Nelson & Gingerich, 2010; The Joint Commission, 2011).

A wide range of medical services can be provided in a person's home. Medicare, the primary payer of home healthcare services, covers six different types of services: skilled nursing, physical therapy, occupational therapy, speech pathology, medical social, and home health aide. These services are provided by licensed professionals to homebound patients according to a plan of care certified by a physician. A home healthcare agency must be approved by Medicare to be able provide service to Medicare beneficiaries and receive reimbursement (Goldberg Dey, Johnson, Pajerowski, Tanamor, & Ward, 2011). Under the prospective payment system, Medicare provides payments to agencies for each 60-day episode of care for each beneficiary. Beneficiaries can receive an unlimited number of episodes as long as they are eligible for care.

The utilization of home healthcare services has increased dramatically in recent years. To illustrate, between 2000 and 2012 the number of users increased from 2.5 million to 3.4 million. During this period the number Medicare-certificated agencies increased by 64 percent (since 2002) to reach 12,311 in 2012. In addition, the average number of care episodes per user increased from 1.6 to 2.0 between 2002 and 2012. (MedPAC, 2013, 2014). Medicare home healthcare expenditures are projected to reach almost $66.9 billion in 2022 (CMS, 2011).

Table 1. Changes in home healthcare utilization

	2000	**2012**	**% Change**
Agencies	7,528	12,311	64
Total spending (in billions)	$8.5	$34.0	298
Home healthcare users	2.5	3.4	38
Number of visits (in millions)	90.6	113.7	25

In spite of the growth in the industry, home healthcare agencies struggle with several challenges such as decreasing reimbursement rates, providing care to patients in rural areas, legal requirements that demand higher quality and clinical outcomes, and a shortage of skilled nursing professionals (Demiris, 2010; Fazzi & Harlow, 2007; Hebert & Korabek, 2004; McCloskey & McCharthy, 2007; Milburn, 2012). Hence, the home healthcare industry is looking for opportunities to improve operational efficiencies and reduce costs while continuing to improve quality of care. Over the next couple of decades, the current practice of providing home healthcare services needs to transform to more productive and cost-effective methods.

Analyzing the US home healthcare industry from a systems point of view and understanding home healthcare utilization and access are the essential steps to develop strategies ensuring effective and sustainable services to patients. The objective of this research is to propose appropriate methodologies addressing major challenges in the home healthcare industry and to provide evidence for policy making. This research aims to study the US home health sector from three perspectives: demonstrating the long-term nationwide impacts of home telehealth technology diffusion, measuring potential spatial accessibility of home healthcare services, and examining the factors that are associated with accessibility across geographic regions.

In chapter 2, we examine the long-term systematic impacts of home telehealth diffusion in the US homecare industry. Home telehealth technology allows remote care delivery between a home health agency and a patient with a chronic illness. The purpose of this study is to understand the diffusion of home telehealth and evaluate its long-term impacts to the US home healthcare system. This is realized by employing a system dynamics model that simulates the diffusion of home telehealth among agencies over time. This model generates a diffusion curve for home telehealth adoption and measures the associated long-term savings in healthcare expenditures.

Secondly, in chapter 3, we study the potential spatial access to home healthcare services. Potential spatial accessibility refers to the availability of a service in a given area based on geographical factors, such as distance and location. The objectives of this research are to create a new measure of patient access to home healthcare services and understand variations across a region. We have developed a new measure to quantify potential spatial access to home healthcare services and illustrated the measure using a case study of Arkansas.

Chapter 4 employs spatial statistical models to explain the associations between accessibility and population characteristics, including racial/ethnic minority groups, income, and rural/urban status. These associations can vary across a study area. Hence, space-varying coefficient models, which allow local estimates of regression parameters, are used. In fact, the results indicate inhomogeneous spatial patterns of associations in the case study area. The findings of this study can help us better understand how the aforementioned socio-economic factors impact access to different home healthcare services. The research methodology and the findings in this chapter can also serve as useful inputs for policy makers and public health planners.

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2. A Study of Home Telehealth Diffusion among US Home Healthcare Agencies Using System Dynamics

2.1. Introduction

Home telehealth (HT) is a type of telemedicine technology that "encompasses remote care delivery or monitoring between a healthcare provider and a patient outside of a clinical facility, in their place of residence" (ATA, 2003). While home telehealth systems on the market vary considerably, they can be grouped broadly into two classes - telemonitoring and interactive home telehealth. Telemonitoring includes the collection and remote transmission of health data from the patient to a healthcare provider, whereas interactive home telehealth includes the utilization of two-way interactive audio/video communication between the patient and healthcare professional. Physiologic monitoring tools (e.g. blood glucose monitor, weight scale, glucometer, thermometer) are the typical equipment included in both classes of home telehealth systems (Alwan, Wilet, & Nobel, 2007; CAST, 2009). By the help of physiologic monitoring tools, patients can collect their own vital signs and report health status data to a provider location. Hence, a healthcare professional can remotely monitor the health progress of patients, especially those with chronic illnesses, on a daily basis.

Home telehealth can offer great benefits to the chronic care management programs of American home healthcare agencies. Regular remote monitoring allows home healthcare nurses to detect deteriorations in health and perform early intervention to avoid unnecessary emergency department, hospital, and physician visits and associated costs. Moreover, patient involvement can be enhanced by sustained self-care and frequent contact between nurse and patient. Last but not least, home healthcare agencies using home telehealth can increase their efficiency by decreasing staff travel time, automating patient data collection, and enabling easier to access information and improved communication between caregivers (CAST, 2013; Coye, Haselkorn, & DeMello, 2009; CTEC, 2009).

By utilizing home telehealth, home healthcare agencies can provide better chronic care while reducing costs (see for example, Alston (2009) and Myers et al. (2006)). Hence, a widespread adoption of HT technologies holds great potential for the current US healthcare system. At present, several HT systems are available on the market: Health Buddy by Bosch, Genesis DM by Honeywell HomMed, TeleStation by Philips, LifeView by American Telecare, IDEAL LIFE Pod by Ideal Life, Inc., etc. To date, however, the US home healthcare system has been slow to adopt HT technologies. A comprehensive survey conducted by Fazzi Associates provides valuable insights into the adoption and utilization of HT systems by US home healthcare agencies (Fazzi Associates, 2014). Approximately 29% of the agencies responding to the survey reported using some type of home telehealth application in 2013.

The barriers against widespread adoption and utilization of HT by US home healthcare agencies are addressed in various reports and articles. Commonly cited barriers include Medicare reimbursement coverage restrictions, lack of studies demonstrating positive economic outcomes, technology acceptance by patients and providers, organizational issues, and legal/licensure issues (CAST, 2009; Coye et al., 2009; FAST, 2009; Finkelstein, Speedie, & Potthoff, 2006; Helitzer, Heath, Maltrud, Sullivan, & Alverson, 2003). In order for HT adoption to become widespread, policy initiatives addressing the number one barrier, inadequate Medicare reimbursement policy, are required (Litan, 2008). In fact, several bills aiming to expand the Medicare coverage of home telehealth were introduced in the U.S. House of Representatives in recent years (H.R. 3306, 2013; H.R. 5380, 2014; H.R. 6719, 2012). Experts agree that, if passed, the legislation would boost home healthcare agencies' utilization of HT by eliminating coverage restrictions (Comstock, 2013; McCann, 2013; Wels-Maug, 2013). Moreover, according to a recent survey, nine in ten agencies report they will consider providing home telehealth service if a bill that allows them to be reimbursed passes (Rowan, 2013).

The term “diffusion” refers to “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 2003). The primary research questions addressed in this study are (i) how will home telehealth diffuse among home healthcare agencies in the US over time, and (ii) what will be the associated long-term impacts to the overall healthcare system? Both questions are addressed via a system dynamics model. A technology diffusion model is embedded in the model to address the first question. The diffusion model is developed by integrating concepts from the innovation diffusion literature with an assessment of the innovation characteristics affecting home telehealth diffusion. Then to demonstrate the impacts of HT diffusion, we consider the overall healthcare service utilization by Medicare beneficiaries who are 65 years or older and receive home healthcare services. We examine the reduction in use of overall healthcare services when home healthcare agencies employ HT in the care of this patient group.

The contributions of this paper are three-fold. First, to the best of our knowledge, this is the first diffusion model to describe the adoption of HT by home healthcare agencies. Second, this is the first SD model to describe the behavior of healthcare utilization over time when HT is used in the care of our target patient populations. Finally, a comprehensive literature review was conducted to gather the data needed for this study. This data could be useful for other health researchers who are interested in modeling healthcare utilization for the elderly population based on age and number of chronic conditions.

The organization of the remainder of this paper is as follows. Section 2.2 provides a summary of relevant literature. The systems dynamic model is presented in Section 2.3, with parameter values for model elements described in Section 2.4. Section 2.5 describes the set of experiments used in the computational study. The model validation is explained in 2.6 and results are provided in Section 2.7. Finally, conclusions and directions for future work are highlighted in Section 2.8.

2.2. Literature Review

Numerous studies have presented the impacts and outcomes of home telehealth pilot programs for patients with different chronic illnesses including, but not limited to, diabetes, hypertension, heart failure (HF), chronic obstructive pulmonary disease (COPD), asthma, and depression. Many of these illnesses are among the most common primary diagnoses for home healthcare admission (Caffrey, Sengupta, Moss, Harris-Kojetin, & Valverde, 2011). Some of these studies investigate the effects of home telehealth on health outcomes for patients with chronic illness whereas others report the economic analysis of the adoption. The vast majority of these studies report positive clinical and financial outcomes. For example, Woods and Snow (2013) examined the impact of home telehealth on the outcomes of home healthcare patients with chronic conditions such as HF and COPD. Their results showed home telehealth reduced the probability of hospitalization and emergency department visits. Chen et al. (2011) also found that remote monitoring of home healthcare patients who are 65 years or older can reduce hospitalization rates and lead to cost savings. In addition, according to two different studies, home telehealth significantly reduced the number of in-person nurse visits needed during an episode of home healthcare while maintaining high patient satisfaction (Alston, 2009; Myers, Grant, Lugn, Holbert, & Kvedar, 2006). Comprehensive reviews of home telehealth application studies can be found in Bowles and Baugh (2007), Brettle et al. (2013), Center for Connected Health Policy (2014), Ekeland et al. (2010), Hersh et al. (2006), Louis et al. (2003), Nangalia et al. (2010), Pare et al. (2007), Polisena et al. (2009), Seto (2008), Stachura and Khasanshina (2007), and VATAP (2010).

Although previous research provides valuable insights via small home telehealth case studies, those studies were conducted with small sample sizes and for limited periods of time. Thus, a macro scale demonstration of the impacts of a widespread adoption is needed. Only a few studies and reports attempt to evaluate the potential long-term systemic impacts of different telemedicine applications. Litan (2008) assessed the savings from the remote monitoring of diabetic, HF, COPD and chronic skin ulcer patients in the US over a 25 year period. The New England Healthcare Institute (2004) projected the value of remote monitoring for heart failure patients in New England region using a cost-effectiveness model. Cusack et al. (2007) demonstrated the national costs and economic benefits of provider-to-provider telehealth technologies in the US. Similar cost benefit analyses were conducted for different telemonitoring interventions in Canada and Australia (Access Economics, 2010; Praxia Information Intelligence, 2007). Nevertheless, these studies do not specifically consider HT in the context of the US home healthcare system nor the industry diffusion curve of the technology over time.

System Dynamics (SD) is a simulation based methodology that can allow modeling systems at an aggregate level for long-term policy decision making analysis (Sterman, 2000). SD methodology has been applied to examine policy interventions and study innovation diffusion in different systems including healthcare. Many researchers utilized SD for policy analysis in various healthcare settings such as chronic care management (Homer, Hirsch, Minniti, & Pierson, 2004), mental health treatment (Schwaninger, Pérez Rios, Wolstenholme, Monk, & Todd, 2010), cardiac catheterization services (Taylor & Dangerfield, 2004), ambulatory healthcare services (Diaz, Behr, & Tulpule, 2012), long-term care services (Ansah et al., 2014), primary and acute care services (Lyons & Duggan, 2014), and the entire national healthcare system (Wolstenholme, 1999). Others performed simulation analysis on patient flow to examine the impacts of Information Technology (IT) diffusion in healthcare (Bayer, Barlow, & Curry, 2007; Osipenko, 2005). Moreover, SD has been used to understand the diffusion behavior of IT and innovations such as electronic health records (Erdil, 2009; Otto & Nevo, 2013) and identification standards (Burbano, 2012). Therefore, SD is an appropriate methodology for modeling the diffusion of HT over time through the home healthcare system.

2.3. Model Formulation/Development

This section presents a system dynamics model that was created to simulate both the diffusion of home telehealth in the US home healthcare industry and its impacts on the utilization of services in the overall healthcare system. The quantitative model generates a diffusion curve for home telehealth adoption and measures the associated long-term savings in healthcare expenditures. Here, we briefly explain the basic system dynamics modelling concepts and follow with the model description.

2.3.1. System Dynamics Modeling

In system dynamics models, stocks are the accumulations in the system and they are filled or drained by flows. Converters are used to model auxiliary variables. Converters can have constant values or convert inputs into outputs using algebraic or graphical relationships. Lastly, connectors (arrows) connect model entities to each other and show causality. Each of these model elements are illustrated in Figure 2.

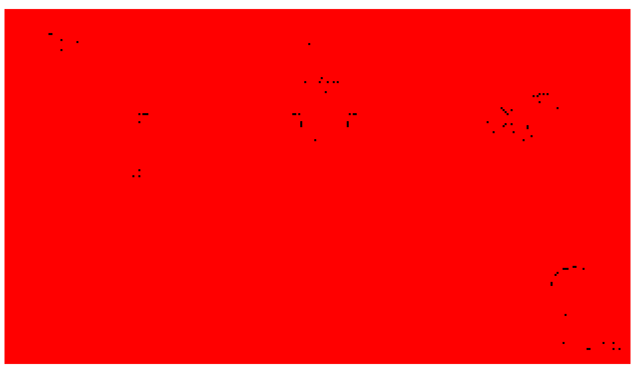

Figure 2. An example of system dynamics blocks

2.3.2. Model Overview

The SD model consists of five main modules: (i) Telehealth Diffusion, (ii) Patient Population, (iii) Telehealth Use, (iv) Healthcare Utilization, (v) Costs and Savings. Figure 3 provides an overview of the relationships between the modules. As illustrated, the Patient Population and Telehealth Diffusion modules influence Telehealth Use. Subsequently, the Telehealth Use module influences to what extent other types of healthcare services are needed (via Healthcare Utilization). Finally, the Costs and Savings module describes how the final outcomes of the model depend on utilization of telehealth and other types of healthcare services. Each of these modules is described in detail in the following subsections.

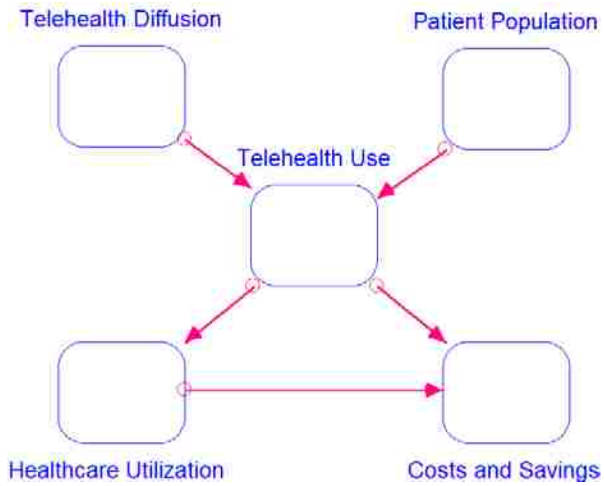

Figure 3. Modules in the home telehealth diffusion model

2.3.3. Telehealth Diffusion Module

This module is designed to simulate the diffusion progress of home telehealth through the US home healthcare agency population. The primary purpose of this module is to produce a future industry diffusion curve for home telehealth based on its historical diffusion and innovation characteristics such as relative advantage and complexity. In the literature, S-shaped curves have been fitted to model the diffusion progress of a number of health technologies in the United States, including electronic health records (Bower, 2005) and personal digital assistants (Garritty & El Emam, 2006). The S-shaped curves have also been used to model the diffusion of healthcare service innovations such as the postoperative recovery room, intensive care unit, respiratory therapy department and diagnostic radioisotope facilities (Russell, 1976). Hence, we assume that home telehealth diffusion can be explained by an S-shaped curve like many other innovations and technologies in healthcare. To generate an S-shaped curve for home telehealth, we propose to embed a Bass diffusion model in the Telehealth Diffusion Module (Bass, 1969). Bass diffusion models have proven to generate diffusion curves that fit the historical diffusions of many innovations accurately (Sultan, Farley, & Lehmann, 1990; Teng, Grover, & Guttler, 2002).

The Telehealth Diffusion Module is depicted in Figure 4. The stocks in this module represent home healthcare agencies that have been separated according to whether they have adopted telehealth at a particular point in time (Adopted Agencies have, Potential Agencies have not). The sum of both stocks of agencies is denoted Total Agencies, and the proportion of Adopted Agencies to Total Agencies is denoted Proportion of Adopters. The rate of flow between these two stocks is denoted Telehealth Diffusion and is modeled based on a generic Bass diffusion model (Bass, 1969). The model elements connecting into the Telehealth Diffusion flow variable (i.e., Diffusion Speed and Saturation Level) are the inputs required by the Bass diffusion model.

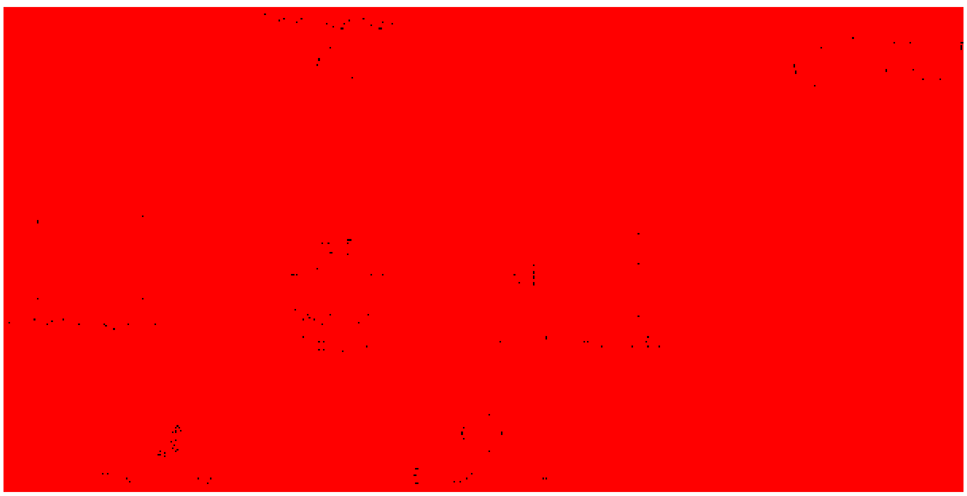

Figure 4. Technology Diffusion Module

In a Bass diffusion model, the adoption rate at a given time t is formulated as:

$$\frac{dN_{(t)}}{dt} = \left(a + \frac{bN_{(t)}}{maxM} \right) \left(maxM - N_{(t)} \right), \tag{1}$$

where $N_{(t)}$ is the Adopted Agencies at time t, M is the Total Agencies, max is the maximum expected proportion of total adopters, and a and b are the coefficients of external and internal influences, respectively. External influences include phenomena such as advertising impact, vendor investment and government publicity, for example. Internal influence refers to the impact of current adopters on potential users which is analogous to epidemic spread (Bower, 2005; Radas, 2006). Parameters a and b in Equation (1) determine the module element named Diffusion Speed, whereas parameter max determines the module element named Saturation Level. A primary challenge in using Bass diffusion models to generate appropriate diffusion curves is estimating the parameter values (i.e. a, b, and max) when sufficient historical adoption rate data is not available. Later, Section 2.4 will describe the efforts to estimate these parameters for this study by considering the unique characteristics of home telehealth technology and the US home healthcare system.

2.3.4. Patient Population Module

Figure 5 depicts the Patient Population Module. The primary purpose of this module is to quantify the number of home healthcare users at various points in time, and separate them into groups that determine their levels of healthcare utilization. In our study we consider only those home healthcare agencies with Medicare certification, as Medicare is the largest payer for home healthcare services in the US (CMS, 2011). While the Medicare home healthcare user population is comprised of people of all ages, including children and non-senior adults, the analysis here is restricted to consider only Medicare beneficiaries who are 65 years or older. This decision is made because Medicare beneficiaries who are younger than 65 years of age have qualified for Medicare coverage because they are either disabled or have end stage renal disease. Therefore, they will have health needs that are different from the majority of home healthcare users (Chen et al., 2011). Also, instead of modeling the healthcare utilization associated with specific conditions explicitly, we instead focus on distinguishing home healthcare patients by age and severity groups. Severity groups are determined based on the number of chronic illnesses a person has. This classification system enables us to take advantage of available data that describes differences in healthcare service utilization rates for patient groups that are constructed based on age and number of chronic conditions. These parameter estimates will be presented in Section 2.4.

Based on this discussion, together the USA Elderly Population (a stock) and the Medicare Fee For Service (FFS) Enrollment Rates (for various age groups) determine the number of FFS Enrollees. The stock of the USA Elderly Population is controlled by the Change In Population bi-directional flow variable, which can increase or decrease the population stock based on the Population Change Rate of that year (whether the rate of death or rate of aging into the elderly population is greater). The Chronic Condition Rates (the fraction of FFS enrollees with different numbers of chronic conditions) and the Home Healthcare Admission Rates (the fraction of the FFS enrollees with chronic conditions who use home healthcare services) are used to calculate the number of Home Healthcare Patients in each age-severity patient group.

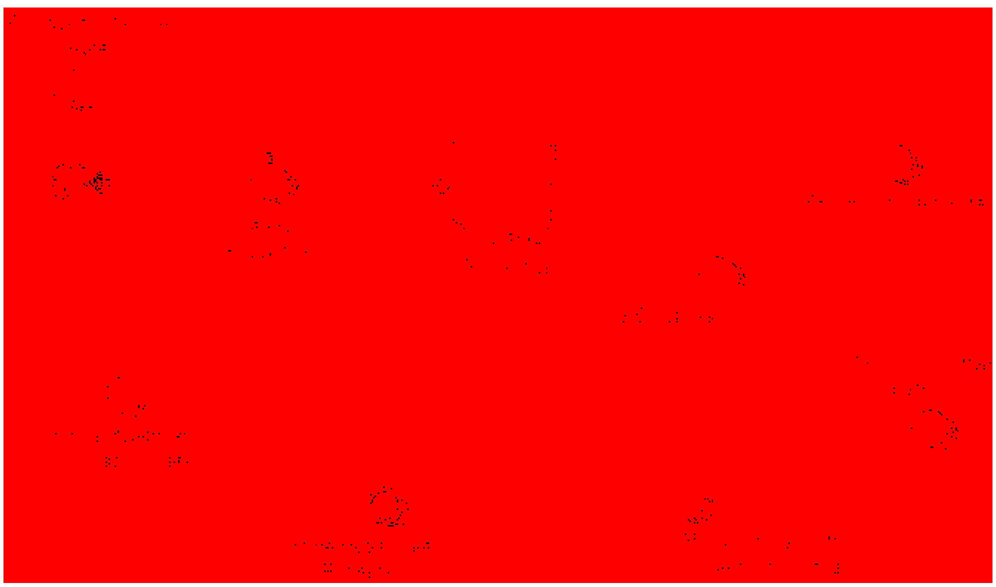

Figure 5. Patient Population Module

2.3.5. Telehealth Use Module

The Telehealth Use Module, depicted in Figure 6, interacts with the Telehealth Diffusion and Patient Population Modules to model the provision of telehealth to home healthcare patients. At an aggregate level, the primary inputs include measures of telehealth capacity and the potential demand for telehealth services among the patient populations considered in this case study. We inherently assume that there are a sufficient number of telehealth devices available and the workforce is the limiting factor with respect to home telehealth capacity. Hence, the determinants of telehealth capacity include the number of nurses allocated to telehealth monitoring and the number of agencies that have adopted home health. Specifically, Telehealth Capacity represents the total capacity of telehealth units in terms of number of patients that can be monitored and is a function of the Number of Telehealth Nurses, Average Telehealth Nurse Capacity (measured in the number of patients a telehealth nurse can manage annually) and Proportion of Adopters (the proportion of Adopted Agencies to Total Agencies, as in the Telehealth Diffusion Module). The Number of Telehealth Nurses is a function of the Telehealth Nurse Dedication Ratio, which represents the percentage of nurses allocated to telehealth monitoring, and the Nurse Workforce in Home Healthcare. The latter is a stock variable representing registered and licensed practical nurses employed in US home healthcare agencies. A bi-directional flow variable, Change in Nurse Workforce, is used to model either the increase or decrease in the total nurse workforce each year.

On the demand side of the equation, the number of Available Patients is a function of Home Healthcare Patients and Patient Acceptance. Although home telehealth can provide remarkable clinical outcomes, some patients may refuse to use this technology due to privacy issues and functional limitations. Hence, the number of Available Patients is calculated by multiplying Home Healthcare Patients (the number of Medicare FFS home healthcare patients with chronic conditions, from the Patient Population Module) with Patient Acceptance rates, the proportion of home healthcare patients willing to use the technology. Telehealth Coverage, which denotes whether certain patient groups are covered for telehealth service or not, affects the number of available patients who demand telehealth service (i.e. Telehealth Demanding Patients). This is a lever we use in our computational study to represent various allocation policies for telehealth. The value of the Telehealth Coverage variable can be set as 0 or 1 for each severity based patient group (0 means not covered and 1 means covered). Telehealth Patients, which represents the actual telehealth users of each severity level, cannot exceed the capacity allocated for monitoring patients of that severity level, nor the total number of patients of that severity level who require (and accept) telehealth services. Lastly, the patients not receiving telehealth service are denoted as Traditional Patients in the model. Note that these patients still receive home healthcare as Medicare FFS enrollees.

Figure 6. Telehealth Use module

2.3.6. Healthcare Utilization Module

In the Healthcare Utilization Module, depicted in Figure 7, the long-term impacts of home telehealth diffusion on overall healthcare service utilization are demonstrated in terms of number of visits. In our model, among many cited impacts of home telehealth, we examine the most tangible and easy to measure impacts in the following areas: hospitalizations, emergency department (ED) visits, physician office (PO) visits, and skilled nursing (SN) home healthcare visits. We refer to this group of impact areas as “service types”. The module quantifies two outputs for each healthcare service type: Number of Visits and Number of Reductions. Number of Visits is the number of total visit encounters (of each type) for Telehealth Patients and Traditional Patients (from the Telehealth Use Module) that can be expected if telehealth is not used. Number of Reductions is used to track the decrease in numbers of visits for each service type if telehealth is used.

Figure 7. Healthcare Utilization Module

To calculate the two outputs, Number of Visits and Number of Reductions, the numbers of Traditional Patients and Telehealth Patients are included as external inputs from the Telehealth Use Module. Two multipliers are used to compute healthcare utilization for these populations. First, Visit Rates is a multiplier that represents the annual number of visits per patient for each service type required in a traditional care model (traditional in that telehealth is not used). Second, the Telehealth Impact multiplier takes on a value between 0 and 1 for each service type to represent the percent reduction in visits for that service type that can be expected when telehealth is used. More formally, for each age-severity group i, the Number of Visits (V_{ij}) for each service type j is calculated using Equation (2):

$$V_{ij} = R_{ij}\left(T_i + H_i\right), \tag{2}$$

where R_{ij} is the visit rate of age-severity group i for visit type j and H_i and T_i are the number of telehealth and traditional patients in age-severity group i, respectively. Then, Equation (3) is used to calculate the Number of Reductions (K_{ij}) for each visit type and age-severity group pair for the patients using telehealth:

$$K_{ij} = R_{ij} T_i I_{ij}, \tag{3}$$

where I_{ij} is the telehealth impact multiplier for age-severity group i and visit type j. Finally, Overall Healthcare Utilization (U_j) for each visit type j is then calculated using Equation (4):

$$U_j = \sum_{\forall i} V_{ij} - \sum_{\forall i} K_{ij}. \tag{4}$$

The savings associated with these reductions are computed in the Costs and Savings Module, which is described in detail in the next section.

2.3.7. Costs and Savings Module

The final module computes the costs associated with telehealth use and also the savings associated with the reduction in healthcare utilization that is enabled when telehealth is used. Costs refer to those associated with the provision of telehealth services, and savings are those associated with the reductions in visits for the service types described in the previous section. Three major cost items are considered: Telehealth Device Cost, Annual Operating Costs, and Nurse Monitoring Cost (Figure 8). The Telehealth Device Cost represents the one-time purchase and installation cost of a telehealth unit, amortized over the technology's useful life. Annual Operating Costs include yearly data transmission and maintenance costs. The Nurse Monitoring Cost represents salaries and benefits paid to telehealth nurses who have the responsibility of monitoring data transmitted via telehealth devices and following up with patients when necessary. With respect to savings, total visit reductions, obtained from the Healthcare Utilization Module, are converted into dollar amounts. Specifically, Number of Reductions (measured in number of visits) is multiplied by Average Visit Charges (measured in dollars per visit) for each service type. Their product comprises the Total Savings of Telehealth for each visit type. Then, the Annual Net Benefit is computed as the difference between the Total Savings of Telehealth (across all service types) and Total Cost of Telehealth.

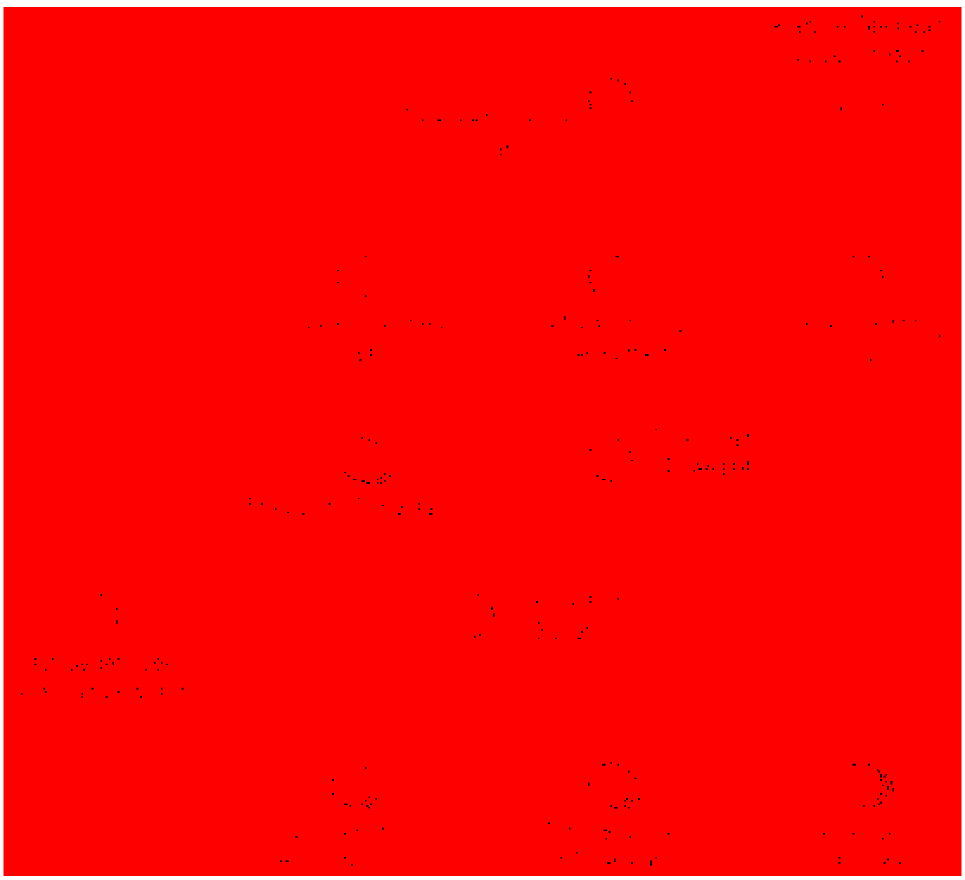

Figure 8. Costs and Savings module

2.4. Model Parameters

This section describes how the system dynamics model is populated with data for the purposes of the computational study. Data collection and modeling efforts for each module are explained below.

2.4.1. Telehealth Diffusion Module

Because historical data is not available for estimating the parameters needed in the Bass diffusion model described in Section 2.3, a technique from the innovation characteristics research is employed. Specifically, various innovation characteristics as they pertain to home telehealth are examined, and then the classification scheme from Teng et al. (2002) is used to map those characteristics to meaningful values for diffusion model parameters.

Teng et al. (2002) provides evidence of the relationship between an information technology's (IT) diffusion pattern and its innovation characteristics. In the paper, nonlinear regression is used to fit Bass models representing the diffusions of 19 different information technologies in the US. The regression models are then used to estimate the parameters a, b and max (as described in Equation (1)) for each IT diffusion. Their results show that for all 19 technologies, the coefficient of external influence (a) is extremely small compared to the coefficient of internal influence (b), suggesting that b is the dominant parameter in the diffusion. Therefore, they exclude any further analysis of how a might depend on various innovation characteristics. Next, the remaining two parameters of the Bass model, the coefficient of internal influence (b) and saturation level (max), are considered in a cluster analysis to find groups of ITs having similar characteristics and diffusion curves. As a result, the innovation characteristics having the largest effects on these Bass model parameters b and max are identified: **relative advantage, compatibility, complexity, network externality, and adoption effort** (each discussed in detail below).

Relative advantage, the degree to which an innovation is perceived as being better than the innovation it supersedes, can include profitability, higher market share, efficiency, social prestige, or other benefits

(Bower, 2005; Menachemi, Burke, & Ayers, 2004; Rogers, 2003). So, if an innovation promises high relative advantages to the potential users, the ultimate proportion of adopters will be larger.

Compatibility is defined as the degree to which an innovation is perceived as being consistent with the existing environment and values, practices, and past experiences of the potential adopters (Cain & Mittman, 2002; England, Stewart, & Walker, 2000; Rogers, 2003). High compatibility of a new technology increases the eventual saturation level of the diffusion.

The degree to which an innovation is perceived as relatively difficult to understand and use is referred to as **complexity** (Rogers, 2003). Research indicates that complex innovations may have lower ultimate diffusion due to lower acceptance by the users (Teng et al., 2002; Tornatzky & Klein, 1982).

Network externality exists if a user’s benefit from the product increases with the number of other users (Peres, Muller, & Mahajan, 2010). Benefit can be seen directly in terms of number of possible communication partners especially in telecommunication products such as fax, e-mail, phone and teleconference. Benefit can also be indirect due to wider availability of other compatible products and services (Hanseth & Aanestad, 2003; Peres et al., 2010). High externality needs hinder the diffusion of the innovation.

Teng et al. (2002) states that system technologies which require an extensive and time consuming implementation phase diffuse more slowly than technologies which can be directly utilized. We refer to this concept as **adoption effort**.

The identified clusters of IT diffusion patterns and their associations with innovation characteristics can provide a practical guide for estimating the parameters of the Bass diffusion model for an information technology. In summary, the results in Teng et al. (2002) suggest that the number of adopters in the market will be higher if an IT innovation has high relative advantage, high compatibility, and low complexity. Additionally, the diffusion will be rapid if adoption efforts and externality needs are low and it is a device, not a system. Figure 9 summarizes the results of their cluster analysis. For each cluster, a descriptor for each innovation characteristic is provided (i.e., high versus low), as are acceptable diffusion parameter values. For example, if an information technology has high relative advantage, low complexity, high compatibility, high adoption efforts, high externality needs, and is a system, not a device, then it belongs in Cluster 1. Therefore, acceptable ranges for the coefficient of internal influence (b) and maximum eventual percentage of adopters (max) are $[0,0.5]$ and $[0.90,1]$, respectively.

We use this framework to select parameter values for the Bass diffusion model in our Telehealth Diffusion Module described in Section 2.3.3. The following discusses our assessment of home telehealth with respect to the framework above. Specifically, an evaluation of home telehealth along each innovation dimension is provided.

Relative advantage: In various case studies, remarkable financial and clinical outcomes of HT implementation are reported (Finkelstein et al., 2006; Myers et al., 2006; NEHI, 2004; Polisena et al., 2009). Under current circumstances, financial benefits are limited and unclear to home healthcare agencies because of two reasons. First, HT may require high initial investment costs as well as ongoing monitoring costs which are not covered by the current home healthcare reimbursement system (CAST, 2013; FAST, 2009). Second, while patients may benefit, the home healthcare agencies do not directly gain any financial benefits from home telehealth outcomes such as reduced hospitalizations and emergency department visits (Coye et al., 2009; CTEC, 2009; FAST, 2009). Therefore, there is no clear return on investment (ROI) from the perspective of the home healthcare organization until the payment/reimbursement model changes. Thus, our assessment is that the relative advantage of home telehealth is limited in the current environment.

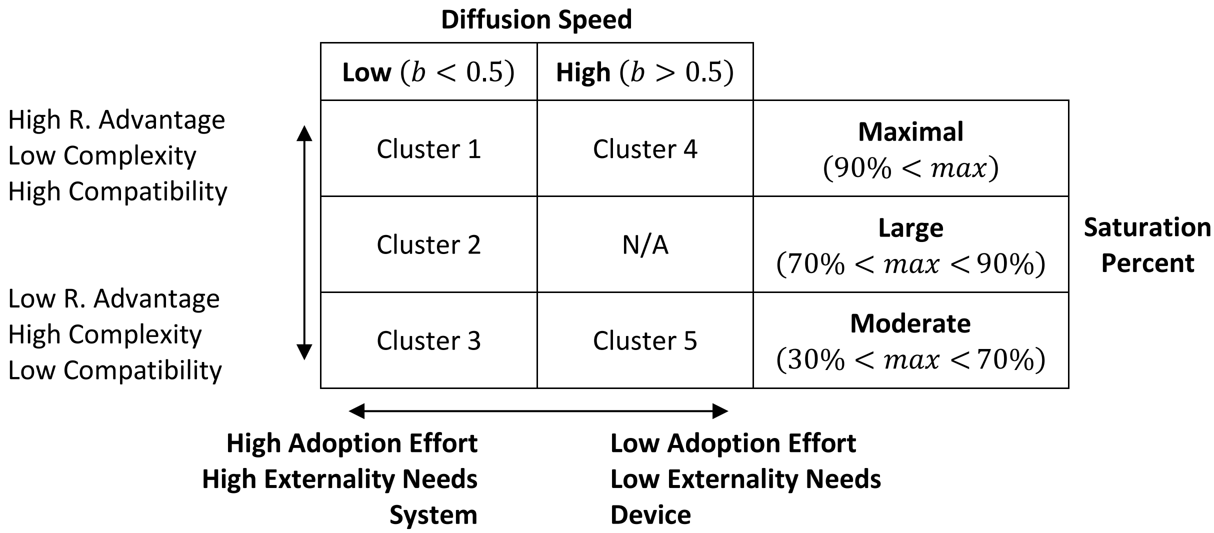

Figure 9. Relationships between IT characteristics and diffusion patterns (Teng et al., 2002)

Compatibility: Compatibility of home telehealth can be investigated over several dimensions. Interoperability is defined as the ability of multiple systems to communicate with each other and electronically exchange data. Without integrating home telehealth systems with other healthcare technologies (e.g. electronic health records, back office solutions, etc.), providers cannot realize the technology's full capabilities for improving efficiency and reducing cost. Adoption of industry-wide standards will not only contribute to resolve interoperability problems but also lower technology implementation cost and efforts. Progress in the development of standards is still continuing (Brantley, Laney-Cummings, & Spivack, 2004; Wang, Redington, Steinmetz, & Lindeman, 2011). Policy issues compose another dimension of compatibility. There is a need for updated regulations related to provider licensing, security, privacy and reimbursement (Brantley et al., 2004; CTEC, 2009; Wang et al., 2011). In addition to the problems associated with interoperability and regulations, compatibility can address the fit between the technology and the user/organization. Telehealth will necessitate a change in care delivery methods and work patterns (CAST, 2013; CTEC, 2009). Taken together, these issues suggest the compatibility of home telehealth with the current home healthcare environment is low.

Complexity: Patient and nurse acceptance of and compliance with HT are reported as very high in various case studies (Agrell, Dahlberg, & Jerant, 2000; Bowles & Baugh, 2007; Darkins et al., 2008; Dimmick, Mustaleski, Burgiss, & Welsh, 2000; Louis et al., 2003). Therefore the current assessment is that the complexity of HT is low.

Network externality: Considering that a "user" in this case refers to a home healthcare agency it must be evaluated whether the relative benefit of HT to a single home healthcare agency increases as the number of other adopting agencies increases. Our assessment is that it does. As the number of adopting agencies increases, it is more likely that telehealth systems become integrated and the sharing of patient information is enabled. Furthermore, an individual agency benefits more as the experience of other adopters and technology providers increase. For example, providers can share lessons learned and best practices with each other. Also, if the demand for HT in a region is high, there will likely be a supply of technical support services for installing HT in patient homes. Finally, as the demand for HT increases, so does the demand for high-speed connectivity in broader geographic areas (including rural). A home healthcare agency that is adopting HT benefits from faster, more reliable and cheaper high-speed connectivity. For example, the Arkansas e-Link Project "extended the Arkansas Telehealth network to communities where medical expertise did not exist" by installing new fiber optic cable and telecommunications infrastructure throughout the state (ARE-ON, 2015). Hence, because HT diffusion can be influenced by network externalities, our assessment is that externality needs are high.

Adoption effort: Home telehealth is a remote clinical technology which integrates in-home devices with a central monitoring system through a communications network. Implementation of home telehealth requires adoption efforts which are related to staff and patient training, device set-up, testing, reorganization of work processes, and documentation. However, many agencies do not have sufficient experience with telemedicine technologies (Coye et al., 2009). We conclude that this situation is a hurdle against diffusion and therefore adoption effort is high.

Our current assessment of home telehealth according to these innovation characteristics is summarized in Table 2. This assessment places home telehealth in Cluster 3 of the Teng et al. (2002) model in Figure 9. This implies home telehealth will achieve a moderate adopter population by a slow rate of diffusion. Appropriate values for Bass diffusion model parameters are $b \in [0,0.5]$ and $max \in [0.30,0.70]$. The parameter a is smaller than 0.01 for all clusters in the Teng et al. (2002) model.

Table 2. Current assessment for home telehealth

Innovation Characteristics	**Assessment**
Relative advantage	Low
Compatibility	Low
Complexity	Low
Network externality	High
Adoption effort	High
System or device	System
Selected cluster	Cluster 3

We select a specific set of parameter values from the prescribed ranges for a, b, and max using a non-linear optimization model. The model minimizes a measure of aggregate error while keeping each parameter's value in the ranges described in the previous paragraph (see Appendix A for details). Three different measures of aggregate error are considered – Root Mean Squared Error, Mean Squared Error, and Mean Absolute Error – and the model is solved once per measure. Error is computed as the deviation between predicted diffusion levels (adopted proportions) and actual diffusion levels according to historical data at discrete points in time. Historical diffusion data is available for eight years in the range 1997-2013. Specifically, the proportion of agencies having adopted HT in years 1997, 2004, 2006-2009 and 2013 is documented in a number of reports and surveys (Fazzi Associates, 2008, 2009, 2014; MedPAC, 2005; NAHC, 2007; Resnick & Alwan, 2010). The starting year of the diffusion is set as 1994 with no initial adopters (note that the first home telehealth nursing projects started in 1995). The optimization returns the following parameter values: $a = 0.00337$, $b = 0.45183$, and $max = 0.30$. To be more precise, each of the three optimization models, based on different measures of aggregate error, return very similar parameter values for a, b, and max, so an average of the three optimization model results is taken for each parameter. Figure 10 depicts the S-shaped diffusion curve that results from this set of diffusion parameter values, shown using a solid red line. It is generated from the simulated proportion of adopters for each year. The curve is overlaid with the data series representing the historical proportion of adopters, depicted using blue diamonds for each year for which data is available.

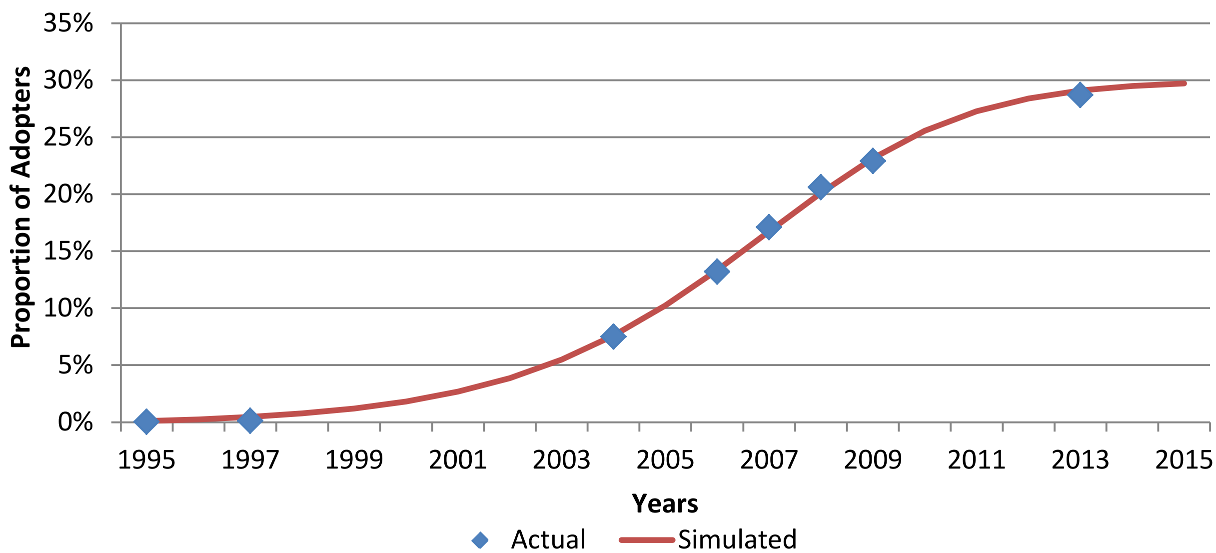

Figure 10. Home telehealth diffusion between 1995 and 2015. For the simulated diffusion curve in red, $a = 0.00337$, $b = 0.45183$, and $max = 0.30$. The data series depicted using blue diamonds are the actual historical proportion of adopters.

Having calibrated the base model against the available data, the Telehealth Diffusion Module of the SD model can be populated with the selected diffusion parameters for the years 1994-2015. This enables the SD model to determine the impacts of telehealth during that time period. However, to model HT diffusion and its associated impacts in the years beyond 2015, we must consider whether the diffusion will continue to follow the same curve. To do so, we re-assess home telehealth along each innovation dimension for the years 2015-2025. The purpose is to project an industry diffusion curve with respect to possible policy improvements.

Home telehealth devices and services are currently not covered by the Medicare homecare reimbursement program and agencies are not allowed to substitute telehealth for services ordered by a physician (ATA, 2013). However, as described in Section 2.1, several bills aiming to expand the Medicare coverage of home telehealth have been introduced in the U.S. House of Representatives in recent years (H.R. 3306, 2013; H.R. 5380, 2014; H.R. 6719, 2012). It is reasonable to anticipate that a policy improvement for home telehealth technology and services will be passed soon. If it is, the relative advantage of HT will improve as the return on investment from the perspective of the home healthcare organization improves. Increasing the relative advantage of HT moves the innovation up the y-axis of the taxonomy presented in Figure 9, from Cluster 3 into Cluster 2 or Cluster 1. Moving along the y-axis of this taxonomy impacts the saturation level parameter in the diffusion model (i.e., max) but does not impact the other parameters (a and b). Therefore, instead of the range for max being [0.30,0.70] as in Cluster 3, it will instead be [0.70,90] as in Cluster 2 or [0.90,1] as in Cluster 1. The other innovation dimension along which the assessment of HT may change if reimbursement policies improve is compatibility. Compatibility of HT may increase if improved reimbursement policies increase interoperability of HT systems and aid in industry-wide adoption of data standards. This change again impacts the y-axis in Figure 9 but not the x-axis, resulting in an increase of the parameter max but not a and b in the diffusion model. The diffusion speed will still be slow.

The future assessment of innovation characteristics for home telehealth is summarized in Table 3. To address uncertainty in how far along the y-axis of Figure 9 HT will move and also uncertainty in when the reimbursement environment will change, six alternative future diffusion curves for the time period 2015-2025 are generated. For all six curves, the diffusion speed parameters are not changed from their values in the historical diffusion curve that was validated ($a = 0.00337$, $b = 0.45183$). However, three levels for saturation percent are considered ($max = 0.70, 0.85, 1.00$), as are two different years for the reimbursement environment change to take place (2015 and 2020). The generated industry diffusion curves are presented in Figure 11. The results show that in the most conservative of the six scenarios (max = 0.70, year = 2020), 66% of home healthcare agencies will adopt HT by 2025, with the proportion of adopters reaching 98.8% by 2025 in the most optimistic scenario (max = 1.00, year = 2015). The latter is the diffusion curve that will serve as input to the overall system dynamics model in the set of experiments presented in this chapter.

Table 3. Future assessment for home telehealth

Innovation Characteristics	**Assessment**
Relative advantage	Medium or High
Compatibility	Medium or High
Complexity	Low
Network externality	High
Adoption effort	High
System or device	System
Selected cluster	Cluster 1 or 2

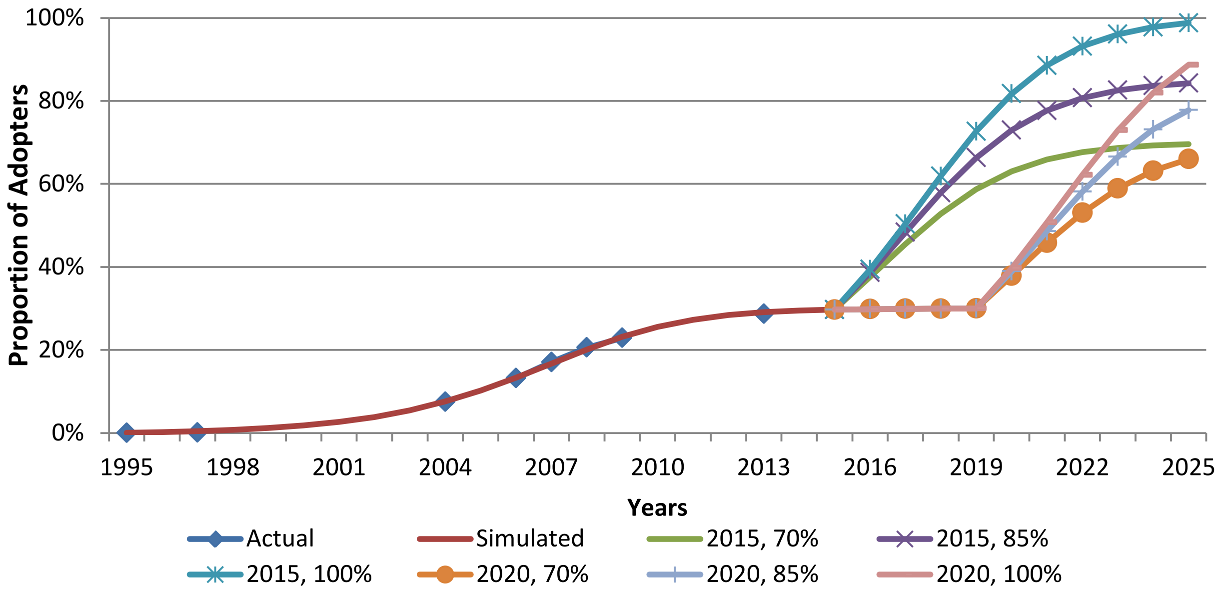

Figure 11. Projection of home telehealth diffusion

2.4.2. Patient Population Module

Based on the explanation in Section 2.3, the patient population in the system dynamics model is disaggregated by both age cohort and severity level. Three age sets are defined: 65 to 74, 75 to 85, and >85 years of age. According to (CMS, 2012), both per capita spending for Medicare FFS beneficiaries and utilization of healthcare services increase with the number of chronic conditions an individual has. Thus, the number of chronic conditions can provide a useful proxy for patient severity. We use four severity levels, determined according to the number of chronic conditions an individual has: very low (0 to 1 chronic conditions), low (2 to 3 chronic conditions), medium (4 to 5 chronic conditions), and high (6+ chronic conditions).

Table 4 provides parameter values for FFS enrollment rates by age group (percentage of the population in each age group that has enrolled in Medicare FFS). It also provides the percentage of persons in each age group of each severity level (based on numbers of chronic conditions) and the home healthcare admission rates for each age-severity group. It is assumed these rates will not change during the horizon of the computational study (through 2025). Population data between years 2015 and 2025 for each age group was taken from the (U.S. Census Bureau, 2014) and was used to model Population Change Rate and the initial stock of USA Elderly Population.

Table 4. Parameter values used in Patient Population Module

Variables	Sources	Values				
FFS Enrollment Rates	(CMS, 2013)	**65-74**	0.68			
		75-84	0.80			
		85+	0.82			
Chronic Condition Rates	(CMS, 2012)		**Very low**	**Low**	**Medium**	**High**
		65-74	0.37	0.34	0.20	0.09
		75-84	0.23	0.33	0.27	0.18
		85+	0.17	0.29	0.29	0.25
Home Healthcare Admission Rates	(CMS, 2012; Cubanski, Huang, Damico, Jacobson, & Neuman, 2010)		**Very low**	**Low**	**Medium**	**High**
		65-74	0.005	0.02	0.08	0.30
		75-84	0.02	0.04	0.16	0.35
		85+	0.02	0.21	0.27	0.47

2.4.3. Telehealth Use Module

The number of nurses employed in home healthcare is determined from Bureau of Labor Statistics data (2014). Average telehealth nurse capacity is assumed to be 100 patients per nurse (Broderick & Steinmetz, 2013; Darkins et al., 2008; Milburn, Hewitt, Griffin, & Savelsbergh, 2014). A number of pilot studies and surveys have evaluated the patient acceptance of home telehealth systems and all reported very high acceptance rates (85%-95%). These pilot studies and surveys do not provide details of patient acceptance rates based on age or severity level however, in the literature it is stated that patient acceptance of technology decreases as a patient's age and severity increase (Mattke et al., 2010; Wang et al., 2011). We use this information to estimate patient acceptance rates for each age-severity group. Our estimates are given in Table 5.

Table 5. Patient acceptance rates

Variable	Sources	Values				
			Very low	**Low**	**Medium**	**High**
Patient Acceptance	(Darkins et al., 2008; Dimmick et al., 2000; FAST, 2009; Fazzi Associates, 2008; Lindeman, 2011; Louis et al., 2003; Mattke et al., 2010; Wang et al., 2011)	**65-74**	0.95	0.95	0.95	0.90
		75-84	0.95	0.95	0.90	0.85
		85+	0.90	0.90	0.85	0.80

2.4.4. Healthcare Utilization Module

In this module, we include four healthcare visit types: hospital, emergency department, physician office, and skilled nursing. The latter refers to in-home visits by home healthcare nurses. The number of annual visits of each type per patient in each severity cohort (the Visit Rates), were estimated from Centers for Medicare & Medicaid Services reports and other related studies and are summarized in Table 6. Note that the visit rates do not vary based on age. Data to support variation along the age dimension is not available in the literature.

Table 6. Visit rates (visits per patient per year) for each patient group

Variables (Visit Rates)	Sources	Values			
		Very low	**Low**	**Medium**	**High**
Hospital	(CMS, 2012)	0.06	0.17	0.44	1.2
Emergency department	(CMS, 2012; Lochner, Goodman, Posner, & Parekh, 2013; Machlin & Soni, 2013)	0.2	0.5	0.8	2
Physician office	(CMS, 2012)	3.3	6.7	8.5	9.6
Skilled nursing	(CMS, 2012, 2013)	14	15.5	16	17.5

To estimate Telehealth Impact for each visit type, we have reviewed the results of a wide range of studies measuring the effect of home telehealth on hospitalization, ED visits, physician office visits, and skilled nursing visits. This research is typically associated with pilot studies of different home telehealth types for small groups of patients with different chronic conditions. Although the outcomes of these studies provide a wide range of impact estimates, they are consistent in reporting reduction in hospitalization, emergency department visit, and skilled nursing visits. The impact of home telehealth on physician office visits is ambiguous compared to the other visit types. Although home telehealth may avoid some unnecessary physician office visits, additional physician office visits may be expected due to early detection and avoided hospital or ED visits (Access Economics, 2010; Litan, 2008; Praxia Information Intelligence, 2007). The list of studies we examined regarding the effect of home telehealth is provided in the Appendix B.

According to our review, higher reductions were mostly seen in hospitalization and emergency department visits whereas generally lower reductions were seen in skilled nursing visits. For physician visits both negative and positive impacts are reported. Due to the challenge to estimate exact impact values from uncertain data in the home telehealth studies, we define three impact scenarios: optimistic (opt.), moderate (mod.), and pessimistic (pes.). These impact scenarios indicate home telehealth's success in reducing healthcare utilization. We assign different Telehealth Impact values for each visit type, based on estimates taken from the literature. That is, we used the estimates corresponding to the first quartile, second quartile (median value), and third quartile for each visit types. Then, we rounded these values to the nearest 5% value. Telehealth Impact values for each scenario are summarized in Table 7.

Table 7. Selected telehealth impact values

Visit Type	**Pessimistic Scenario**	**Moderate Scenario**	**Optimistic Scenario**
Hospitalization	30% decrease	50% decrease	60% decrease
Emergency department visit	30% decrease	45% decrease	60% decrease
Physician office visits	10% increase	0% change	10% decrease
Skilled nursing visits	25% decrease	30% decrease	40% decrease

2.4.5. Cost and Savings Module

Costs related to home telehealth provision can change according to the selected technology and the size of the home healthcare agency, among other things. For the purpose of this study, we conservatively estimate average Telehealth Device Cost and Annual Operating Costs based on the limited data provided in market research and pilot studies. The telehealth device is assumed to be replaced every five years so one-time costs are distributed over five years. To find the Nurse Monitoring Cost, the average nurse salary is divided by Average Telehealth Nurse Capacity (this was described in the Telehealth Use module). We rely on publicly available sources and studies for costs associated with visits. This data is summarized in Table 8.

Table 8. Parameter values used in Cost and Savings Module

Variable	Sources	Values
Telehealth Device Cost	(FAST, 2009; Milburn et al., 2014; The Greenlining Institute, 2009)	\$1,500/5
Annual Operating Costs	(FAST, 2009; Milburn et al., 2014; The Greenlining Institute, 2009)	\$200
Nurse Monitoring Cost (per year)	(Bureau of Labor Statistics, 2014)	\$55,000/100
Average Visit Charge (Hospital)	(Pfuntner, Wier, & Steiner, 2013)	\$11,600
Average Visit Charge (ED)	(AHRQ, 2009)	\$1,306
Average Visit Charge (PO)	(Milburn et al., 2014; NEHI, 2009)	\$160
Average Visit Charge (SN)	(CMS, 2013)	\$159

2.5. Experiments

In the computational study presented in this paper, the quantitative system dynamics model described above is implemented using the STELLA 10.0.6 simulation tool.

Uncapacitated models

We first run uncapacited models in which there are no limits on telehealth capacity that patients can use. The purpose of uncapacitated models is to determine whether home telehealth is cost-effective for each patient cohort. In this case, we set Telehealth Patients equal to Telehealth Demanding Patients in the Telehealth Use Module. In each run, we set Telehealth Coverage as 1 for different patient cohorts.

Capacitated models

For capacitated experiments, we limit the Telehealth Nurse Dedication Ratio as 10%. With capacity limited in this way, it is not possible to allocate telehealth units to all patient groups who present demand for them. The application of capacitated models is illustrated using two telehealth allocation strategies, namely Proportional Allocation (PA) and Severity-based Allocation (SA). In the Proportional Allocation strategy, telehealth units are allocated to patient groups based on their proportion in the overall patient population whereas in the Severity-based Allocation patient groups with higher severity have priority to use telehealth units. That is, a patient from a lower severity group cannot receive a telehealth unit until all patients from all higher severity groups have received them. Let S represent the set of severity groups, and let D_i and T_i represent the demand and telehealth users in patient group i in S, respectively. Let C be the telehealth capacity. The parameters D_i, T_i, and C are measured in number of patients. Then, the Proportional Allocation strategy is formulated as follows:

$$T_i = \min\left(C\frac{D_i}{\sum_{i \in S} D_i}, D_i \right). \tag{5}$$

Alternatively, the formulation for the Severity-based Allocation strategy is:

$$T_i = \min\left(\max\left(C - \sum_{i \in P_i} D_i, 0 \right), D_i \right), \tag{6}$$

where P_i is the set of severity groups having higher priority than group i.

2.6. Model Validation

Validation of system dynamics models is seen a continuous process that can take place in every step of modelling (Barlas, 1996; Forrester & Senge, 1980). Several tests can be performed to validate system dynamics models (Sterman, 2000).

2.6.1. Structure Validation

The purpose of structure tests is to establish confidence in the structure of the model by checking the consistency between the model and the real world. The model was tested under the following structure validation tests:

Structure and Parameter Confirmation Tests

Parameter values and mathematical equations in each module are explained in detail in Section 2.3 and 2.4. To populate Bass diffusion model parameters in the Telehealth Diffusion Module, we derive data from historical diffusion and assessment of innovation characteristics for home telehealth. Values of all other factors in the model are derived from home telehealth case studies, official reports and national statistics.

Dimensional Consistency Test

This test assesses whether units of all variables are specified and both sides of all equations are balanced dimensionally. The model was tested for dimensional consistency by using the “Check Units” feature in Stella.

Extreme Conditions Test

The model should respond logically when it is simulated with extreme values. This test is conducted by assigning extreme values to selected variables and comparing the simulated output to the observed (or anticipated) behavior in real life. In this study, extreme conditions tests were performed with specific parameters and the model generated expected behaviors. The details of the extreme condition tests are given in Appendix C.

2.6.2. Behavior Validation

Behavior validation tests examine whether the model can accurately reproduce the historical behavior patterns (e.g. periods, frequencies, trends, etc.) of the real system. Two tests were carried to assess the behavior validation of the model.

Behavior Reproduction Tests

Behavior reproduction tests analyze the pattern match between simulated and historical data. The model's main behavioral output is the S-shaped diffusion curve of home telehealth. Due to the S-shaped pattern, the model has a non-stationary behavior and thereby graphical/visual comparison of behavior-pattern characteristics can be more suitable (Barlas, 1996). As explained in Section 2.4.1, the model is able to generate a diffusion pattern similar to the historical trend.

Behavior Prediction Tests

Unlike behavior reproduction tests, behavior prediction tests focus on the future behavior. In Section 2.4.1, we explicitly examine the impact of a policy improvement for home telehealth technology and services on the diffusion pattern. The model is responsive to the policy improvement and the simulated output pattern is within a reasonable range.

2.7. Results

In this section, results are presented for both uncapacitated and capacitated experiments. For each allocation strategy, all impact scenarios are tested.

2.7.1. Uncapacitated Models

The annual net benefit per patient receiving a telehealth unit is reported in Table 9 for each patient severity group for pessimistic, moderate, and optimistic telehealth impact scenarios. Providing home telehealth to the patients in low, medium, and high severity groups is cost effective in all impact scenarios. Providing telehealth to very low severity patients is cost effective in the moderate and optimistic scenarios. Thus, patients with very low severity level are excluded from consideration in the capacitated models by setting their Telehealth Coverage as 0 in those experiments.

Table 9. Net benefits ($)

Patient Cohorts	Pessimistic Scenario	Moderate Scenario	Optimistic Scenario
Very low severity	-370	83	467
Low severity	123	969	1,618
Medium severity	1,167	2,735	3,792
High severity	4,312	7,920	10,135

2.7.2. Capacitated Models

Figure 12 presents the simulated demand for and supply of home telehealth through 2025, according to the SD model. The contribution of different patient cohorts to overall home telehealth demand are depicted as stacked bars. Note that throughout the simulation horizon, almost half of the total demand results from high severity patients while medium and low severity patients constitute approximately 34 percent and 17 percent of the total demand each year, respectively. The total demand for telehealth is projected to rise from 3,139,693 persons in 2015 to 4,228,404 persons in 2025; a 25.7% growth. This expected increase is primarily due to the increase in the elderly population during the simulation horizon. The supply of home telehealth (home telehealth capacity) rises from one-half million in 2015 to 2.8 million in 2025; a 79% increase. The supply increase is due to increases in numbers of adopted agencies and in the telehealth nurse workforce. Despite a more than fourfold increase, telehealth capacity is lower than the demand for it throughout the entire simulation horizon.

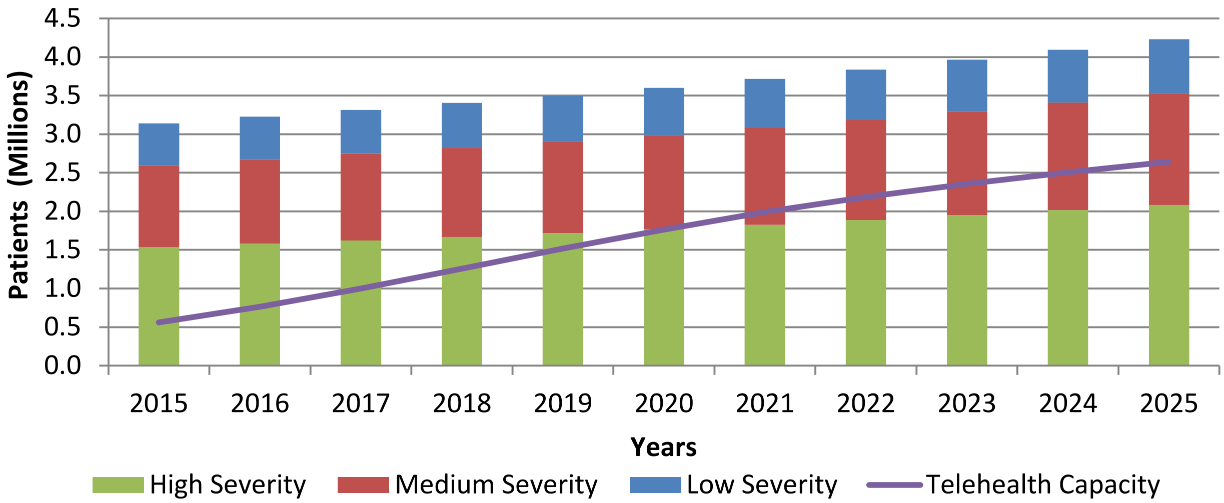

Figure 12. Telehealth capacity and patient demand

Figure 13 depicts the distribution of telehealth throughout the simulation horizon that results when the two different allocation strategies are used. The y-axis describes the number of patients in each severity group who receive telehealth. Figure 13a corresponds to the Severity-based Allocation strategy. Note that for years 2015-2020, the high-severity group is the only patient group receiving telehealth. This is because the demand of this group exceeds the capacity of telehealth until year 2021. For example, in year 2019, approximately 1.6 million high-severity patients receive telehealth; this is the capacity of telehealth in 2019, while the demand of the high-severity group is 1.7 million patients. In year 2021, patients with medium severity begin to receive telehealth in addition to those with high severity. By year 2025, there is capacity for approximately 2 million high severity and one-half million medium severity patients to receive home telehealth. Low severity patients never receive telehealth according to this strategy. Figure 13b presents the results of the Proportional Allocation strategy. Compared with the Severity-based strategy, it generates a more equitable distribution of telehealth among patient severity groups. The patient groups receive home telehealth proportionally to their share of the whole patient population. For example, the distribution of low-medium-high severity groups in the overall patient population is 17%-34%-49%. In 2015 the numbers of patients in low, medium and high severity groups receiving telehealth are 97,235, 189,700, and, 274,687, respectively. Thus, the low severity group is allocated 17% of telehealth capacity, while medium and high severity groups are allocated 34% and 49%. By year 2025, the total number of patients receiving telehealth increases to over 2.6 million. However, the percent distribution across the severity groups remains the same.

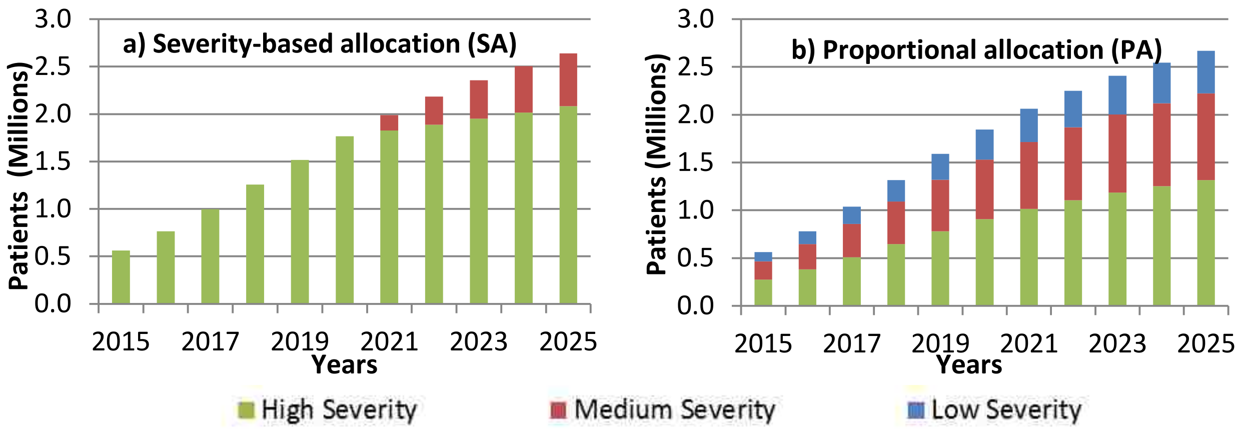

Figure 13. Patients receiving telehealth

The system dynamics model provides further insights by projecting overall healthcare utilization numbers for each service type. Utilization of these services depends not only on the allocation strategy used but also the impact scenario. Hence, the results of six simulation runs are presented: Severity-based Allocation with three impact scenarios (SA- opt, SA-mod, and SA-pes) and Proportional Allocation with three impact scenarios (PA-opt, PA-mod, and PA-pes). Figure 14 presents hospitalization and ED visit projections for each simulation run, while Figure 15 presents the physician office and skilled nursing visits. These outputs are separated into the two figures due to the difference in their scales (millions of hospitalizations/ED visits compared with tens of millions of physician office and skilled nursing visits). Observations that can be deduced from the two figures are as follows. First, for all service types, the SA strategy results in lower service utilizations than the PA strategy, regardless of impact scenario. For example, it can be seen in Figure 14a and 14b that ED utilization in year 2025 is under 4 million using the SA strategy and over 4.4 million using the PA strategy. This occurs because the higher severity groups, with the highest baseline service utilizations, benefit the most from the telehealth impact. The SA allocates more telehealth devices to the higher severity groups than the PA strategy does. A second

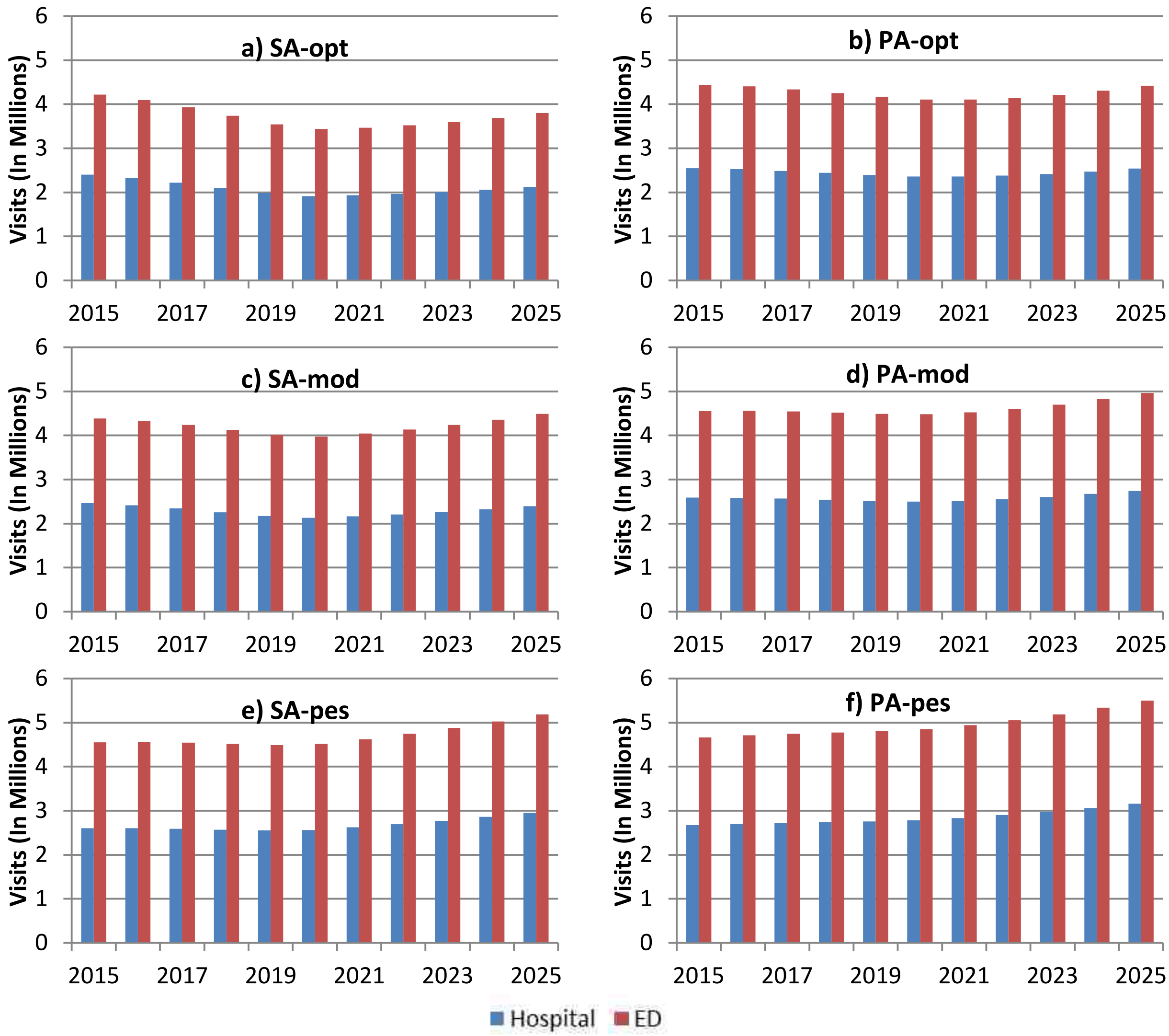

Figure 14. Hospitalization and ED visits

observation applies to Figure 14a, 14b, and 14c, corresponding to SA-opt, PA-opt, and SA-mod for hospital and ED visits. In these figures, the data series follow first a decreasing, then increasing trend. For example, in Figure 14a the number of hospitalizations per year decreases each year until 2020, and then increases each year from 2021 to 2025. This can be explained by the relationship between telehealth diffusion and the rate of demand increase. The size of each severity group increases monotonically throughout the simulation horizon, and thus does the demand for each service type, such as hospitalizations. However, telehealth diffusion follows an S-shaped curve. Initially, the rate of diffusion is higher than the rate of demand increase, such that the telehealth impact is able to decrease the number of hospitalizations required overall. Eventually (by year 2021) the rate of demand growth is faster than the rate of diffusion. This trend is most apparent in the figures corresponding to the SA strategy because telehealth offers the most benefit for the high severity patient group, which is favored under the SA strategy. It is also most apparent in the figures corresponding to hospital and ED visits because their telehealth impacts are much larger than for PO and SN visits (see Table 7).

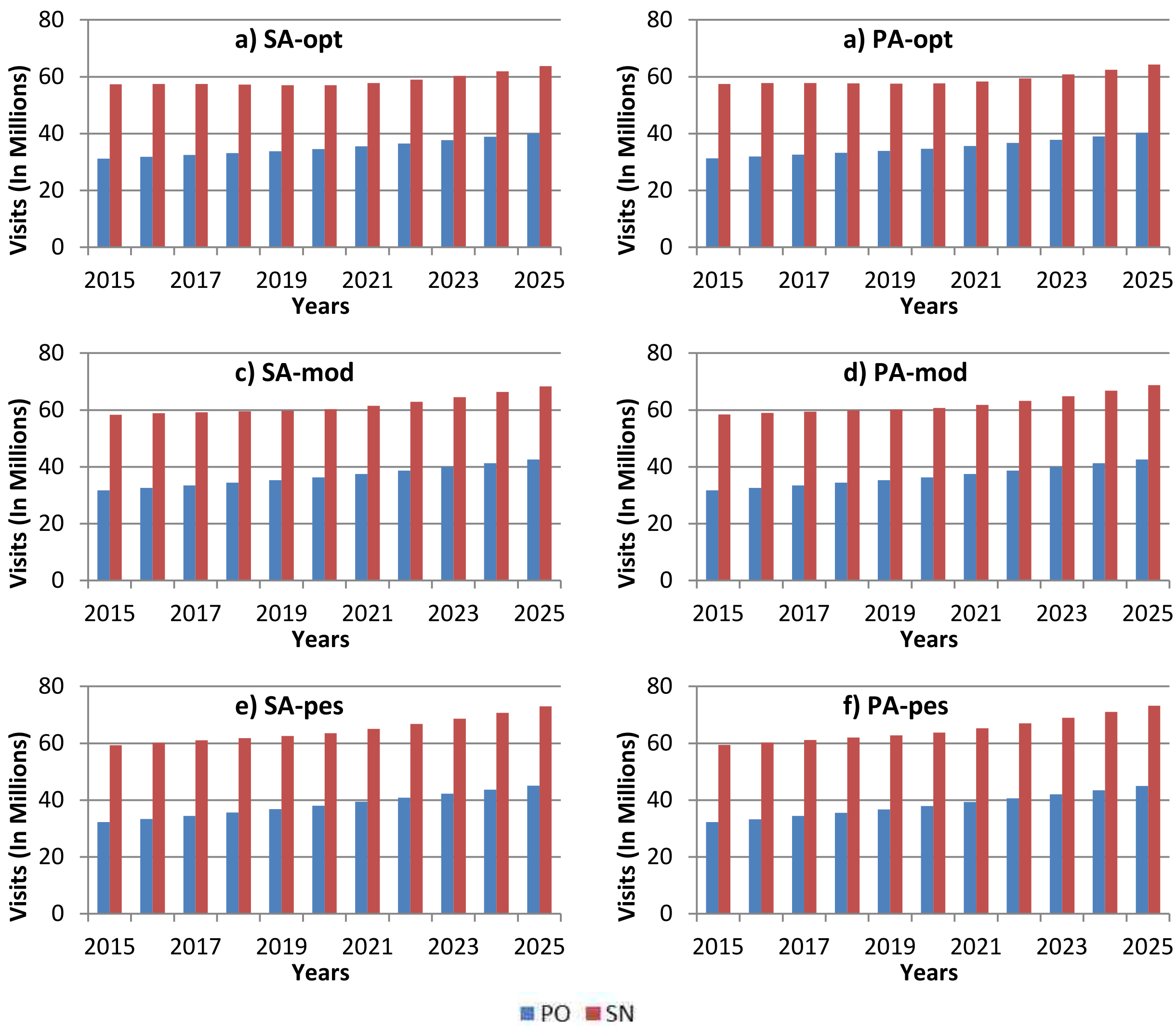

Figure 15. Physician office and skilled nursing visits

The annual net benefits and average net benefits per telehealth patient, both measured in dollars, are provided in Figure 16 for each experiment. As expected, experiments using the SA strategy result in greater net benefits than those using the PA strategy. Once the vast majority of home healthcare agencies have adopted home telehealth technology (98% of all agencies by 2025), annual net benefits peak at 23.3 billion dollars in the SA-opt experiment and 17.5 billion dollars in the PA-opt experiment. Estimated annual net benefits are much more conservative in the SA-pes and PA-pes experiments, reaching maximum values of 10.4 and 7.5 billion dollars, respectively. Note that in all experiments, annual net benefits increase at a faster rate until year 2020 before slowing down in 2021. This marks when the annual rate of HT diffusion begins to slow according to its S-shaped curve. This difference is most pronounced in those experiments where the telehealth impact is also most pronounced (i.e., SA-opt). When considering the net benefit per telehealth patient in Figure 16b, the three experiments corresponding to the SA strategy yield a different trend than the PA strategy. In the SA strategy, net benefit per telehealth patient decreases markedly after year 2020. This is because patients from both the high and medium severity groups receive telehealth after that point in time, while only high severity patients were receiving them previously. The net benefit per patient is greatest for the high severity group. As expected under the PA strategy, the net benefit per patient does not change from year to year, because the relative distribution of telehealth among severity groups does not change.

Sensitivity analysis on uncertain parameters and breakdown analysis on Total Savings of Telehealth are provided in Appendix D and Appendix E, respectively.

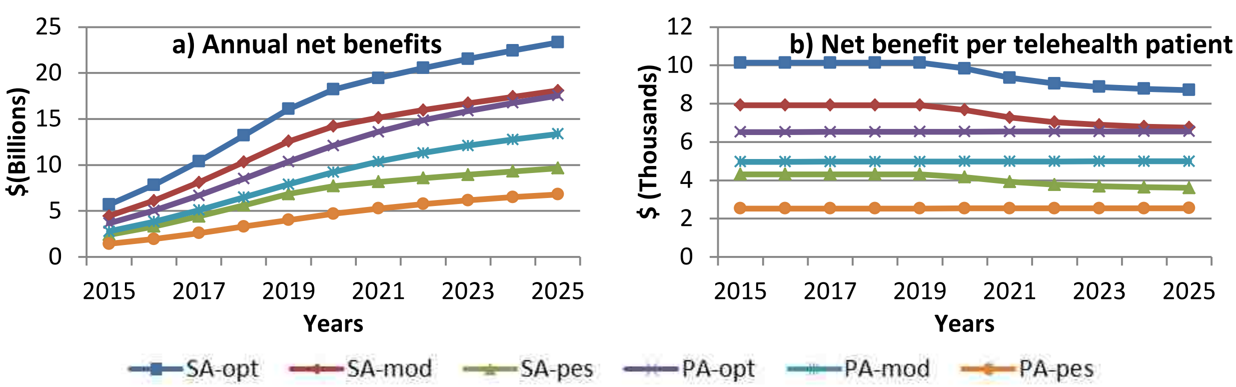

Figure 16. Annual net benefits and average net benefit per telehealth patient

2.8. Conclusion

This study aims to utilize SD to examine the long-term macro-level impacts of home telehealth diffusion in the US homecare industry. The methodology presented includes a Bass diffusion model to examine the home telehealth diffusion pattern over time. Generating the diffusion model required an examination of home healthcare technology with respect to a number of innovation characteristic dimensions. Then, the diffusion model was embedded within a larger SD model to capture the impacts of the HT diffusion at a macro level in terms of healthcare service utilization and healthcare spending. Specifically, the telehealth benefits explicitly considered in the model were visit reductions for four healthcare service types: number of hospitalizations, number of emergency department (ED) visits, number of physician office (PO) visits, and number of skilled nursing (SN) visits. The patient population in the simulation study was comprised of a group representing the majority of home healthcare users: Medicare Fee-for-Service (FFS) enrollees with multiple chronic conditions.

We classified patients in terms of their severity level by using the number of chronic conditions a patient has as a proxy for their severity. Then, we studied two different allocation strategies for telehealth, namely, Proportional Allocation (PA) and Severity-based Allocation (SA). The first strategy considers an equitable distribution of limited telehealth capacity across patient groups while the latter prioritizes allocation towards those with the most potential to benefit from telehealth (high severity patients). Due to the uncertainty in the estimation of telehealth's impact on the reduction of service types, we define optimistic, moderate, and pessimistic impact scenarios and use them to compare the allocation strategies. In the computational study, the SA strategy results in lower healthcare service utilization and greater net benefit than the PA strategy.

The model requires high quality data in order to demonstrate accurate results. The data used in our model was extracted from home telehealth case studies, official reports and national statistics. The literature provides results for home telehealth pilot studies with small numbers of patients across limited time periods. The results of these pilot studies are highly variable, providing a wide range of telehealth impact observations. Due to this, estimating population level telehealth impacts is challenging. Thus, the results presented in this paper should be interpreted with caution. The model can be used to obtain more reliable results as higher quality data becomes available. Specifically, it would be helpful to have a validated estimate for telehealth impact, if results across various demonstration studies begin to converge. It would be especially helpful if the impact could be determined separately for each age and severity group. Finally, FFS enrollment rates, home healthcare admission rates and chronic condition rates are assumed to be constant during our simulation horizon. If these rates are expected to change significantly by the year 2025, updated parameter estimates may lead to different results. However, we expect that overall benefits of telehealth would only increase in that situation, not decrease, as the population ages and chronic disease diagnoses continue to rise. Our results represent a conservative lower bound on the potential impact of telehealth in that regard.

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Appendix A: Bass Model Parameter Estimation

We use the below non-linear model to select Bass model parameters.

Data elements:

A : Aggregate error value.

a : The coefficient of external influences.

b : The coefficient of internal influences.

m : The maximum expected proportion of total adopters.

Objective function:

Minimize A

Subject to:

$0 < a \leq 0.1$,

$0 \leq b \leq 0.5$,

$0.3 \leq m \leq 0.7$,

$a, b, m \in \mathbb{R}^{+}$.

To calculate the aggregate error value (A), we consider different measures that have been used to estimate the accuracy of Bass models (Hsiao, Jaw, & Huan, 2009; Lee, Kim, Park, & Kang, 2014; Venkatesan, Krishnan, & Kumar, 2004). The lower the performance measures, the better the prediction model. These measures are formulated below:

Root mean squared error (RMSE): $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$, Mean squared error (MSE): $MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2$,

Mean absolute error (MAE): $MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$,

where y_i is the actual (historical) value and $\hat{y}_i$ is the predicted value by the model in time period i . Based on the Bass diffusion model, the predicted proportion of adopters, $\hat{y}_i$, is calculated by;

$$\hat{y}_i = \left(a + \frac{b\hat{y}_{(i-1)}}{m}\right)\left(m - \hat{y}_{(i-1)}\right) + \hat{y}_{(i-1)} .$$

The non-linear model is solved for each measure in Microsoft Excel Solver. This software uses the Generalized Reduce Gradient Algorithm for optimizing non-linear models. Note the software cannot guarantee whether a local or global optimum has been found. The results are provided in Table A.1. The values are close to each other so we decided to use the average values of each parameter in the system dynamics model.

Table A.1. Parameter estimations

Bass Model Parameters	**RMSE**	**MSE**	**MAE**
a	0.00339	0.00339	0.00333
b	0.45213	0.45214	0.45122
m	0.30000	0.30000	0.30000

Appendix B: Impact of Home Telehealth

Table B.1. Studies reporting the impact of home telehealth

Authors	Interventions	Patients	Outcomes
(Meyer, Kobb, & Ryan, 2002)	TM, IHT, messaging	Multiple chronic conditions	ED visits reduced by 29% Hospitalization reduced by 55% PO visits reduced by 20%
(Noel, Vogel, Erdos, Cornwall, & Levin, 2004)	TM	Elderly with chronic conditions	ED visits reduced by 19% Hospitalization reduced by 19% PO visits increased by 10%
(Finkelstein et al., 2006)	TM, IHH	Elderly with chronic conditions	Hospitalization reduced by 58%
(Bolch, Rosengart, & Piette, 2009)	TM	Multiple chronic conditions	Hospitalization reduced by 54%
(Woods & Snow, 2013)	TM	Multiple chronic conditions	ED visits reduced by 64% Hospitalization reduced by 66%
(Darkins et al., 2008)	TM, IHT, messaging	Multiple chronic conditions	Hospitalization reduced by 19%
(Brookes, 2005)	TM	Elderly with HF	Hospitalization reduced by 72%
(Kobb, Hoffman, Lodge, & Kline, 2003)	TM, IHT	Elderly with chronic conditions	Hospitalization reduced by 60% ED visits reduced by 66%
(Broderick & Lindeman, 2013)	TM	HF	Hospitalization reduced by 51%
(Broderick & Steinmetz, 2013)	TM	Multiple chronic conditions	Hospitalization reduced by 62%
(Myers et al., 2006)	TM	HF	SN visits reduced by 29%
(Britton, 2010)	TM	Mostly elderly with chronic conditions	ED visits reduced by 81% Hospitalization reduced by 71%
(Barnett et al., 2006)	TM, IHT	Elderly with diabetes	Hospitalization reduced by 25%
(Alston, 2009)	TM	HF, COPD	SN visits reduced by 25% Hospitalization reduced by 44%
(UK Department of Health, 2011)	TM, IHT	Diabetes, heart failure, COPD	ED visits reduced by 20% Hospitalization reduced by 14%
(Marshall, 2009)	TM	Elderly with COPD	Hospitalization reduced by 50%
(Lehmann, Mintz, & Giacini, 2006)	TM	Elderly with HF	ED visits reduced by 33% Hospitalization reduced by 29%
(Benatar, Bondmass, Ghitelman, & Avitall, 2003)	TM	Mostly elderly with HF	Hospitalization reduced by 45%
(Chumbler, Neugaard, Ryan, Qin, & Joo, 2005)	TM	Veterans with diabetes	Hospitalization reduced by 52%
(Jerant, Azari, & Nesbitt, 2001)	IHT	HF	ED visits reduced by 61% Hospitalization reduced by 41%
(Schneider, 2004)	TM	HF	Hospitalization reduced by 84% SN visits reduced by 55%
(NEHI, 2004)	TM	HF	Hospitalization reduced by 32%

Table B.1. Studies reporting the impact of home telehealth (Cont.)

Authors	**Interventions**	**Patients**	**Outcomes**
(Trappenburg et al., 2008)	TM	Lung disease	PO visits reduced by 17%
(Cleland et al., 2005)	TM	HF	PO visits increased by 71%
(Takahashi et al., 2010)	TM	Elderly with chronic conditions	ED visits reduced by 36% Hospitalization reduced by 43%
(Maeng et al., 2014)	TM	Elderly with chronic conditions	Hospitalization reduced by 23%
(Johnston, Wheeler, Deuser, & Sousa, 2000)	IHT	Elderly with chronic conditions	PO visits increased by 12%
(Huddleston & Kobb, 2004)	TM	Mostly elderly with chronic conditions	PO visits reduced by 4% Hospitalization reduced by 43% ED visits reduced by 54%

TM: Telemonitoring, IHT: Interactive home telehealth

Appendix C: Extreme Conditions Tests

Extreme conditions tests were performed by setting extreme values to certain selected parameters and observing the generated outputs of the model. The results of the extreme conditions tests are described below.

Extreme Condition Test 1: Changing Proportion of Adopters

In this test, we excluded the Telehealth Diffusion module and set the Proportion of Adopters to 30% and 100% beginning with 2015. The simulation shows that telehealth capacity in a 100% Proportion of Adopters case is higher than the capacity with a 30% Proportion of Adopters and telehealth capacity in the S-shaped diffusion is in between them through years.

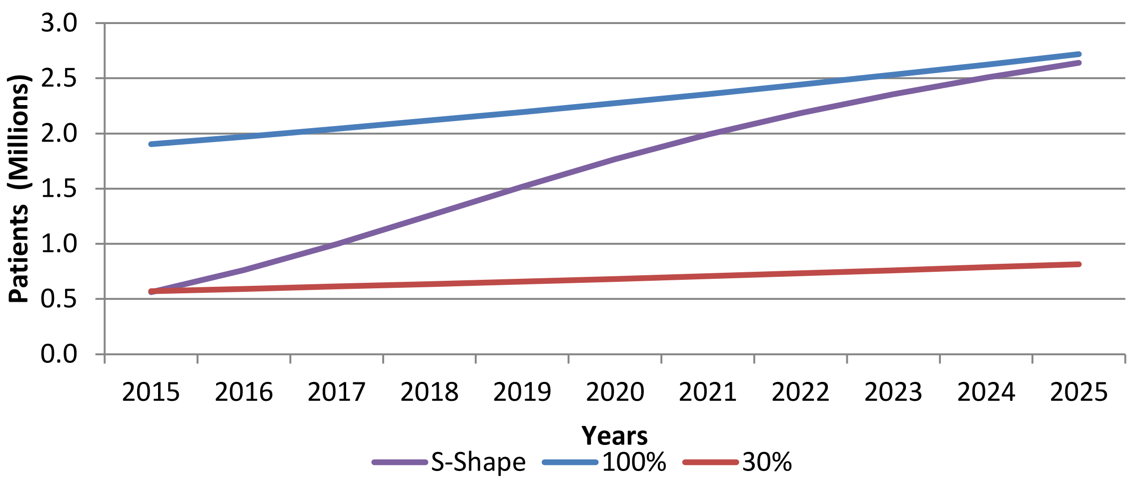


Figure C.1. Telehealth capacity under extreme conditions of Proportion of Adopters

Extreme Condition Test 2: Changing Patient Acceptance

In our model, we define Patient Acceptance for each age-severity group. If Patient Acceptance is lower, then the demand for telehealth should decline. To test this, we decrease Patient Acceptance rates by 50%. It is apparent that the simulation properly responds to this extreme condition.

Table C.1. Extreme values for Patient Acceptance

		Extreme Condition Values			
		Very low	**Low**	**Medium**	**High**
Patient Acceptance	**65-74**	0.475	0.475	0.475	0.450
	75-84	0.475	0.475	0.450	0.425
	85+	0.450	0.450	0.425	0.400

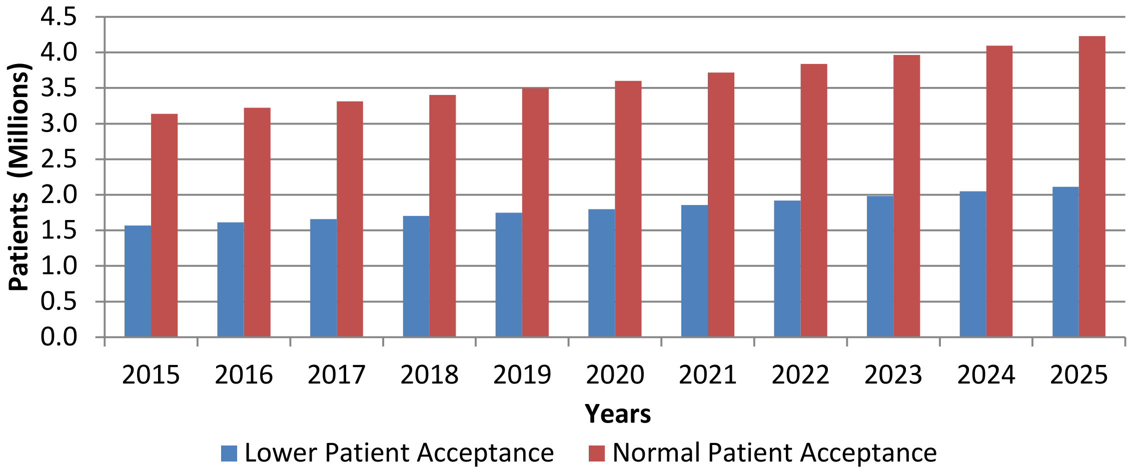


Figure C.2. Telehealth demand under extreme conditions of Patient Acceptance

Extreme Condition Test 3: Changing Average Telehealth Nurse Capacity

We tested two extreme values of Average Telehealth Nurse Capacity (i.e. 20 and 200 patients per year).

As seen in Figure C.3., Telehealth Capacity increases as Average Telehealth Nurse Capacity increases.

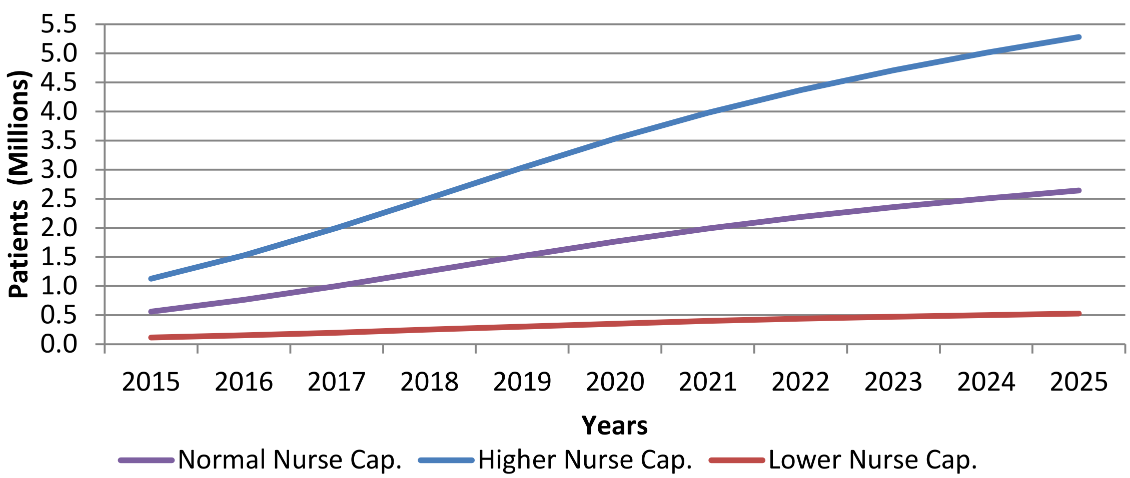


Figure C.3. Telehealth capacity under extreme conditions of Average Telehealth Nurse Capacity

Extreme Condition Test 4: Changing Telehealth Coverage

Telehealth Coverage parameter denotes whether certain patient groups are covered for telehealth service or not. According to the Severity-based Allocation strategy, patient groups with higher severity have priority to use telehealth units. In this test, we change this strategy to the opposite, in that patient groups with lower severity have higher priority to use telehealth units. The simulation responded properly to this extreme allocation strategy (see Figure C.4)

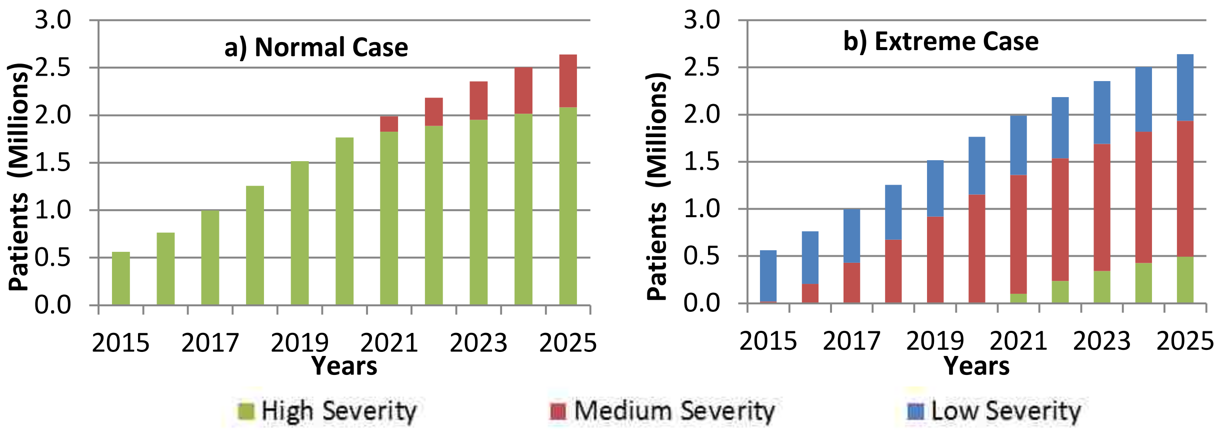


Figure C.4. Patients receiving telehealth

Extreme Condition Test 5: Changing Telehealth Impact

The telehealth Impact parameter takes on a value between 0 and 1 for each service type to represent the percent reduction in visits for that service type that can be expected when telehealth is used. If Telehealth Impact is zero, then we wouldn’t expect to see any reduction in healthcare utilization. As it can be seen in Figure C.5, the simulation produces higher healthcare utilization numbers for each service type.

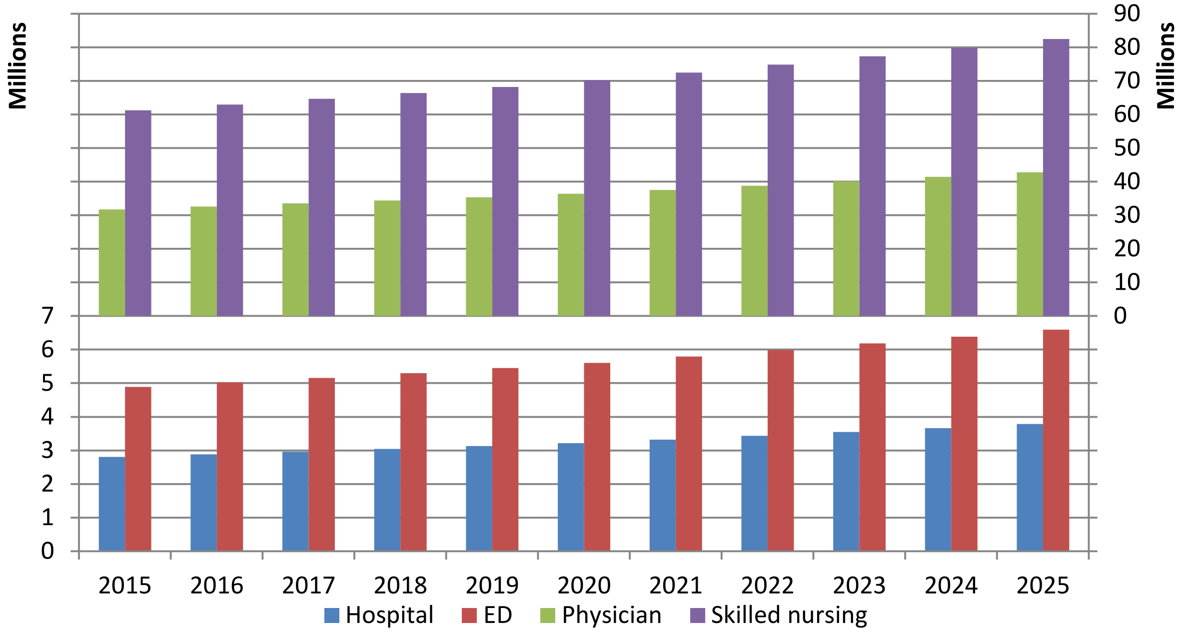


Figure C.5. Healthcare utilization with zero Telehealth Impact

Appendix D: Sensitivity Analysis

Sensitivity analysis identifies the impact of uncertain factors on simulation results. First, we applied statistical screening method (Ford & Flynn, 2005) for sensitivity analysis. Statistical screening method identifies the importance of model parameters by observing the correlation coefficients between the main output variable and model parameters at different time periods in the simulation. The correlation coefficient at time period t (r_t) is calculated by the formula below:

$$r_t = \frac{\sum\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum\left(X_i - \overline{X}\right)^2\left(Y_i - \overline{Y}\right)^2}}, \tag{D.1}$$

Where X_i is the selected model parameter at run i and Y_i is the model's main output at run i. The correlation coefficient ranges from -1 to +1.

Annual Net Benefit is determined as the model's main output and the selected model parameters and the corresponding distributions are provided in Table D.1. The number of runs is selected as 50 and a period of 11 years (2015-2025) is defined as the horizon to run the sensitivity analysis test.

Table D.1. Sensitivity analysis parameters

Parameter	**Ranges of Uncertainty**	**Units**
Diffusion Speed (b)	Uniform (0.3, 0.5)	Dimensionless
Saturation Level	Uniform (0.7, 1.0)	Percentage
Average Telehealth Nurse Capacity	Uniform (80, 120)	Number of patients per nurse/year
Dedication Ratio	Uniform (0.08, 0.12)	Percentage
Telehealth Impact on Hospitalization	Uniform (0.3, 0.6)	Percentage
Telehealth Impact on ED Visits	Uniform (0.3, 0.6)	Percentage
Telehealth Impact on PO Visits	Uniform (-0.1, 0.1)	Percentage
Telehealth Impact on SN Visits	Uniform (0.25, 0.4)	Percentage

Figure D.1 shows the time series of the correlation coefficients in each allocation strategies. The parameters with an $|r| > 0.4$ can be considered to have an impact in the main output. All the high influence parameters have positive correlations with Annual Net Benefit. Telehealth Impact on hospitalization, Average Telehealth Nurse Capacity, and Dedication Ratio emerge as the most important parameters through the whole simulation period, implying sensitivity analysis may be most important for these three parameters. Saturation Level has an increasing correlation and after 2018 it becomes the fourth dominant parameter. Diffusion Speed has a nonlinear correlation over time. The correlation coefficient for Diffusion Speed increases till 2018 and then constantly falls down during the rest of the simulation. The results of the statistical screening method provide insights on the model structure and identify the relevant model parameters. Future data collection effort should prioritize the most relevant model parameters. This would able us obtain more accurate simulation outputs.

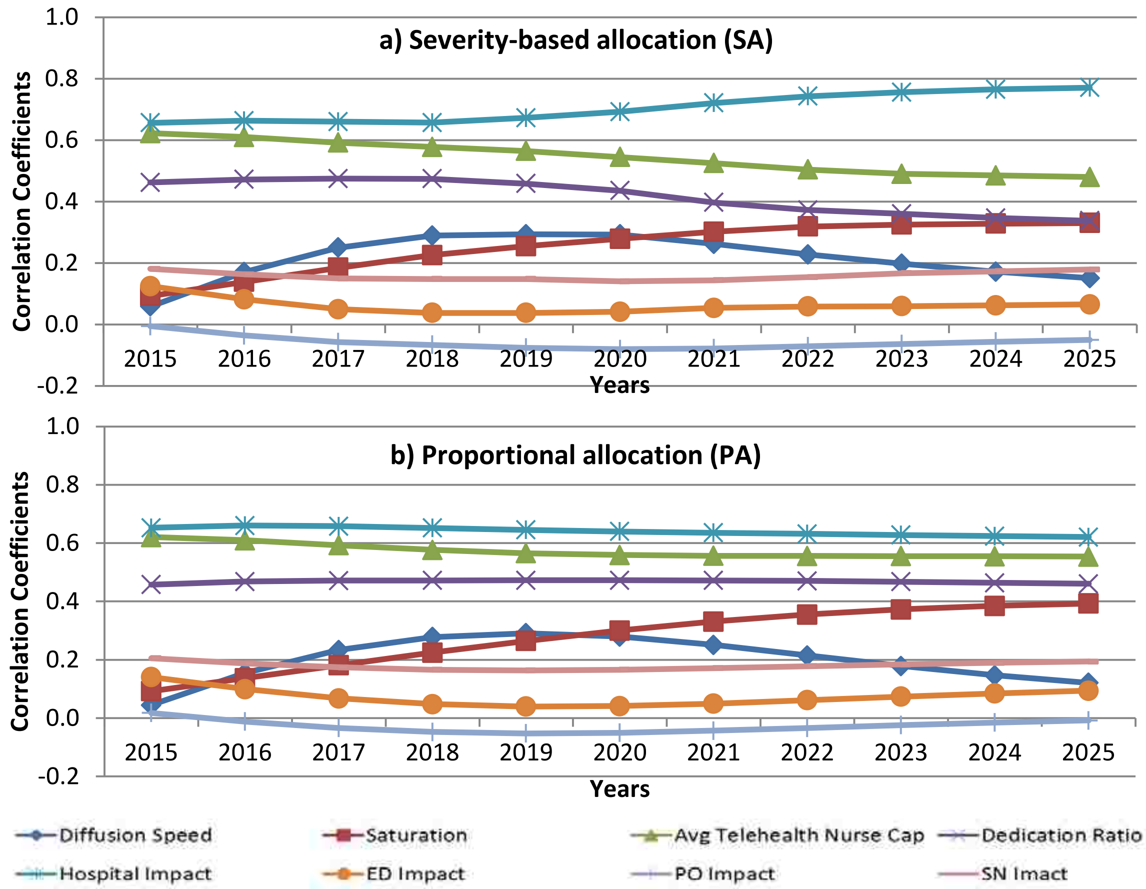


Figure D.1. Correlation coefficient plots

To see the individual impacts of the high influence parameters (e.g. the parameters with an $|r| > 0.4$), we employ one-at-a-time sensitivity analysis. The parameters of interest are Telehealth Impact on Hospitalization, Average Telehealth Nurse Capacity, and Dedication Ratio.

Telehealth Impact on Hospitalization

The system dynamics model assumes a 30% decrease, 50% decrease, and 60% decrease in hospitalization for pessimistic, moderate, and optimistic scenarios, respectively. To apply one-at-a-time sensitivity analysis on this parameter, we change its values ±20% in each scenario and observe Annual Net Benefit. For all cases, the Annual Net Benefit increases as home telehealth's success in reducing hospitalization increases.

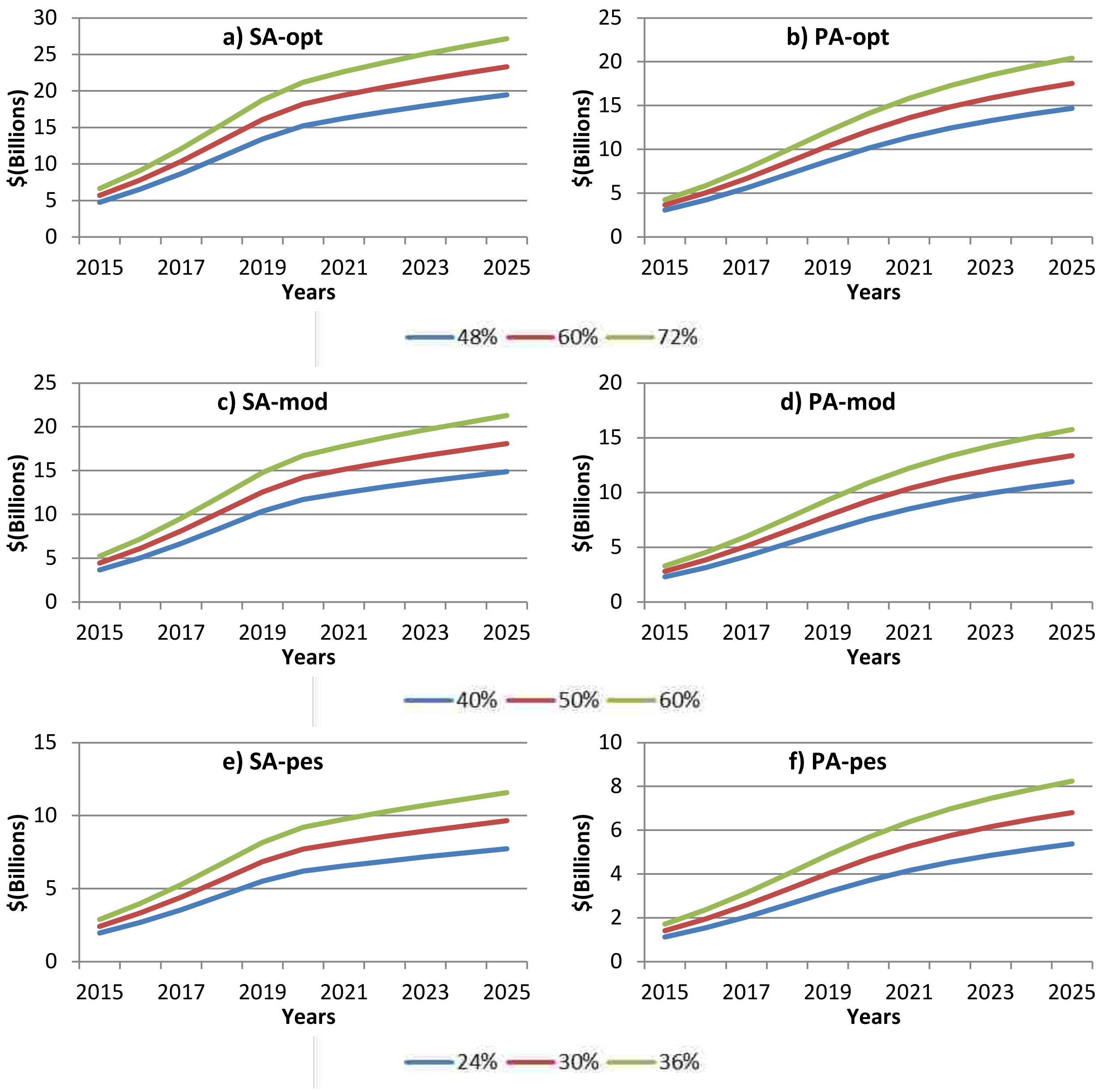


Figure D.2. Sensitivity analysis - Telehealth Impact on Hospitalization

Average Telehealth Nurse Capacity

The system dynamics model assumes that a telehealth nurse can provide service to 100 patients annually on average. We change this parameter's values ±20% in each scenario and observe Annual Net Benefit. Annual Net Benefit is more sensitive to the changes in average telehealth nurse capacity in proportional allocation strategy cases.

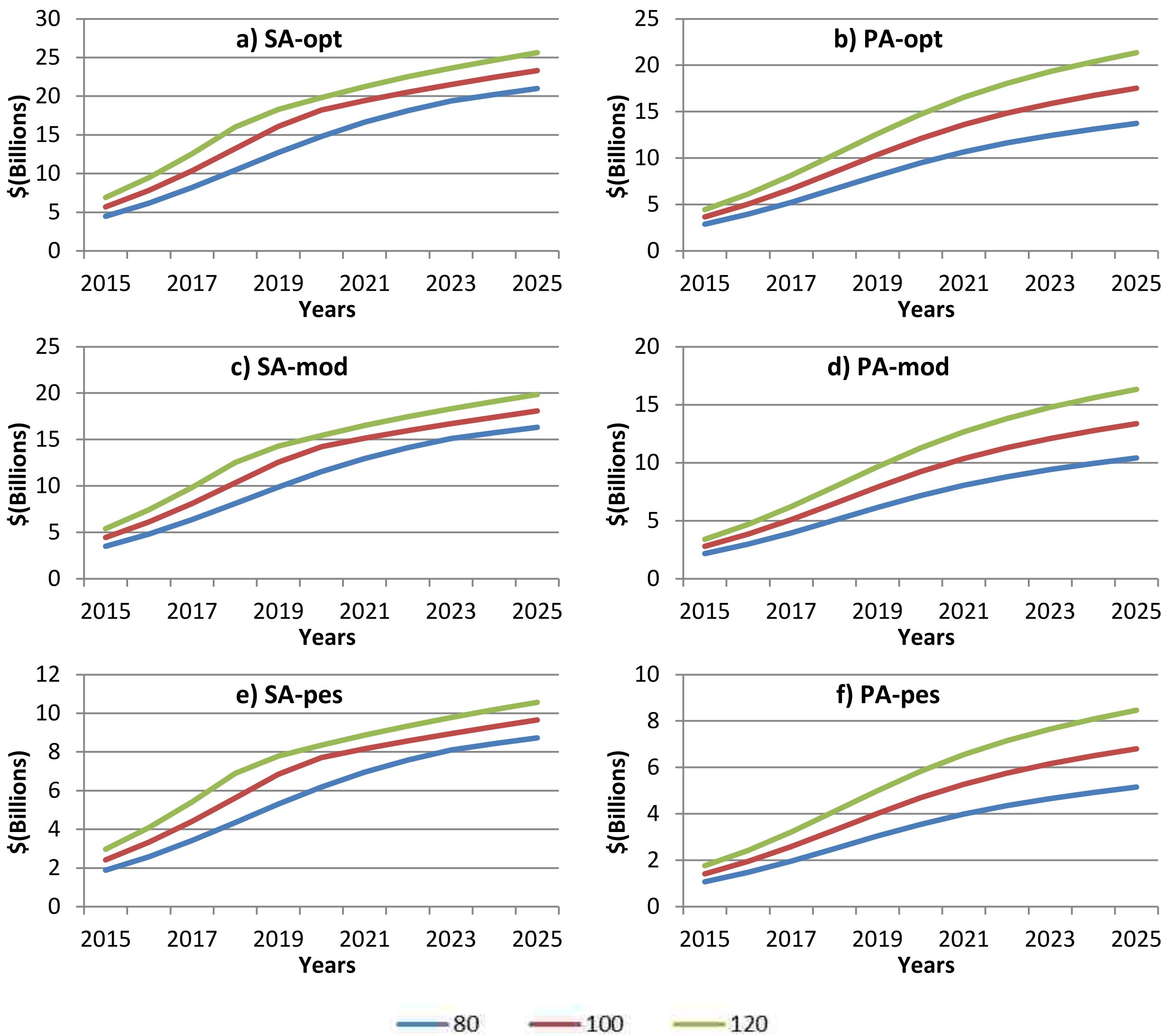


Figure D.3. Sensitivity analysis - Average Telehealth Nurse Capacity

Dedication Ratio

This parameter represents the represents the percentage of nurses allocated to home telehealth monitoring and it is assumed to be 10% in the model. The model outputs reflecting ±20% of change in the value of the parameter is presented. Proportional allocation cases are more sensitive to dedication ratio than severity-based allocations cases.

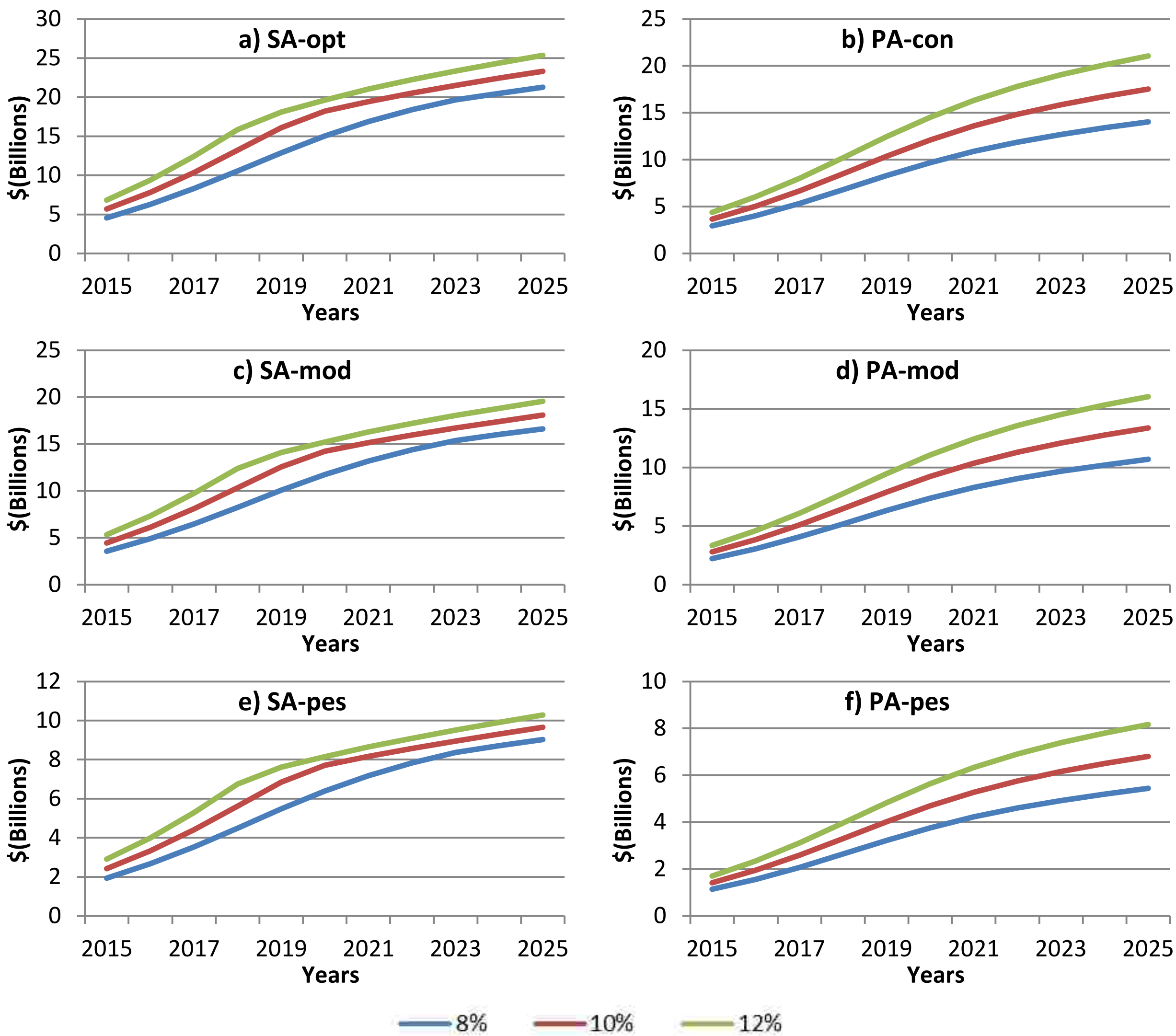


Figure D.5. Sensitivity analysis - Dedication Ratio

Appendix E: Breakdown Analysis

The total cost of telehealth in each year is provided in Table E.1. These costs are the same regardless of which allocation strategy and telehealth impact scenarios are considered, as those factors do not impact telehealth system cost.

Table E.1. Total cost of telehealth

Years	Total Cost
2015	$ 589,703,740
2016	$ 801,696,091
2017	$ 1,049,747,340
2018	$ 1,320,356,033
2019	$ 1,594,950,899
2020	$ 1,855,660,571
2021	$ 2,090,701,082
2022	$ 2,296,250,916
2023	$ 2,474,739,451
2024	$ 2,631,749,060
2025	$ 2,773,480,404

The results of the six different experiments (two types of allocation strategies, three levels of telehealth impact) are broken down into individual savings for each healthcare service type. Tables from E.2 to E.7 provide the savings from each visit type in each year. The tables provide individual savings from healthcare visits that comprise the total savings due to home telehealth diffusion.

Table E.2. Savings for each visit type in SA-opt experiment

Years	Hospital	ED	PO	SN	Total Savings
2015	$ 4,690,672,031	$ 880,174,953	$ 86,265,233	$ 625,085,964	$ 6,282,198,180
2016	$ 6,446,413,961	$ 1,209,628,827	$ 118,554,740	$ 859,058,757	$ 8,633,656,284
2017	$ 8,549,637,698	$ 1,604,285,465	$ 157,234,716	$ 1,139,337,495	$ 11,450,495,374
2018	$ 10,883,270,870	$ 2,042,176,976	$ 200,152,108	$ 1,450,320,938	$ 14,575,920,892
2019	$ 13,255,709,845	$ 2,487,350,152	$ 243,783,170	$ 1,766,475,701	$ 17,753,318,868
2020	$ 14,999,512,797	$ 2,819,140,231	$ 282,833,466	$ 2,052,252,667	$ 20,153,739,161
2021	$ 16,003,306,023	$ 3,016,410,666	$ 314,891,768	$ 2,290,033,467	$ 21,624,641,925
2022	$ 16,898,360,660	$ 3,191,104,504	$ 341,636,653	$ 2,487,976,509	$ 22,919,078,325
2023	$ 17,704,998,671	$ 3,347,367,817	$ 363,949,443	$ 2,652,672,638	$ 24,068,988,568
2024	$ 18,454,462,438	$ 3,491,581,463	$ 383,195,444	$ 2,794,333,842	$ 25,123,573,187
2025	$ 19,175,277,814	$ 3,629,569,537	$ 400,618,281	$ 2,922,261,493	$ 26,127,727,125

Table E.3. Savings for each visit type in SA-mod experiment

Years	Hospital	ED	PO	SN	Total Savings
2015	$ 3,908,893,359	$ 660,131,215	$ -	$ 468,814,473	$ 5,037,839,047
2016	$ 5,372,011,634	$ 907,221,620	$ -	$ 644,294,068	$ 6,923,527,322
2017	$ 7,124,698,082	$ 1,203,214,098	$ -	$ 854,503,121	$ 9,182,415,302
2018	$ 9,069,392,391	$ 1,531,632,732	$ -	$ 1,087,740,704	$ 11,688,765,828
2019	$ 11,046,424,871	$ 1,865,512,614	$ -	$ 1,324,856,776	$ 14,236,794,261
2020	$ 12,499,593,997	$ 2,114,355,173	$ -	$ 1,539,189,500	$ 16,153,138,671
2021	$ 13,336,088,353	$ 2,262,308,000	$ -	$ 1,717,525,100	$ 17,315,921,453
2022	$ 14,081,967,216	$ 2,393,328,378	$ -	$ 1,865,982,382	$ 18,341,277,976
2023	$ 14,754,165,559	$ 2,510,525,863	$ -	$ 1,989,504,478	$ 19,254,195,900
2024	$ 15,378,718,698	$ 2,618,686,097	$ -	$ 2,095,750,382	$ 20,093,155,177
2025	$ 15,979,398,178	$ 2,722,177,153	$ -	$ 2,191,696,120	$ 20,893,271,451

Table E.4. Savings for each visit type in SA-pes experiment

Years	Hospital	ED	PO	SN	Total
2015	$ 2,345,336,015	$ 440,087,476	$ (86,265,233)	$ 312,542,982	$ 3,011,701,241
2016	$ 3,223,206,980	$ 604,814,413	$ (118,554,740)	$ 429,529,379	$ 4,138,996,033
2017	$ 4,274,818,849	$ 802,142,732	$ (157,234,716)	$ 569,668,748	$ 5,489,395,613
2018	$ 5,441,635,435	$ 1,021,088,488	$ (200,152,108)	$ 725,160,469	$ 6,987,732,284
2019	$ 6,627,854,922	$ 1,243,675,076	$ (243,783,170)	$ 883,237,851	$ 8,510,984,679
2020	$ 7,499,756,398	$ 1,409,570,116	$ (282,833,466)	$ 1,026,126,334	$ 9,652,619,381
2021	$ 8,001,653,012	$ 1,508,205,333	$ (314,891,768)	$ 1,145,016,733	$ 10,339,983,310
2022	$ 8,449,180,330	$ 1,595,552,252	$ (341,636,653)	$ 1,243,988,255	$ 10,947,084,184
2023	$ 8,852,499,335	$ 1,673,683,908	$ (363,949,443)	$ 1,326,336,319	$ 11,488,570,120
2024	$ 9,227,231,219	$ 1,745,790,731	$ (383,195,444)	$ 1,397,166,921	$ 11,986,993,428
2025	$ 9,587,638,907	$ 1,814,784,769	$ (400,618,281)	$ 1,461,130,746	$ 12,462,936,141

Table E.5. Savings for each visit type in PA-opt experiment

Years	Hospital	ED	PO	SN	Total
2015	$ 2,990,176,454	$ 587,506,205	$ 78,414,806	$ 594,620,289	$ 4,250,717,754
2016	$ 4,112,091,085	$ 807,839,002	$ 107,786,048	$ 817,236,856	$ 5,844,952,991
2017	$ 5,457,238,721	$ 1,071,968,247	$ 142,979,197	$ 1,083,932,888	$ 7,756,119,052
2018	$ 6,951,255,551	$ 1,365,273,115	$ 182,039,141	$ 1,379,872,231	$ 9,878,440,037
2019	$ 8,471,946,539	$ 1,663,746,857	$ 221,762,406	$ 1,680,765,020	$ 12,038,220,822
2020	$ 9,888,844,765	$ 1,941,770,106	$ 258,734,940	$ 1,960,737,996	$ 14,050,087,807
2021	$ 11,112,946,007	$ 2,181,924,152	$ 290,678,882	$ 2,202,570,763	$ 15,788,119,804
2022	$ 12,127,726,642	$ 2,380,937,094	$ 317,130,614	$ 2,402,737,274	$ 17,228,531,624
2023	$ 12,967,503,227	$ 2,545,557,193	$ 338,991,965	$ 2,568,083,189	$ 18,420,135,574
2024	$ 13,685,689,448	$ 2,686,278,635	$ 357,662,832	$ 2,709,223,999	$ 19,438,854,914
2025	$ 14,330,999,524	$ 2,812,669,255	$ 374,418,728	$ 2,835,828,455	$ 20,353,915,962

Table E.6. Savings for each visit type in PA-mod experiment

Years	Hospital	ED	PO	SN	Total
2015	$ 2,491,813,712	$ 440,629,654	$ -	$ 445,965,217	$ 3,378,408,582
2016	$ 3,426,742,571	$ 605,879,252	$ -	$ 612,927,642	$ 4,645,549,465
2017	$ 4,547,698,934	$ 803,976,185	$ -	$ 812,949,666	$ 6,164,624,785
2018	$ 5,792,712,959	$ 1,023,954,836	$ -	$ 1,034,904,173	$ 7,851,571,969
2019	$ 7,059,955,449	$ 1,247,810,143	$ -	$ 1,260,573,765	$ 9,568,339,357
2020	$ 8,240,703,970	$ 1,456,327,580	$ -	$ 1,470,553,497	$ 11,167,585,047
2021	$ 9,260,788,339	$ 1,636,443,114	$ -	$ 1,651,928,072	$ 12,549,159,526
2022	$ 10,106,438,869	$ 1,785,702,820	$ -	$ 1,802,052,956	$ 13,694,194,645
2023	$ 10,806,252,689	$ 1,909,167,894	$ -	$ 1,926,062,391	$ 14,641,482,975
2024	$ 11,404,741,206	$ 2,014,708,976	$ -	$ 2,031,917,999	$ 15,451,368,182
2025	$ 11,942,499,603	$ 2,109,501,941	$ -	$ 2,126,871,341	$ 16,178,872,886

Table E.7. Savings for each visit type in PA-pes experiment

Years	Hospital	ED	PO	SN	Total
2015	$ 1,495,088,227	$ 293,753,103	$ (78,414,806)	$ 297,310,144	$ 2,007,736,668
2016	$ 2,056,045,543	$ 403,919,501	$ (107,786,048)	$ 408,618,428	$ 2,760,797,424
2017	$ 2,728,619,360	$ 535,984,123	$ (142,979,197)	$ 541,966,444	$ 3,663,590,731
2018	$ 3,475,627,776	$ 682,636,558	$ (182,039,141)	$ 689,936,115	$ 4,666,161,308
2019	$ 4,235,973,269	$ 831,873,428	$ (221,762,406)	$ 840,382,510	$ 5,686,466,802
2020	$ 4,944,422,382	$ 970,885,053	$ (258,734,940)	$ 980,368,998	$ 6,636,941,493
2021	$ 5,556,473,003	$ 1,090,962,076	$ (290,678,882)	$ 1,101,285,382	$ 7,458,041,579
2022	$ 6,063,863,321	$ 1,190,468,547	$ (317,130,614)	$ 1,201,368,637	$ 8,138,569,891
2023	$ 6,483,751,614	$ 1,272,778,596	$ (338,991,965)	$ 1,284,041,594	$ 8,701,579,839
2024	$ 6,842,844,724	$ 1,343,139,318	$ (357,662,832)	$ 1,354,611,999	$ 9,182,933,209
2025	$ 7,165,499,762	$ 1,406,334,628	$ (374,418,728)	$ 1,417,914,228	$ 9,615,329,889

When we consider individual benefits of visit types, only the cost savings from hospitalization is more than the total cost of telehealth in each experiment. Individual savings from ED and SN are more than the cost of telehealth in the corresponding year (except for 2015 for ED in the PA-opt) only in the optimistic cases (SA-opt and PA-opt). When considering optimistic and moderate cases, telehealth is not cost-effective compared with the visit reductions for PO (note that the number of PO visits is expected to increase in the pessimistic cases). Home telehealth is cost-effective with those visit reductions taken together. The percent distributions of individual savings are provided in Tables E.8 to E.13.

Table E.8. Percent distributions of savings in SA-opt

Years	Hospital	ED	PO	SN
2015	74.67	14.01	1.37	9.95
2016	74.67	14.01	1.37	9.95
2017	74.67	14.01	1.37	9.95
2018	74.67	14.01	1.37	9.95
2019	74.67	14.01	1.37	9.95
2020	74.43	13.99	1.40	10.18
2021	74.00	13.95	1.46	10.59
2022	73.73	13.92	1.49	10.86
2023	73.56	13.91	1.51	11.02
2024	73.45	13.90	1.53	11.12
2025	73.39	13.89	1.53	11.18

Table E.9. Percent distributions of savings in SA-mod

Years	Hospital	ED	PO	SN
2015	77.59	13.10	0.00	9.31
2016	77.59	13.10	0.00	9.31
2017	77.59	13.10	0.00	9.31
2018	77.59	13.10	0.00	9.31
2019	77.59	13.10	0.00	9.31
2020	77.38	13.09	0.00	9.53
2021	77.02	13.06	0.00	9.92
2022	76.78	13.05	0.00	10.17
2023	76.63	13.04	0.00	10.33
2024	76.54	13.03	0.00	10.43
2025	76.48	13.03	0.00	10.49

Table E.10. Percent distributions of savings in SA-pes

Years	Hospital	ED	PO	SN
2015	75.71	14.21	n/a	10.09
2016	75.71	14.21	n/a	10.09
2017	75.71	14.21	n/a	10.09
2018	75.71	14.21	n/a	10.09
2019	75.23	14.17	n/a	10.61
2020	74.64	14.12	n/a	11.24
2021	74.25	14.08	n/a	11.66
2022	74.00	14.06	n/a	11.94
2023	73.84	14.05	n/a	12.11
2024	73.75	14.04	n/a	12.21
2025	73.69	14.04	n/a	12.27

Table E.11. Percent distributions of savings in PA-opt

Years	Hospital	ED	PO	SN
2015	70.35	13.82	1.84	13.99
2016	70.35	13.82	1.84	13.98
2017	70.36	13.82	1.84	13.98
2018	70.37	13.82	1.84	13.97
2019	70.38	13.82	1.84	13.96
2020	70.38	13.82	1.84	13.96
2021	70.39	13.82	1.84	13.95
2022	70.39	13.82	1.84	13.95
2023	70.40	13.82	1.84	13.94
2024	70.40	13.82	1.84	13.94
2025	70.41	13.82	1.84	13.93

Table E.12. Percent distributions of savings in PA-mod

Years	Hospital	ED	PO	SN
2015	73.76	13.04	0.00	13.20
2016	73.76	13.04	0.00	13.19
2017	73.77	13.04	0.00	13.19
2018	73.78	13.04	0.00	13.18
2019	73.78	13.04	0.00	13.17
2020	73.79	13.04	0.00	13.17
2021	73.80	13.04	0.00	13.16
2022	73.80	13.04	0.00	13.16
2023	73.81	13.04	0.00	13.15
2024	73.81	13.04	0.00	13.15
2025	73.82	13.04	0.00	13.15

Table E.13. Percent distributions of savings in PA-pes

Years	Hospital	ED	PO	SN
2015	71.67	14.08	n/a	14.25
2016	71.67	14.08	n/a	14.24
2017	71.68	14.08	n/a	14.24
2018	71.69	14.08	n/a	14.23
2019	71.70	14.08	n/a	14.22
2020	71.70	14.08	n/a	14.22
2021	71.71	14.08	n/a	14.21
2022	71.71	14.08	n/a	14.21
2023	71.72	14.08	n/a	14.20
2024	71.72	14.08	n/a	14.20
2025	71.73	14.08	n/a	14.19

3. Measuring the Potential Spatial Accessibility of Home Healthcare Services

3.1. Introduction

Home healthcare encompasses a range of services that are provided in the patient's home, including skilled nursing, physical therapy, and occupational therapy. The sector constitutes an important and growing component of the US healthcare continuum, serving over 12 million homebound patients in 2010 alone (NAHC, 2010). Home healthcare can be a cost-effective therapy option when used as step-down care from an inpatient hospitalization or from a nursing home stay. In spite of the less intensive level of care, home healthcare has been shown to improve health outcomes and quality of care while reducing total cost of a treatment episode (The Joint Commission, 2011).

The benefits of home healthcare can only be realized if patients have access to these services. Home healthcare is provided to patients according to a physician's prescription, which specifies three attributes of an episode of care: (1) the type(s) of service needed, such as nursing, physical therapy and occupational therapy; (2) the frequency of visits needed from each service provider type; and (3) the duration of the care episode, usually given in weeks. In addition to a physician's prescription, access to home healthcare is dependent on whether there is a home healthcare agency that serves the patient's neighborhood. Agencies' service regions are typically defined by the ZIP codes in which they are authorized to operate. Finally, if one or more agencies serve the patient's ZIP code, access also depends on the number of staff of a particular service provider type relative to the number of patients requiring that type of service in the agency's service region. Thus, the supply of and demand for home healthcare services in a region directly impact a prospective patient's ability to access care.

In the literature, access to healthcare is considered as a multidimensional concept. Khan (1992) and Guagliardo (2004) provided a valuable taxonomy of healthcare access where access is divided into four types: realized spatial, realized non-spatial, potential spatial, and potential non-spatial (Figure 17).

		Dimensions	
		Spatial	**Non-spatial**
Stages	**Realized**	Utilization studies that consider distance, location and other geographic factors	Utilization studies that consider affordability, culture and other non-geographic factors
	Potential	Studying the availability of a service in a given area based on geographic factors	Studying the availability of a service in a given area based on non-geographic factors

Figure 17. Classification of healthcare accessibility (Guagliardo, 2004; Khan, 1992)

Potential accessibility refers to the availability of healthcare resources whereas *realized accessibility* explains the actual utilization of those resources (Luo & Qi, 2009). For example, the number of primary care visits per patient is one measure of realized accessibility of primary care. In contrast, potential accessibility emphasizes the availability of a primary care provider in a location. The ratio of the number of primary care providers to the population living in an area is an example measure of potential accessibility.

Each of these two categories can be further divided into *spatial accessibility* based on factors such as geographic location and distance, and *non-spatial accessibility* based on demographic and socioeconomic variables including but not limited to income, age, race and sex (F. Wang, 2012). We choose to measure potential spatial accessibility of home healthcare services in the proposed work because it allows one to assess whether the distribution of services across a region is equitable (Bissonnette, Wilson, Bell, & Shah, 2012). Geographical inequities in the provision of home healthcare services can lead to insufficient access to these services and poorer health outcomes as a result. Evaluating the geographical disparities in healthcare access is an essential step in designing an equitable healthcare system and improving overall population health status (Bowerman, 1997). Quantitative models are required to reveal the populations or areas with low access to healthcare services and identify the geographic barriers that people experience in accessing healthcare services.

Past attempts to measure accessibility of home healthcare services may not have adequately captured the distribution of services across a region. For example, one study measured only realized spatial accessibility (not potential spatial accessibility) by considering the utilization of home healthcare services (Freedman et al., 2004). Studies that measure potential spatial accessibility do exist in the literature. For example, Hawes et al. (2005) measured the number of home healthcare agencies per square mile and Kenney and Dubay (1992) measured the proportion of home healthcare agencies offering ancillary services. However, these studies accounted for the supply of services in a region but not the demand. Both the supply of health services and population demand have been identified as critical factors influencing access to health services (Luo & Qi, 2009). Therefore, by failing to account for supply and demand within a region simultaneously, access estimates may have been flawed.

In this chapter, we develop a new measure to quantify the potential spatial accessibility of home healthcare services within a geographic region. The access measure is determined at the local level and simultaneously considers both the staffing levels of agencies serving the locality and demand from persons within the locality. It is created by adapting the two-step floating catchment area (2SFCA) method (Luo & Wang, 2003; Radke & Mu, 2000). The measure is demonstrated via a case study using the state of Arkansas. For simplicity of exposition we may use the terms accessibility and potential spatial accessibility interchangeably throughout the remainder of this dissertation.

The organization of this chapter is as follows. Section 3.2 provides a review of the potential spatial accessibility measurement literature. Section 3.3 presents the new method for measuring the potential spatial accessibility of home healthcare services. The measure is demonstrated via a case study using the state of Arkansas in Sections 3.4 and 3.5. Finally, conclusions are provided in Section 3.6.

3.2. Measures of Potential Spatial Accessibility

Numerous measures of potential spatial accessibility to healthcare services have been proposed in the literature. Below, we review potential spatial access measures across five categories of measures we frequently observed in the literature.

Distance and travel time measures

Distance and travel time measures capture traveling time or distance between demand and provider locations. Commonly used measures are the average distance (or time) to the nearest provider, the average distance (or time) to a set of providers and the number of providers within a certain distance. Travelling time or distance can be measured in units of Euclidean distance (straight line) or actual travel distance along a road network via a geographic information system (GIS) (Bagheri, Benwell, & Holt, 2006; Guagliardo, 2004). These measures may be used in rural areas where provider choices are very limited (Guagliardo, 2004). The major limitation of these measures is that they ignore at least one dimension of availability: either the capacity of the service provider, the size of the population, or both (McGrail & Humphreys, 2009b).

Provider-to-population ratios

Provider-to-population ratios refer to the ratio of healthcare supply and population demand within an area such as a state, a county, a census tract, or a primary care service area (Luo & Whippo, 2012; Wan, Zou, & Sternberg, 2012). They are the most popular type of spatial accessibility measure because they are highly intuitive and readily understood. For example, the U.S. Department of Health and Human Services designates primary care shortage areas based on a physician-to-population ratio of 1:3,500 (U.S. Department of Health & Human Services, n.d.). The data for both the demand side (e.g. population size, number of Medicare beneficiaries, senior citizens, etc.) and supply side (e.g. number of physicians, clinics, hospital beds, etc.) of the ratio are commonly available. Calculating provider-to-population ratios does not necessarily require GIS tools and expertise (Guagliardo, 2004; McGrail & Humphreys, 2009b). However, these ratios have two criticized assumptions. First, they assume that people are restricted to one area and cannot travel beyond that area to seek healthcare. Second, they assume that all individuals within the same area have equal access to services. They do not consider internal variations in access within an area or travel impedance, which represents a patient's willingness to travel due to cost or time (Guagliardo, 2004; McGrail & Humphreys, 2009b; F. Wang, 2012). The first assumption can be realistic when the areas for which the ratios are computed are large, but the second assumption requires areas be small (Luo & Qi, 2009; Luo & Wang, 2003). Therefore, choosing an appropriate level of aggregation for the spatial data is a challenge.

Kernel density models

Kernel density models use a kernel density function (e.g. Gaussian function) to represent supply and demand catchment areas in a smooth density surface (Figure 18). As seen in Figure 18, there is a kernel function and a bandwidth for each location in the study area. The kernel function models the distance decay effect and the bandwidth indicates threshold distance. The influence of the location is biggest in the center of the kernel function and decreases with distance. The value of the bandwidth has a great impact on the density surface whereas the choice of kernel function has limited impact on results (Schuurman, Bérubé, & Crooks, 2010; Wan, 2012).

Generally, there are two steps in this model. The first step is to generate two kernel density surfaces: one for the provider sites and one for the population centroids. This provides an estimate of service provider density and a separate estimate of population density for each discretized cell in the two surfaces. In the second step, the provider surface is overlaid on the demand surface to obtain the combined surface. The provider-to-population ratios on the combined surface are calculated by dividing the estimates of provider density by population density for each location.

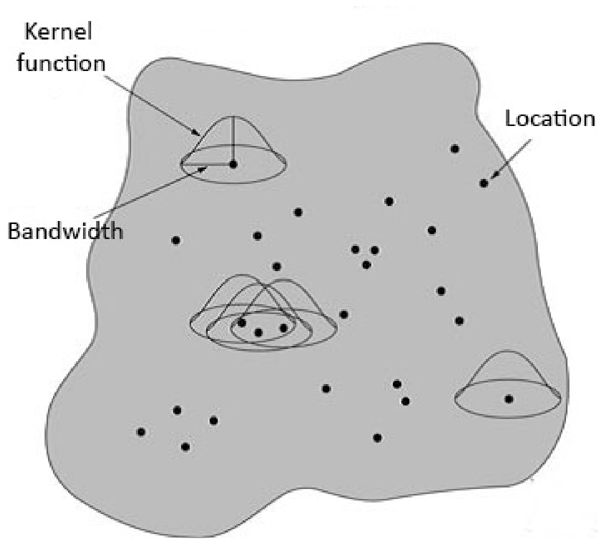


Figure 18. Kernel density estimation (Schuurman et al., 2010)

One drawback of kernel density models is the use of straight-line distances to determine the kernel bandwidth. This does not correspond to transportation networks. This problem can be solved by introducing a road network kernel density (Schuurman et al., 2010). However, other problems associated with the placement of provider and population locations on the surface exist. For example, portions of the provider circles may end up in non-populated areas such as lakes, airports, or forests. In addition, this model assumes that most of the population lives near the centroid of the population surface and that population density decreases along the radius. The population, however, could be distributed homogeneously, or may peak at a different point than the centroid (Schuurman et al., 2010; Wan, 2012; Wan, Zhan, Zou, & Chow, 2012).

Gravity models

Gravity models, which are based on Newton's Law of Gravitation, can assess the potential spatial interaction between a population location and all provider locations within reasonable distance from it (Joseph & Bantock, 1982). In the gravity model, A_i represents the spatial accessibility of provider services for population location i and is formulated as:

$$A_i = \sum_j \frac{S_j d_{ij}^{-\beta}}{\sum_k P_k d_{kj}^{-\beta}}, \tag{7}$$

where S_j is the supply at provider location j, P_k is the demand magnitude at population location k, d_{ij} is the distance between population location i and provider location j, and β is a distance decay coefficient. The gravity model captures both supply and demand and assumes that access to services decreases as the travel distance between a population location and provider location increases. A primary drawback of this formulation is that the distance decay coefficient, β, is often unknown and empirical investigation is required to estimate it (Guagliardo, 2004).

Two-step floating catchment area (2SFCA) method

The two-step floating catchment area method (2SFCA, Radke and Mu 2000; Luo and Wang 2003) integrates provider-to-population ratio and gravity model concepts (Delamater, 2013; Luo & Qi, 2009; Luo & Whippo, 2012). The 2SFCA method generates catchment areas around both demand and service locations based on travel time or travel distance buffers (Delamater, 2013). The method is implemented in two steps (Delamater, 2013; Luo & Whippo, 2012), described below.

Step 1: For each service location j, calculate the provider-to-population ratio (R_j) by searching all population locations i within the catchment area defined by a threshold travel time d_0:

$$R_j = \frac{S_j}{\sum_{i \in L_j} P_i}, \tag{8}$$

where P_i is the population of demand unit i, S_j is the supply capacity of j, d_{ij} is the travel time between i and j, and L_j is the set of population locations in the catchment of j $(d_{ij} \leq d_0)$.

Step 2: For each demand location i, sum up the provider-to-population ratios R_j (derived in step 1), by searching all service locations j within the catchment area defined by a threshold travel time d_0:

$$A_i = \sum_{j \in L_i} R_j \ , \tag{9}$$

where L_i is the set of all service locations in the catchment of i $(d_{ij} \leq d_0)$ and A_i represents the accessibility of healthcare services for the population at location i.

The 2SFCA method has been used extensively to estimate potential spatial accessibility of various healthcare services such as primary care (Guagliardo, 2004; Mitchel Langford & Higgs, 2006; F. Wang, McLafferty, Escamilla, & Luo, 2008; L. Wang, 2011), mental health facilities (Ngui & Vanasse, 2012), cancer care (Russell et al. 2011; Shi et al. 2012) and dialysis services (Yang, Goerge, & Mullner, 2006). Since 2SFCA was first proposed, several modified versions of this method have been developed. These include accounting for traveling distance decay within a catchment area (Dai, 2010; Dai & Wang, 2011; M. Langford, Fry, & Higgs, 2012; Luo & Qi, 2009; McGrail & Humphreys, 2009c), using variable catchment sizes instead of fixed catchment sizes (Luo & Whippo, 2012; McGrail & Humphreys, 2009c; Paez, Mercado, Farber, Morency, & Roorda, 2010), using relative accessibility ratios (Paez et al., 2010; Wan, Zhan, et al., 2012; Wan, Zou, et al., 2012), considering competition of providers (Delamater, 2013; Wan, Zou, et al., 2012), and incorporating non-spatial factors (McGrail & Humphreys, 2009a; Ngui & Apparicio, 2011; Paez et al., 2010).

Measure for home healthcare accessibility

Home healthcare accessibility differs from other healthcare services in that individuals do not choose a provider location to visit. Rather, home healthcare agencies choose the regions (ZCTAs) in which they will offer services (subject to approval of state health authorities, in some cases), and then providers travel to patients' homes. Thus, a new measure for home healthcare accessibility is needed to account for the unique features of this system.

Four of the five categories of potential spatial accessibility measures have characteristics that limit their applicability for measuring access to home healthcare services. Distance and travel time measures are easy to calculate but they do not incorporate the capacities of individual home healthcare agencies or demands of population locations. Provider-to-population ratios do consider capacity and demand information, but they ignore that a home healthcare agency may provide service in multiple population locations and allocate its staff among these locations. Thereby, it is not reasonable to assume that the numerator of the provider-to-population ratio is always equal to the total capacity of an agency. Kernel density models are not appropriate for home healthcare because a home healthcare agency's catchment area cannot be represented by a kernel density function. Instead, an agency's catchment area typically consists of a list of population locations (e.g., ZIP codes) that the agency has been licensed to serve. Gravity models are not appropriate for home healthcare because they require travel times between provider and demand location pairs and coefficients describing willingness of the population to travel. However, the office location of a home healthcare agency does not describe the service region of the agency or the locations of its home-based service providers. Furthermore, individuals do not travel to the home healthcare agency to receive services; instead, nurses from the home healthcare agency travel to the patients.

In contrast, the 2SCFA method offers a way to compute a provider-to-population ratio by specifying a catchment area for each provider. The original 2SFCA method defines the catchment area of a provider as all population locations within a threshold travel time of the provider. This can be readily adapted for the home health setting, in which agencies explicitly define their catchment areas by determining which population locations (e.g., ZIP codes) to serve. Hence, in this work, we propose an adaptation of 2SFCA that is uniquely designed for the home healthcare setting, where catchment areas are determined explicitly by providers. The access measure proposed in this study quantifies potential spatial accessibility of home healthcare services by capturing supply and demand simultaneously.

3.3. Methodology

Medicare home healthcare covers six different types of skilled professional services: skilled nursing, physical therapy, occupational therapy, speech therapy, medical social work, and home health aide (MedPAC, 2013). Under the Prospective Payment System (PPS), home healthcare agencies receive payments for 60-day care episodes. If a patient needs additional home healthcare services at the end of the episode, another episode may be permitted. The average number of care episodes per home healthcare user was 2.0 in 2010 (MedPAC, 2013). During an episode, each home healthcare service is provided by the appropriate type of skilled professional allocated by the agency. The demand for each service and the supply of each provider type may vary. Hence, an access score for each provider type is needed individually. The service area of a home healthcare agency consists of postal ZIP codes where the agency provides services. Each agency can decide its service area but these decisions may be limited by state licensing procedures. In some cases, agencies may provide services in multiple states. Over time, home healthcare agencies can discontinue service to some ZIP codes and/or expand service to other ZIP codes (Porell, Liu, & Brungo, 2006). Therefore, service region size varies among agencies.

We propose an adapted version of the 2SFCA method for measuring potential spatial accessibility of home healthcare services. The following two steps are applied to calculate an access score for each population location in the study region for each service provider type (e.g., nursing, physical therapy, etc.).

Step 1: For each home healthcare agency j, calculate the provider-to-population ratio (R_{jk}) for each service provider type k by searching all eligible populations within the catchment area of agency j :

$$R_{jk} = \frac{S_{jk} c_k}{\sum_{i \in Z_j} P_i d_k}, \tag{10}$$

where S_{jk} is the number of full-time-equivalent (FTE) service providers of type k employed by agency j, c_k is the average number of annual visits per FTE by service provider type k, Z_j is the set of population locations in the catchment of agency j, P_i is the eligible population in population location i, and d_k is the average number of annual visits needed per person for service type k.

This is different from Step 1 of the 2SFCA methodology in the following ways. In home healthcare, providers travel to visit patients instead of patients traveling to visit providers. Hence, the catchment area of a provider is not associated with the travel impedance of patients. Here, the catchment area of an agency is defined by all the service locations of an agency instead of a threshold travel time for patients. Secondly, this formulation allows for adjustment among different service types by considering their relative demands and supplies.

Step 2: For each population location i in the area of interest, sum up the provider-to-population ratios R_{jk} (derived in Step 1) for each service provider type k by searching all agencies j that serve i:

$$A_{ik} = \sum_{j \in H_i} R_{jk}, \tag{11}$$

where H_i is the set of all home healthcare agencies that serve i and A_{ik} represents the accessibility of provider type k in population location i.

Example: To illustrate this calculation, consider an instance consisting of three population locations, two agencies, and one type of service provider (service type 1), with instance parameters summarized in Table 10. Assume that the average number of annual visits per FTE is 1000 and the average number of visits needed per person is 10. This example is depicted in Figure 19. The two “plus” symbols labeled 1 and 2 represent the two agencies and their surrounding circles represent their service areas (note home healthcare agency service areas will most likely not be circular in practice due to the irregularity in shape of ZIP codes). The three home symbols represent the population locations. Observe that population location 3 is in the service region of both agencies, while population locations 1 and 2 are only in the service regions of agencies 1 and 2, respectively.

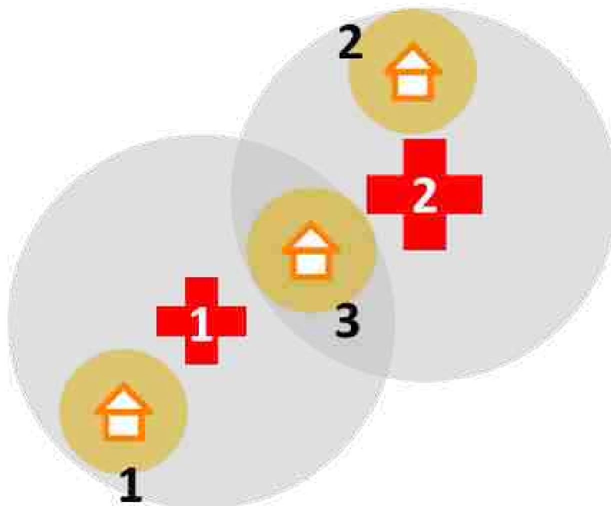


Figure 19. An illustrative example

Table 10. Example access score calculation

Location	Population	In Agency 1's Service Region (50 FTEs)	In Agency 2's Service Region (75 FTEs)	Accessibility Scores
1	900	yes		3.57
2	1700		yes	3.41
3	500	yes	yes	6.98

In the first step, provider-to-population ratios are calculated for each agency. Considering agency 1, for example, the set of population locations in its catchment area are locations 1 and 3 (hence $Z_1 =$ {Location 1, Location 3}). Then, the provider-to-population ratio for agency 1, R_{11}, is computed as:

$$R_{11} = \frac{S_{11}c_1}{\sum_{i \in Z_1} P_i d_1} = \frac{50 \times 1000}{(900 + 500) \times 10} = 3.57.$$

Similarly, the provider-to-population ratio of agency 2 is computed as:

$$R_{21} = \frac{S_{21}c_1}{\sum_{i \in Z_2} P_i d_1} = \frac{75 \times 1000}{(1700 + 500) \times 10} = 3.41.$$

In the next step, accessibility scores for the population locations are calculated. Considering location 3, agencies 1 and 2 are both in the set of home healthcare agencies serving this location and the associated access score is:

$$A_{31} = \sum_{j \in H_3} R_{j1} = 3.57 + 3.41 = 6.98.$$

The access scores of the other ZCTAs are simply 3.57 for location 1 (served only by agency 1) and 3.41 for location 2 (served only by agency 2), as indicated in Table 10.

3.4. Case Study Development

We demonstrate the proposed 2SFCA adaptation to measure accessibility of home healthcare services in a case study of Arkansas. Arkansas is a southern state with an area of 53,104 square miles. Its population is almost 3 million people. Population demographics are summarized in Table 11 across the dimensions of ethnicity, age and rural vs. urban location. Arkansas has one of the highest poverty rates (19.6 percent) in the country (University of Arkansas, 2015).

Table 11. Population structure of Arkansas (University of Arkansas, 2015)

Population Group	**2013 estimates**
White alone, not Hispanic	73.7%
Black alone, not Hispanic	15.4%
Other races, not Hispanic	4.1%
Hispanic, all races	6.9%
Rural population*	42.4%
65 years old and over	15.4%
75 years old and over	6.5%
Median Age	39.8

*Number of people living in nonmetropolitan counties

We illustrate the implementation at the ZIP Code Tabulation Area (ZCTA) aggregation level. ZCTAs are approximate area representations of five-digit ZIP Codes and were created by the US Census Bureau to present statistical data from censuses. The ZCTA is chosen because it is the lowest level of aggregation at which both supply and demand side data are available, and small levels of aggregation are necessary to capture any local effects that may be present. Therefore the catchment area of home healthcare agencies is defined here as all ZCTAs in the service region of that agency. There are approximately six hundred ZCTAs in the study area. We excluded seven ZCTAs that represent either university campuses or army bases from consideration.

Only secondary-source data are required for the study. The following data inputs are required for the study region: (1) list of home healthcare agencies serving the case study region; (2) list of ZCTAs served by each home healthcare agency; (3) population of persons over age 65 in each ZCTA; and (4) number of full time equivalent (FTE) nurses, therapists, and aides employed by each home healthcare agency.

Home healthcare agency data

A list of home healthcare agencies providing service to in Arkansas is obtained from the Medicare Home Health Compare database (Centers for Medicare & Medicaid Services, 2010b). This data was collected in 2010 and included 227 agencies.

Service region data

The list of ZIP codes served by each home healthcare agency is obtained from the Medicare Home Health Compare database (Centers for Medicare & Medicaid Services, 2010b) in 2010. Home healthcare agencies report their geographic service areas to this database by ZIP code. Because population data is reported by ZCTA instead of ZIP codes, a crosswalk developed by Robert Graham Center (2013) is used to map each ZIP code to its corresponding ZCTA. Note that some ZCTAs located outside of Arkansas may be included in the service regions of some agencies. This occurs when the catchment area of a particular agency spreads beyond Arkansas borders. A total of 2579 ZCTAs receive service from the agencies included in this case study. Of these ZCTAs, 589 are located within Arkansas.

Population data

The population of persons over age 65 in each ZCTA in Arkansas is extracted from the TIGER/Line Shapefiles which contain ZCTA level 2010 US Census data (U.S. Census Bureau, 2012). The over-65 population is used as a proxy for home healthcare demand because this group accounts for a significant majority of individuals receiving home healthcare (NAHC, 2010). Obviously, using the population of people 65 years old and older overestimates the demand for home healthcare services. However, this does not impact the quality of the output of the model because the goal is to measure the potential access, and access scores of ZCTAs will only be interpreted relative to each other. That is, the access scores measure how likely someone in a particular ZCTA is to be able to obtain home healthcare service relative to someone in another ZCTA. An inherent assumption of our model is that per capita demand for home healthcare services among the over-65 population does not vary throughout the state. This assumption is discussed in more detail in Section 3.6.

Even though our study area is Arkansas, we obtained the population data for the ZCTAs that are not located within Arkansas but do fall within a catchment area of at least one agency providing service in Arkansas. This way, we can calculate provider-to-population ratios accurately because some portion of supply (i.e., FTEs) may be allocated for ZCTAs outside of Arkansas. Disregarding the population of a ZCTA outside of Arkansas, even though it is in the service region of an agency, would bias our results by causing overestimation of provider-to-population ratios for that particular agency.

Staffing data

The FTE staffing data for each home healthcare agency are derived from two different sources. The FTE data for the majority of the agencies (144 out of a total of 227 agencies) were derived from the

Healthcare Cost Report Information System (HCRIS) provided by the Centers for Medicare & Medicaid Services (CMS) (Centers for Medicare & Medicaid Services, 2010a). CMS HCRIS databases contain self-reported cost report files that provide annual employment data for each service provider type in terms of FTEs. The HCRIS database consists of Hospital, Skilled Nursing Facility, Home Health Agency, Renal Facility, Health Clinic and Hospice subsystems. Information related to home healthcare services can be found in Hospital, Skilled Nursing Facility and Home Health Agency subsystems. For each home healthcare agency in the study, we recorded the FTE data for 2010 if it was available. Some agencies did not provide FTE data for all required service types in fiscal year 2010, so cost reports from adjacent years were inspected to find the missing data. Specifically, if FTE data were missing for a particular agency in their 2010 HCRIS report, we searched for it first in their 2009 cost report and then in 2011 and 2012 cost reports, in that order. The aim of this data collection method was to obtain supply data (staffing levels) from a commensurate time period as the demand data (population numbers from 2010 census). Approximately three-fourths of the collected staffing data originated from the 2010 cost report files, with the remaining one-fourth originating from the cost reports of 2009, 2011 and 2012.

The second source for FTE staffing data was Arkansas Department of Health In-Home Services Service Reports from calendar year 2015 (S. Heffington, personal communication, April 29, 2015). The FTE data of non-profit agencies affiliated with the Arkansas State Board of Health were obtained from these reports because it was not available in the HCRIS database. The data for 74 agencies was obtained in this way.

During the data collection process, FTE data could not be obtained for the remaining nine of the 227 agencies providing service in Arkansas. We proceeded in the analysis using only the 218 agencies for which FTE data were available (96 percent of the total agencies). The provider-to-population ratio, calculated by Equation (10), is zero for those nine agencies that did not provide cost reports in HCRIS. These agencies with missing FTE data provide service to 136 different ZCTAs across state. Missing FTE data potentially result in lower access scores for those 136 ZCTAs. We believe this impact is limited for two reasons. First, all of these ZCTAs get service from at least one agency that has FTE data available. Also, we observe that many of the ZCTAs for which data of associated agencies is missing also tend to be served by many agencies. Figure 20 and 21 exhibit the total number of agencies serving each ZCTA and the number of agencies serving each ZCTA with no missing data, respectively. We do not observe dramatic differences between these two maps.

The proposed 2SFCA method requires two additional parameters describing the annual per capita demand for each service (d_k) and the annual productivity of service providers (c_k). The demand parameter d_k is measured using the average number of visits needed per person for service type k. This was obtained from the data provided in the Medicare Payment Advisory Commission (MedPAC) report outlining the average number of visits of each service type that occurred during a patient episode of care (MedPAC, 2011). According to the report, the average number of care episodes per home healthcare user was 2.0 and the average number of total visits per episode was 21.4. The breakdown of total visits per episode by service type is provided in Table 12. Multiplying these values by 2.0, the number of care episodes per patient per year, yields the needed demand parameter d_k for each service type k.

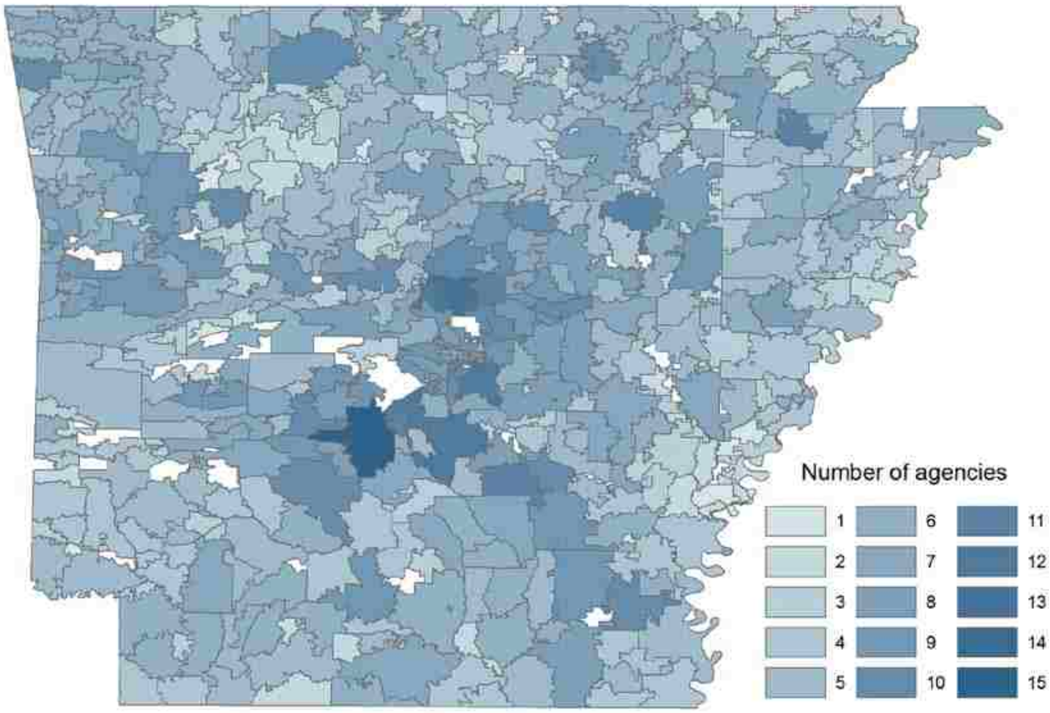


Figure 20. Number of agencies serving in each ZCTA

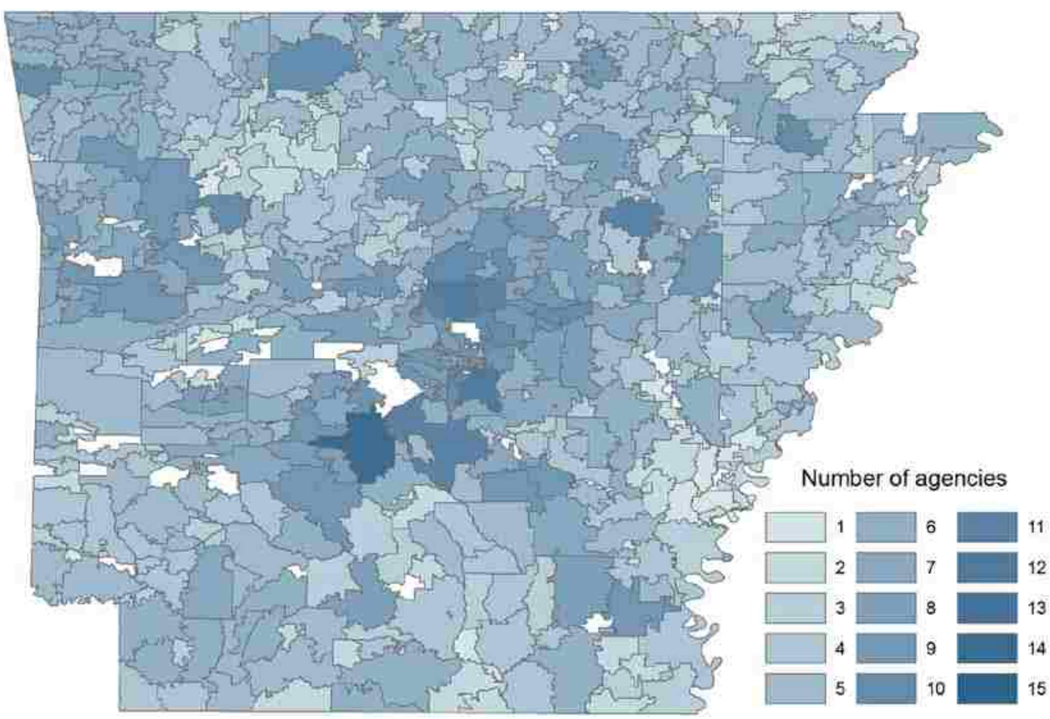


Figure 21. Number of agencies with NO missing FTE data in each ZCTA

The second parameter c_k, representing the annual productivity of service provider type k, is computed as:

$$c_k = \frac{t_k w_k}{a_k}, \tag{12}$$

where t_k is the amount of time per day a service provider of type k has available for direct patient care, w_k is the total working days per year, and a_k is the average visit duration for service type k.

To estimate the time per day a service provider has available for direct patient care, we first assume they work a standard eight-hour shift. Next, we conservatively assume they spend half of their working hours on nonclinical tasks including traveling, documentation, and other duties (Hedtcke, MacQueen, & Carr, 1992). Therefore, the direct care time per day, t_k, is assumed to be four hours. After excluding federal holidays, weekends, and a two-week vacation we assume w_k, the total working days in a year, to be 230 days. This yields a numerator for Equation (12) equal to 920 hours per year for all service types. To populate the denominator, the average visit duration for each service provider type k is obtained from data provided by Cheh and Schurrer (2010). In the study, the authors calculated the average visit duration of each service provider by analyzing the 2005 CMS Datalink files, which contain 100 percent of all the fee-for-service Medicare claims. The average visit durations for service type k (a_k) are given in Table 12. The annual productivity of service provider type k (c_k) in Table 12 is found by using Equation (12).

Table 12. Demand and capacity values

Service Provider Type	Number of visits in an episode	d_k (visits/year)	a_k (min)	c_k (visits/year)
Skilled Nursing (SN)	11.8	23.6	49.9	1106
Physical Therapy (PT)	4.8	9.6	46.9	1177
Occupational Therapy (OT)	1.0	2.0	48.1	1148
Speech Pathology (SP)	0.2	0.4	50.6	1091
Medical Social (MS)	0.1	0.2	59.1	934
Home Health Aide (HA)	3.5	7.0	66.9	825

3.5. Results

Accessibility scores for all ZCTAs in Arkansas are calculated using the proposed 2SFCA adaptation method described in Section 3.3. Choropleth maps are created in ArcGIS 10.2 to display the variability in access across the state. A quantile classification scheme with five classes (each class with 20% of the ZCTAs) is used for map classification (Table 13). The 1st quantile has lowest relative access and the 5th quantile has highest relative access. Darker shading represents higher relative accessibility while lighter shading represents lower relative accessibility. Access to the six types of service providers is displayed in Figures 22-27. Note that we only interpret values relative to one another and that there is not an absolute threshold between "bad" access and "good" access.

Table 13. Relative accessibility groups

Access Score Ranges	Quantiles
0.000000 - 0.019550	1st (Lower access)
0.019551 - 0.046704	2nd
0.046705 - 0.071680	3rd
0.071681 - 0.128066	4th
0.128067 - 2.338953	5th (Higher access)

Skilled nursing (SN)

Many ZCTAs in the higher access quantiles can be identified across state. Primary concentrations are in the West Central and East Central portions of the state. ZCTAs classified in the lower access quantiles for skilled nursing services tend to fall in Central and Northwest Arkansas. It is interesting to note that the

Arkansas Department of Health In-Home Services Division does not operate agencies in many Northwest Arkansas counties.

Physical therapy (PT)

The geographical pattern of physical therapy accessibility across the study area is different than skilled nursing accessibility. Large portions of Southeastern Arkansas are primarily in the 1st and 2nd quantiles, exhibiting relatively lower access. In contrast, the number of ZCTAs in the 5th quantile for PT access (with relatively higher access) is very limited. Interestingly, ZCTAs located in close proximity to the major cities of the state (such as Little Rock, Fayetteville, Fort Smith, and Jonesboro) tend to have better PT access than the rest of the state.

Occupational therapy (OT)

Similar to physical therapy accessibility, the Southeastern corner of the state has relatively lower occupational therapy accessibility. ZCTAs near Jonesboro and other parts of the Northeastern region of the state also tend to have relatively lower access. ZCTAs in the highest quantile for occupational therapy accessibility are clustered in the urban portions of the Northwest and Southwest corners.

Speech pathology (SP)

The concentration of ZCTAs in the higher access quantiles and lower access quantiles are distinctive across the state. The ZCTAs in the lowest quantile for SP accessibility tend to fall along the Eastern border and some parts of the inner West and North Central regions of the state. In contrast, the ZCTAs in the highest access quantile are concentrated in the Northwest, Southwest, Central (around Little Rock), and some of the Northeastern portions of the state. Please recall that dark blue in Figure 25 corresponds to the same magnitude of access score as for other service types. So, the variability in access scores for speech pathology may be contributing to the behavior that is observed in this map.

Medical social (MS)

The higher access ZCTAs for medical social services are primarily located along the Northwest and Northeast parts of the state, while ZCTAs with relatively lower accessibility are in Southeast Arkansas. This is similar to what was observed for physical and occupational therapy services. ZCTAs around Little Rock have better accessibility than their neighbors in the north and south but have lower accessibility than their neighbors in the west and east.

Home health aide (HA)

As for home health aide services, ZCTAs in the 4th and 5th quantiles are clustered in Central and Southwest Arkansas, with some also in the East Central region. Important metropolitan areas in the state (e.g., ZCTAs surrounding Little Rock, Conway, Fayetteville and Rogers) tend to have relatively poor access to home health aide services.

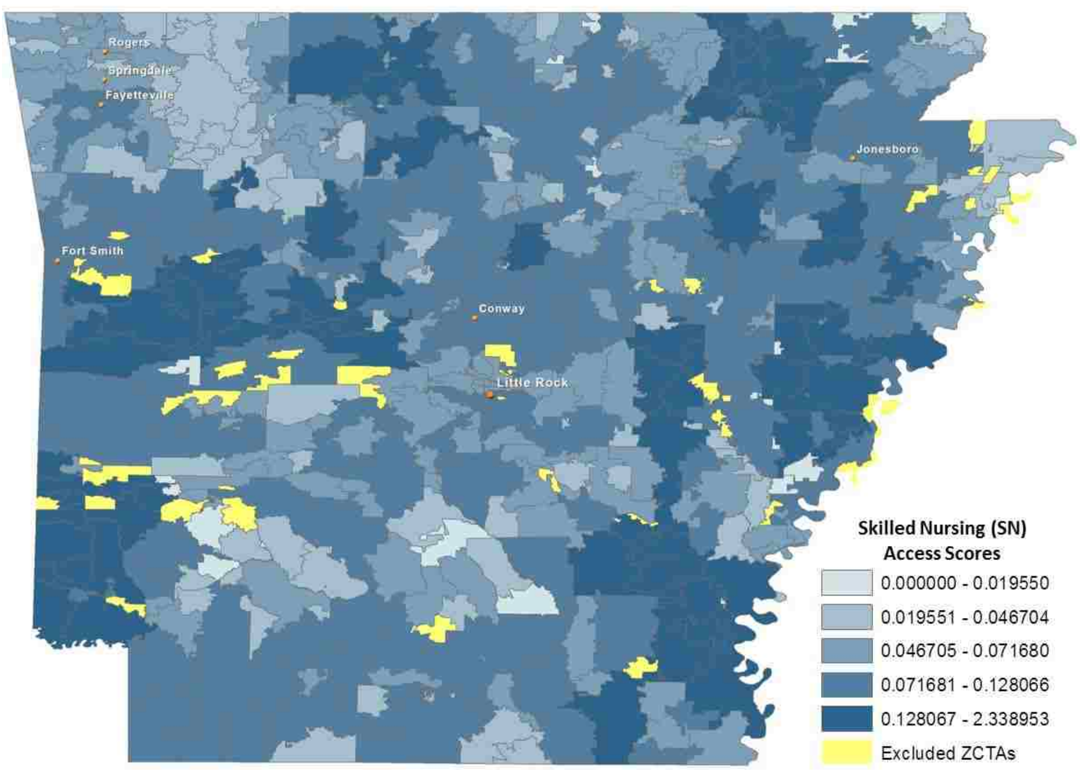


Figure 22. Results for skilled nursing

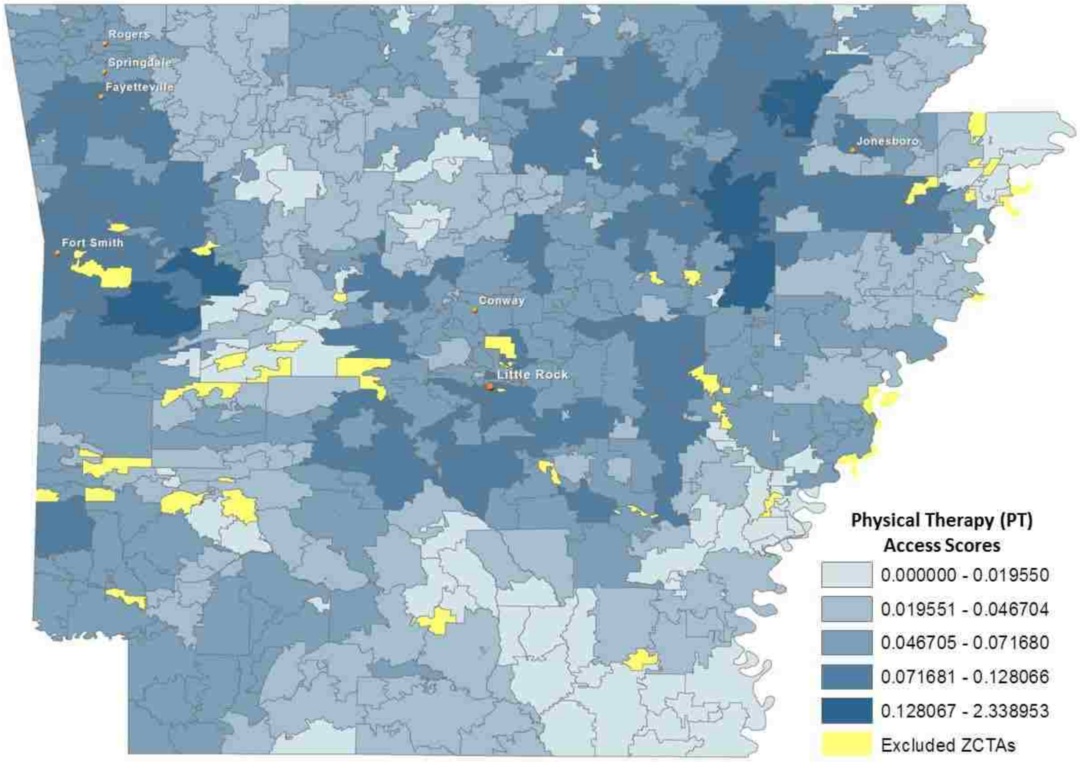


Figure 23. Results for physical therapy

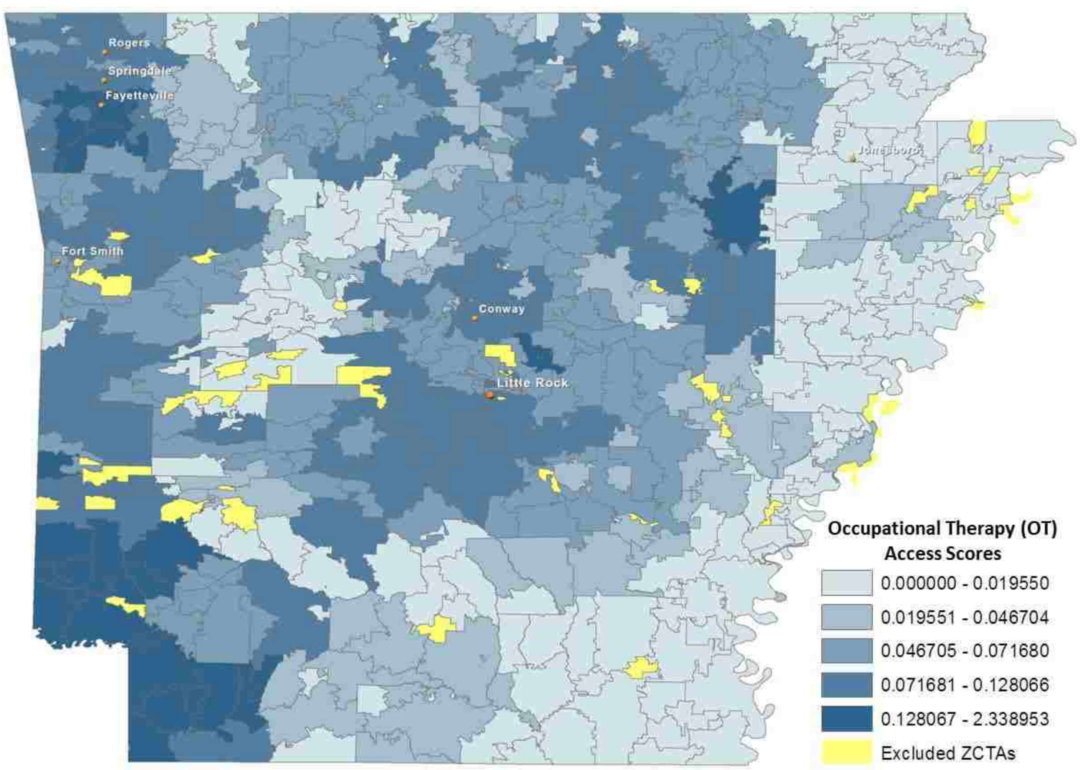


Figure 24. Results for occupational therapy

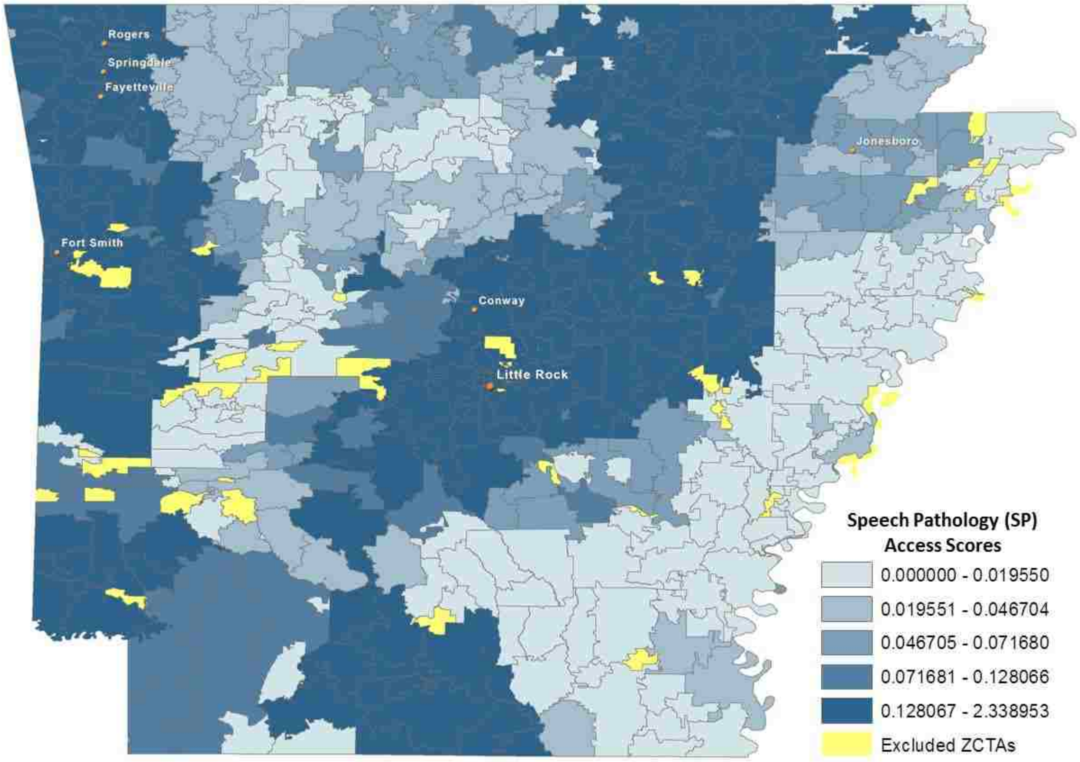


Figure 25. Results for speech pathology

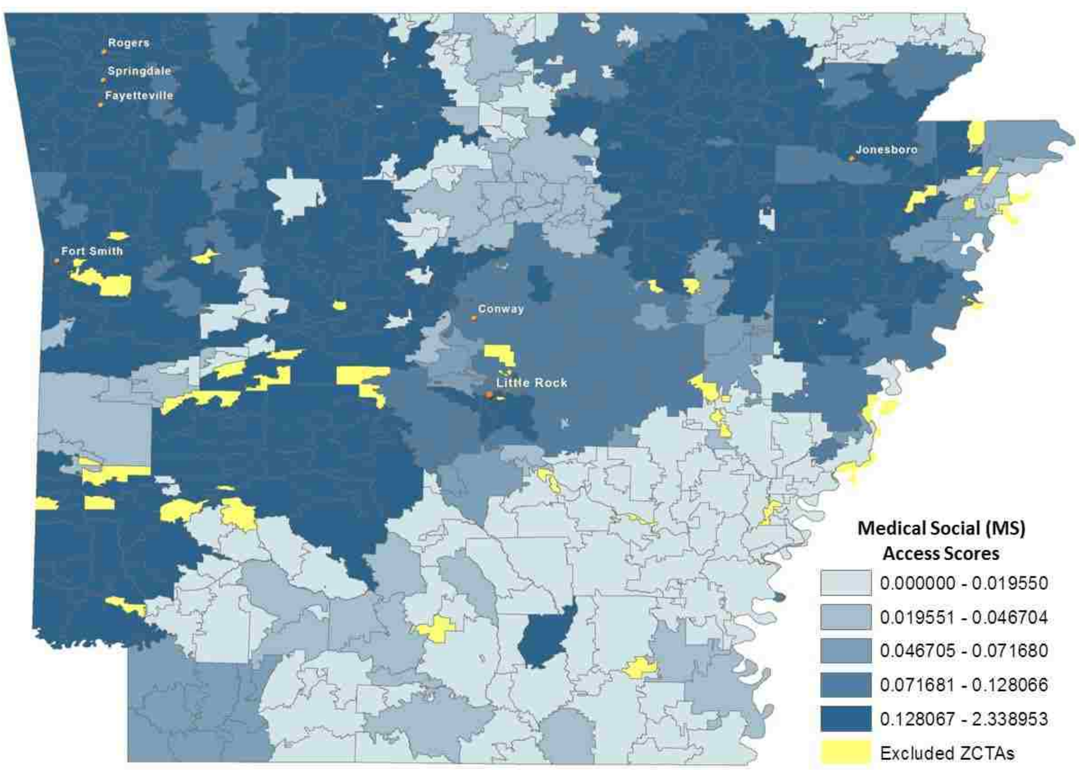


Figure 26. Results for medical social

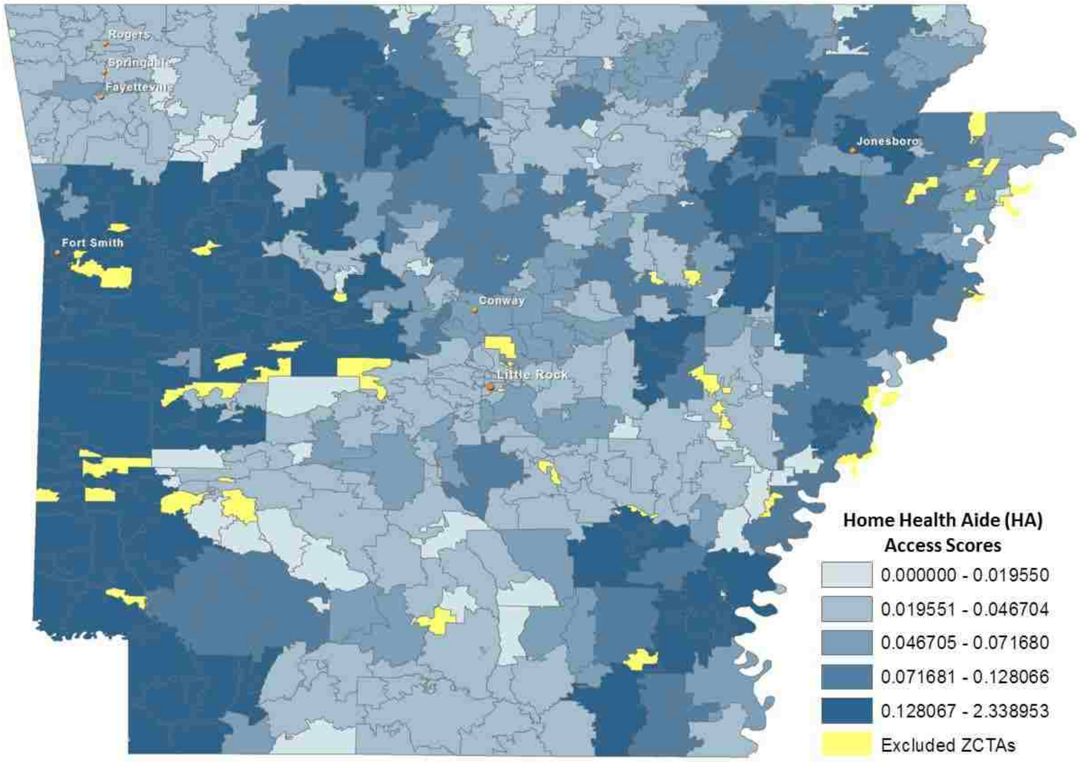
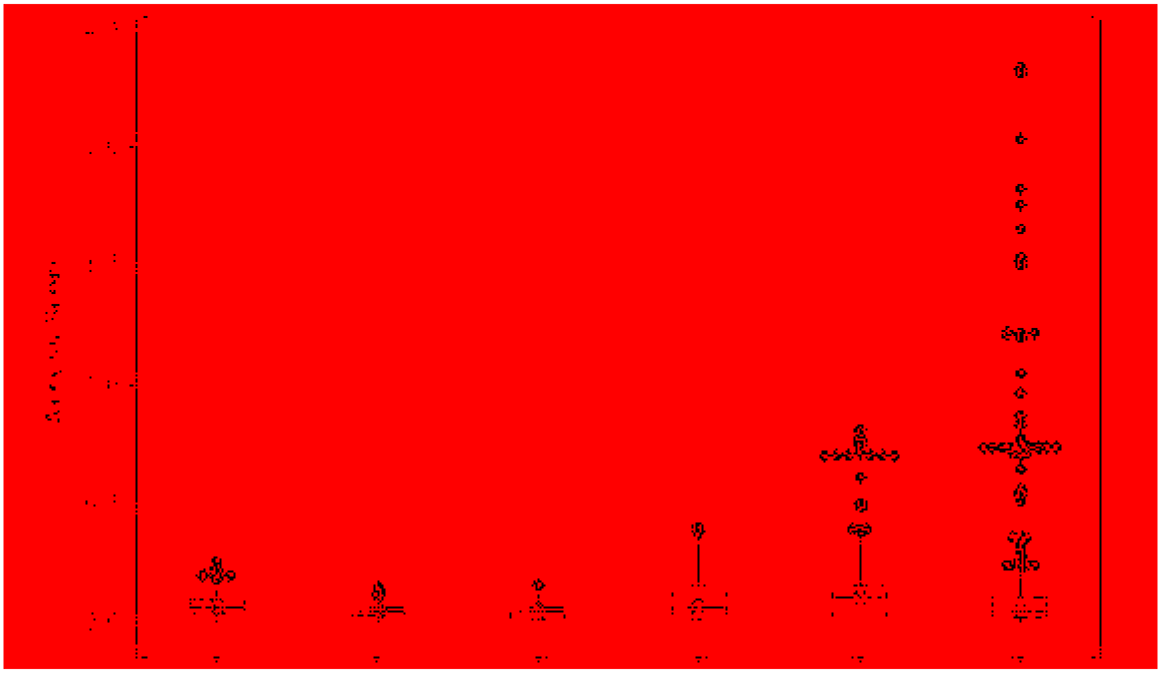


Figure 27. Results for home health aide

Observe that spatial variability in access exists for all six types of services across the state. In general, relatively higher access areas are concentrated along the western border of the state for occupational therapy, speech pathology, and medical social services. Home health aide accessibility is also relatively higher in large portions of west Arkansas, with the exception of the northwest. On the other hand, access to physical therapy, occupational therapy, speech pathology, and medical social services are relatively limited in large portions of eastern and southeastern Arkansas.

Figure 28 provides boxplots to depict the distributions of accessibility scores computed for the case study region for each service type. Higher scores indicate relatively better accessibility. Note the maximum and mean access scores for home health aide are greater than their counterpart access scores for any other services throughout the case study region. Also, medical social has the largest median value among all service types. This is due to some agencies having very high provider-to-population ratios for home health aide and medical social services. These agencies may be considered as outliers and verification of their FTE data would be helpful. There is also greater variability in access to home health aides than in access to other service types.



	SN	PT	OT	SP	MS	HA
Mean:	0.0790	0.0509	0.0474	0.1019	0.1147	0.1472
Median:	0.0722	0.0504	0.0489	0.0687	0.1136	0.0511

Figure 28. Boxplot of ZCTA level access scores

The results so far are presented at the ZCTA level and the maps exhibit the spatial variation of accessibility. However, the population of each ZCTA is different so it is also important to analyze access scores considering the populations of ZCTAs. Figure 29 provides the distribution of the over-65 population by access level for each service provider type. For skilled nursing, only 6 percent of the over-65 population lives in a ZCTA considered in the 1st or 2nd quantiles. The majority of the over-65 population (76 percent) lives in a ZCTA within the 3rd or higher access quantiles for physical therapy. Only 4.7 percent of the people over 65 years old have physical therapy accessibility in the 1st quantile. Occupational therapy has the highest 1st quantile population ratio (18.0 percent) while speech pathology has the largest 5th quantile population ratio (58.5 percent). Although home health aide services have the highest mean access score (0.1472), 44.2 percent of all people over 65 years old in the case study area live in a ZCTA within the 1st or 2nd access quantile. This indicates that ZCTAs with better home health aide accessibility tend to have lower over-65 population. We provide circular cartograms in Appendix F to further visualize access scores and over-65 populations of ZCTAs.

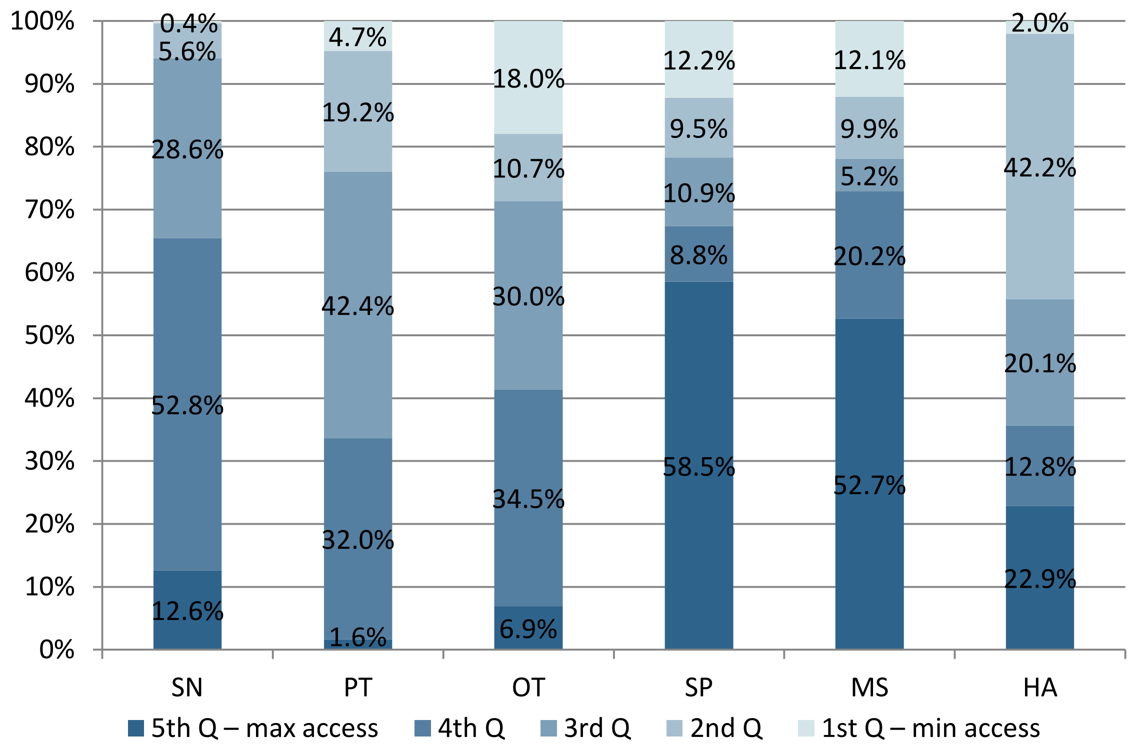


Figure 29. Distribution of over 65 population by access level

The results of the proposed 2SCFA adaptation allow a comparison among access to different service type providers in a single ZCTA. Table 14 below, for example, provides access scores of a single ZCTA. According to the table, people living in this location have better access to medical social services than any other service types. Access to home health aide services is the lowest.

Table 14. Access scores for 72701 ZCTA

Skilled Nursing	Physical Therapy	Occupational Therapy	Speech Pathology	Medical Social	Home Health Aide
0.0772	0.0881	0.1329	0.2296	0.3662	0.0432

3.6. Conclusion

In this paper, we introduce a new measure to quantify the potential spatial accessibility of home healthcare services and use the measure in a case study to highlight the spatial disparities in access in Arkansas. The proposed measure can be used to quantify spatial accessibility of home healthcare services within a geographic region while simultaneously considering both staffing levels and eligible populations. Additionally, the proposed method incorporates demand for different service types and their supply by introducing weights based on visit duration per service type and average number of visits of each type per episode of care. Hence, it provides more refined estimates of accessibility. The advantage of the proposed access measure for home healthcare services is that it allows for making comparisons between ZCTAs (for a particular service provider type) as well as between access scores (for a particular ZCTA). Unlike many other spatial potential accessibility studies, our method mitigates potential border effects by including the demand of locations out of the case study region if those locations are in an included home healthcare agency's service region. Similarly, the capacity of agencies located outside of the study region are included if they provide service to at least one ZCTA within the study region.

Results from the case study indicate spatial variability for all six types of home healthcare service across the state. On average, 24.4 percent of the population lives in ZCTAs classified in the first and second access quantiles. In general, ZCTAs with relatively higher access to occupational therapy, speech pathology, and medical social services are mainly located along the west border of Arkansas while ZCTAs with relatively lower access are situated mostly in the eastern and southeastern parts of the state. By using the outputs of the proposed 2SFCA, geographical variations for different service provider types can be easily revealed and disparities among areas can be explicitly identified. Health system planners can benefit from the results and design proper policies addressing the inequities in access. For example, instead of defining a single add-on payment rate for all rural locations, add-on rates can be determined based on the access score of a location.

A number of limitations exist in our study. First, some ZCTAs and ZIP codes may not completely overlap after matching them using a crosswalk. ZCTAs are not an exact geographic match to ZIP codes and therefore the relationships that exist between ZCTAs and ZIP codes can become quite complicated. A ZCTA may be comprised of one or more ZIP Codes; likewise, within the boundaries of a single ZIP code, there may exist more than one ZCTA. The US Census Bureau does not release an official crosswalk between ZIP Codes and ZCTAs. Hence, we attempted to match ZCTAs and ZIP codes using a publicly available crosswalk with our best effort. Second, for the demand side of the formulation, we use the over-65 population as a proxy for home healthcare demand and assume that per capita demand for home healthcare services among the over-65 population does not vary throughout the state. This situation obviously overestimates the demand, however, this does not impact the quality of the output of the model since the goal is to measure the potential access. To obtain more accurate outputs, we can include elderly people's home healthcare needs for each population location. For example, ZCTA level chronic condition prevalence data may be a suitable proxy measure for elderly people's home healthcare needs. Third, this study did not consider home health users under 65 years old which constitute around 13 percent of all Medicare home healthcare users (CMS, 2013). Fourth, FTE data for some home healthcare agencies are not available in the Healthcare Cost Report Information System (HCRIS). This could potentially impact the supply side of equation and thereby result in lower access scores for ZCTAs that are in the catchment areas of agencies with missing FTE data. Fifth, one should be aware that the Healthcare Cost Report Information System (HCRIS) is self-reported, which may lead to misinterpretation, misunderstanding, and incorrect data entry (Johnson, Pope, & Tone, 2013). In other words, measurement error may exist in responses. The model proposed to measure the access to home healthcare services in this study is employed with the best available data. The problems of missing data and measurement error need to be noted as a limitation when applying and making inferences based on this study. For more accurate estimation of access scores, complete and verified data are required. Lastly, the size of ZCTAs may vary and therefore the traveling distances of service providers can change among ZCTAs. Longer traveling requirements in a large ZCTA may decrease the available direct care time of service providers.

Future work can improve our knowledge in accessibility of home healthcare services: (i) the proposed method can be applied across all states; (ii) the proposed method can be improved by accounting for quality of services and service providers' traveling requirement due to ZCTA size; and (iii) spatial regression models can be used to examine factors that may be associated with spatial variations in access.

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Appendix F: Cartograms

A circular cartogram is a type of map where the original territory polygons are replaced by circles and the size of each circle is proportional to the value of a given variable (Anselin, 2004). In the figures below, each circle represents a ZCTA and the size of the circle is proportional to the over-65 population in that ZCTA. Larger circles represent higher over-65 population while smaller circles represent lower over-65 population. Colors of circles represent the access scores and are based on the quantile classification scheme with five classes (each class with 20% of the ZCTAs). As in Section 3.6, darker shading represents higher accessibility while lighter shading represents lower access scores.

Cartograms display access scores in relation to over-65 population and provide a convenient way to make inference on this relationship. For example, recall that home health aide services have the highest mean ZCTA level access score among all service types. Nevertheless, we observe that almost half of the over-65 population (44.2 percent) lives in ZCTAs within the 1st or 2nd access quantile. The reason for this situation is that the majority of the ZCTAs with better home health aide accessibility scores tend to have lower over-65 population as seen in Figure F.6.

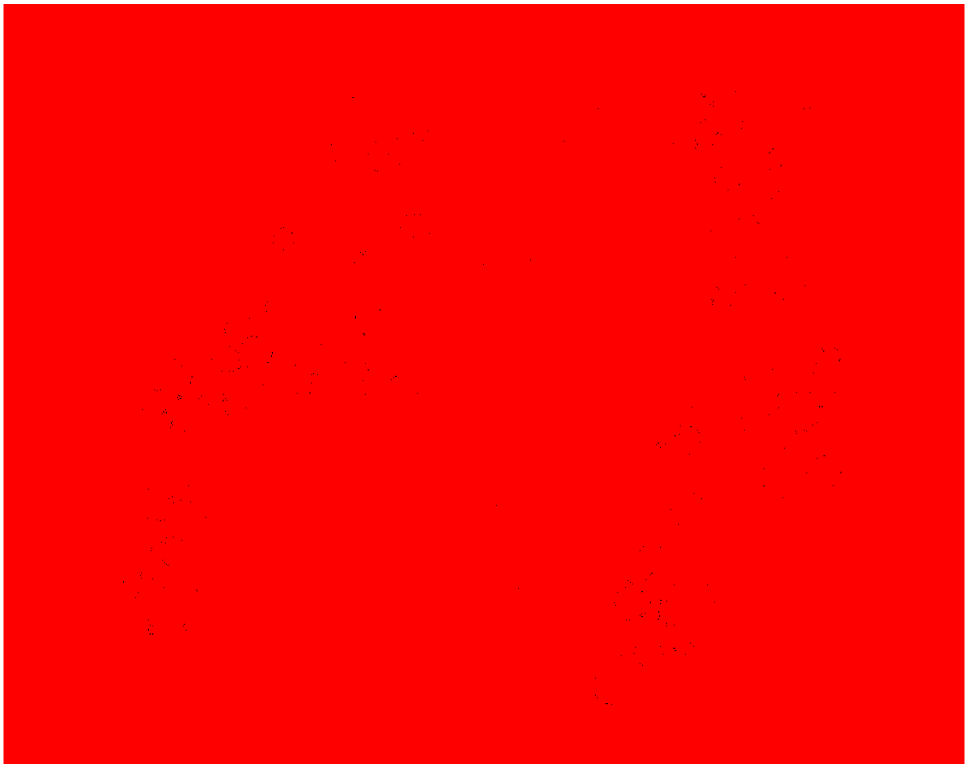


Figure F.1. Circular cartogram for skilled nursing

Figure F.2. Circular cartogram for physical therapy

Figure F.3. Circular cartogram for occupational therapy

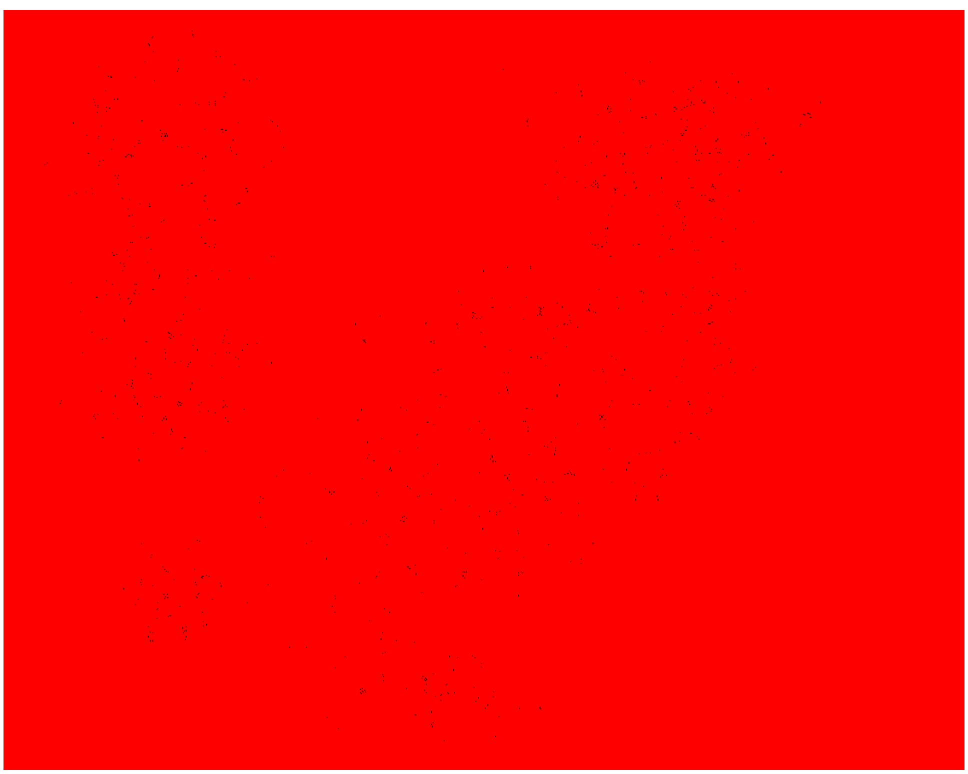


Figure F.4. Circular cartogram for speech pathology

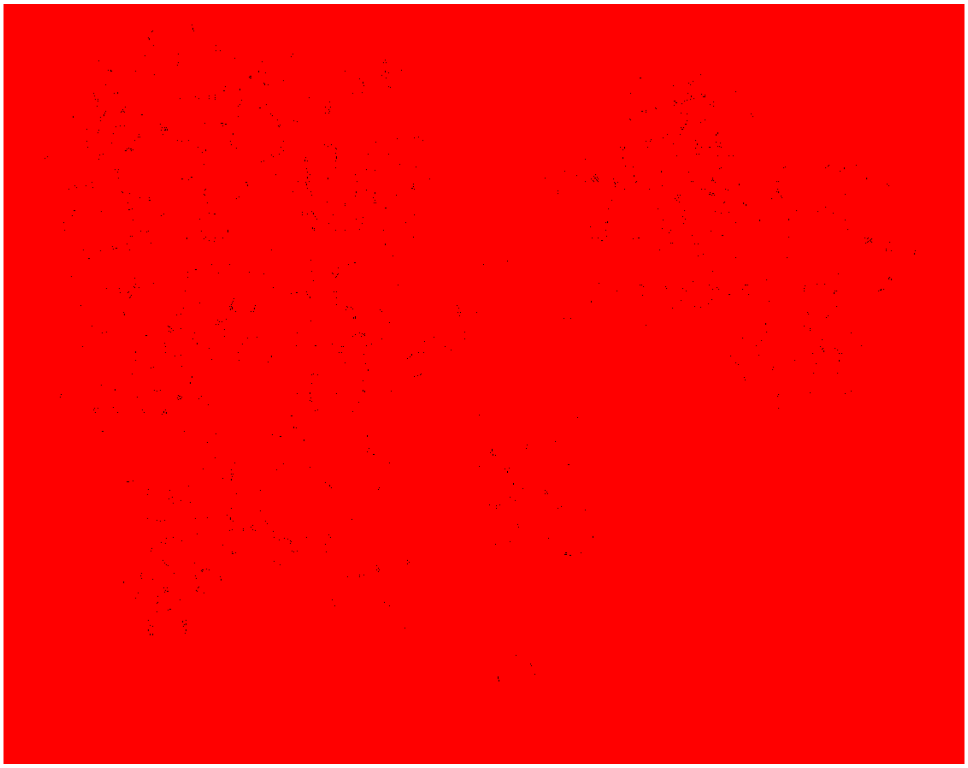


Figure F.5. Circular cartogram for medical social

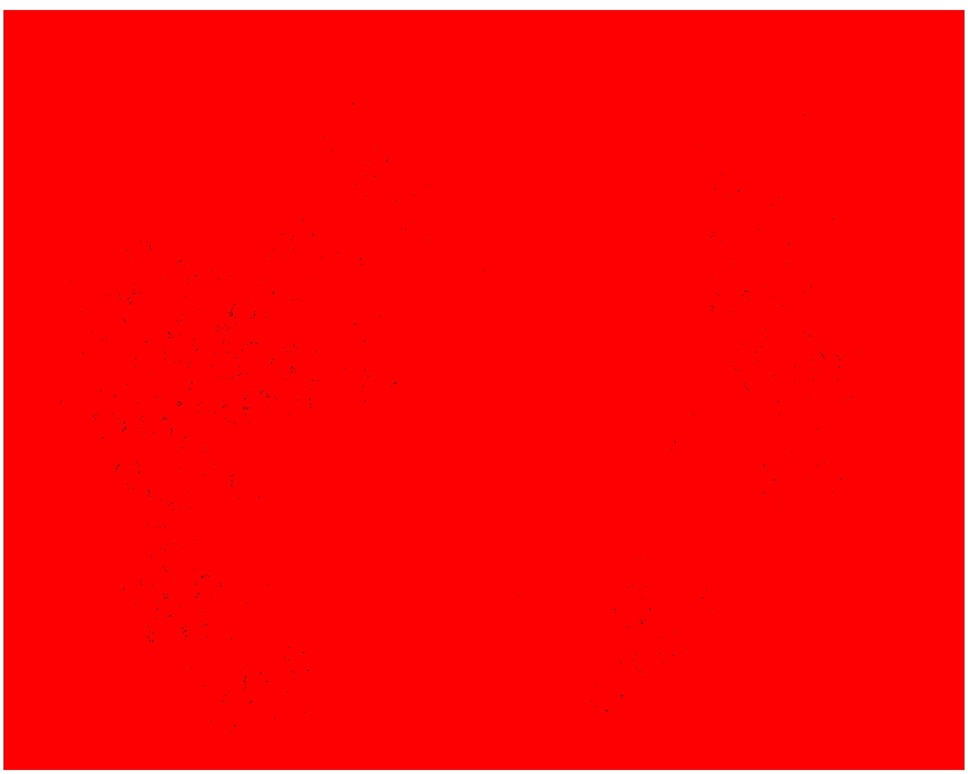


Figure F.6. Circular cartogram for home health aide

4. Assessing Socioeconomic Disparities in Potential Spatial Accessibility of Home Healthcare

4.1. Introduction

Realizing the full individual and societal benefits of home healthcare requires that the supply of services in a geographic region be sufficient to meet potential demand in that area. This concept is known as potential spatial accessibility (Andersen, McCutcheon, Aday, Chiu, & Bell, 1983; Khan, 1992), or the availability of a service as a function of geographic factors like location or distance. Quantifying potential spatial accessibility makes it possible to study factors that may influence or be associated with disparities in access, which in turn makes it possible to explicitly address these factors through policy changes, if desired.

In chapter 3, a potential spatial accessibility measure is determined at the local level (in our case, for each ZIP code tabulation area, or ZCTA) using an adapted version of the two-step floating catchment area (2SFCA) method (Luo & Wang, 2003; Radke & Mu, 2000). Rather than specifying catchments in terms of distance, as in traditional applications of 2SFCA, we take the catchment of each home health agency to be those ZCTAs served by the agency. Similarly, the catchment of each ZCTA consists of those agencies that provide service to the ZCTA. Then, we use the measure in a case study to investigate spatial disparities in home healthcare accessibility.

The purpose of this chapter is to demonstrate how space-varying coefficient models can be used explain spatial variability in accessibility across a study area. A case study region of Arkansas is used and statistically significant associations between accessibility and population characteristics are identified. Factors of interest include rural/urban status, income, racial/ethnic composition and primary care accessibility of an area. If associations between independent factors and access to home healthcare are identified, it could influence reimbursement or other types of public policies, perhaps incentivizing agencies to operate in regions that meet specific demographic criteria.

The values of both the response (accessibility) and the predictor variables (population characteristics) are spatially varying, making traditional regression inappropriate in this context. We propose to use space-varying coefficient models to estimate statistically significant associations between response and predictor variables. A large number of alternative space-varying coefficient models comprised of various combinations of predictor variables are analyzed and a set of best-fitting models is chosen through a model selection procedure that identifies statistically significant associations.

The remainder of this chapter is organized as follows. Section 4.2 provides a summary of relevant literature. The data and the methods used in the analysis are described in Section 4.3 and 4.4, respectively. Section 4.5 presents the results. Finally, conclusions and directions for future work are highlighted in Section 4.6.

4.2. Literature Review

We review the health services research literature to identify population characteristics that may be of interest in explaining access to home healthcare services. Separately, we review the literature on spatial regression modeling.

Associations between demographic characteristics and healthcare access

Researchers in multiple disciplines have shown that access to health care and other critical services can be associated with factors such as income, race, and ethnicity (Burton et al., 2010; Dai, 2010; Krieger, Chen, Waterman, Rehkopf, & Subramanian, 2005; Wang & Luo, 2005; Ye & Kim, 2015). Disparities in potential spatial accessibility of home healthcare services associated with geographic or socioeconomic characteristics, such as population density, race or ethnicity, or income, would be concerning if confirmed. However, limited research has explored these relationships to date, and methods that aim to do so must explicitly account for the spatial elements of the problem.

Past research on factors associated with home healthcare access has largely focused on differences between rural and urban areas and on utilization-based measures of access. Researchers have found that people in rural areas have less access to home healthcare services than do urban residents (Cheh & Phillips, 1993; Franco & Leon, 2000; Goldberg Dey, Johnson, Pajerowski, Tanamor, & Ward, 2011; Hawes, Phillips, Holan, Sherman, & Hutchison, 2005; Kenney & Holahan, 1990; Probst, Towne, Mitchell, Bennett, & Chen, 2014). Even in rural areas where home healthcare agencies do operate, the agencies tend to be smaller, are more likely to use lower skilled staff, and are more likely to offer a narrower mix of services (Calkins, 1999; Franco & Leon, 2000; Hutchison, Hawes, & Williams, 2010).

Other demographic characteristics that may be associated with differences in access to home healthcare services include race and income. Past research has found that racial/ethnic minority elders are less likely to receive formal home healthcare services, relying more heavily on care from family and friends, compared with non-Hispanic whites (Dilworth-Anderson, Williams, & Gibson, 2002; Mitchell, Mathews, & Hack, 2000; Mui & Burnette, 1994). Some researchers have attributed these racial differences in the use of home healthcare to economic factors. Yet the association between income and access remains opaque. While one study did identify a correlation between low income and access to home healthcare services, this relationship was explained largely by differences in health mix by income group (Nelson, Brown, Gold, Ciemnecki, & Docteur, 1997). Another recent study failed to identify diminished home healthcare access for persons of lower income (Freedman et al., 2004). However, this study used utilization as a proxy for access, meaning that the authors found no correlation between income and utilization – not income and access.

Spatial regression models

Statistical models to quantify significant associations between accessibility and independent variables, such as geographic and socioeconomic characteristics, must account for the spatial variation inherent in both the predictor and response variables. Two main types of spatial effects can be considered: (i) spatial dependence (spatial auto-correlation) and (ii) spatial heterogeneity (Anselin, 1988). The former one implies observations in different locations are dependent on each other and neighboring observations are more related than distant ones. If the association is positive, then similar values tend to cluster in space whereas if the association is negative, then dissimilar values tend to cluster in space. The second type of spatial effect, spatial heterogeneity, arises due to the instability in observational units across space. This means that the relationship structure (e.g. regression coefficients) varies by location and a single or "global" parameter estimated for the entire area cannot adequately capture the "local" association. Existence of spatial dependency and heterogeneity in a dataset violates the basic assumptions of ordinary least squares (OLS) regression and may cause unstable parameter estimation and statistically misleading results (Anselin, 2003; Feng, 2008; Little, 2013; Martens, 2006; Yin, 2008). The field of spatial regression modeling addresses these challenges.

Several spatial regression methods have been proposed in the literature. The spatial lag model and the spatial error model (Anselin, 1988) are two well-known spatial regression models. Both of them can address spatial auto-correlation (Little, 2013). In the spatial lag model, spatial auto-correlation is introduced by including a spatially lagged dependent variable whereas in the spatial error model the spatial auto-correlation is limited to the error term. Recall the standard linear regression model in matrix notation:

$$y = X\beta + \varepsilon, \tag{13}$$

where y is a vector of dependent variables, X is a matrix of explanatory variables, β is the vector of regression coefficients, and ε is the vector of model errors. In the spatial lag model, a spatially lagged dependent variable (Wy) is added, as in Equation (14):

$$y = \rho Wy + X\beta + \varepsilon. \tag{14}$$

In the above equation, Wy is the spatial lag of the dependent variable for spatial weights matrix W, ρ is a spatial autoregressive parameter and ε is the vector of model errors. Spatial weights determine the effects of the neighbors. In the spatial error model, however, spatial auto-correlation is included by a spatial weight matrix in the error component, as in Equation (15):

$$y = X\beta + \lambda W\varepsilon + \xi, \tag{15}$$

where λ is a spatial autoregressive parameter, ξ is the independent model error and W is the spatial weights matrix, as before (Cellmer, 2013; Chrostek & Kopczewska, 2013; Little, 2013).

Both spatial lag and spatial error models have similar structures and account for the impact of proximal locations on observations (Chrostek & Kopczewska, 2013). To explain a specific phenomenon, they estimate a single (global) value for the whole system. Their assumption is that the associations between the dependent variable and the explanatory variables are homogeneous (stationary) across all locations. In many real life practices, however, the association may be dynamic and there is a possibility of variation (heterogeneity) of model parameters throughout geographical space (Chen, Deng, Yang, & Matthews, 2012; Fan & Zhang, 2008; Finley, 2011). Formally, in the case of heterogeneity, the regression formula is expressed as below:

$$y = f\left(X\beta\right) + \varepsilon, \tag{16}$$

where f is the vector of functional forms that can define different sets of regression coefficients β associated with each observation (Little, 2013).

Geographically weighted regression models (Fotheringham, Brunsdon, & Charlton, 2002) and space-varying coefficients models (Assunção, 2003; Gelfand, Kim, Sirmans, & Banerjee, 2003; Serban, 2011) are the two main approaches available in the literature for incorporating spatial heterogeneity (Finley, 2011; Waller, Zhu, Gotway, Gorman, & Gruenewald, 2007). A geographically weighted regression (GWR) model estimates regression coefficients for each location based on nearby observations by applying local regression and kernel estimation methods (Chen et al., 2012; Little, 2013). This allows investigating the spatial variations of regression relationships. In space-varying coefficients (SVC) models, the variability of parameters is specified in a distribution form which can utilize a stochastic structure (Finley, 2011; Little, 2013; Waller et al., 2007). Regression coefficients can vary as smooth functions of other variables (Assunção, 2003). GWR and SVC models have been compared in the literature. The results suggest that SVC models produce more robust results than GWR models when collinearity exists. Also, SVC models provide a more complete basis that offers opportunity for model-based estimation and inference (Finley, 2011; Waller et al., 2007; D. C. Wheeler & Calder, 2007; D. C. Wheeler & Waller, 2008). Hence, a space-varying coefficient model is used in this research to identify statistically significant associations, if they exist, between home healthcare accessibility and geographic or socioeconomic factors.

Spatial statistical models have been applied to understand spatial effects in other health-related contexts, including H1N1 vaccine accessibility (Heier Stamm, 2010; Heier Stamm, Serban, Swann, & Wortley, 2015), physical activity levels in pregnant women (Reich, Fuentes, Herring, & Evenson, 2010), incidence of limiting long-term illness (Brunsdon, Fotheringham, & Charlton, 1998), incidence of zoonotic disease (Assunção, 2003), prevalence of late-stage breast cancer (Dai, 2010) and access to primary care physicians (Ye & Kim, 2015).

4.3. Choice of Independent Variables

In this study, we consider three important socio-economic characteristics of population locations: income, rural/urban status, and racial/ethnic structure. We define a series of variables related to each characteristic by considering the availability and completeness of data at the ZCTA level of aggregation (recall access scores were computed at the ZCTA level as described in Chapter 3). The 2009-2013 5-Year American Community Survey and 2010 Census Summary File 1 contain data related to these characteristics at the ZCTA level (U.S. Census Bureau, 2011, 2014). Throughout the remainder of this chapter, these datasets are referred to as ACS and SF1 respectively. Each characteristic and related variables are summarized below.

Income

Variables related to income available in ACS at the ZCTA level include per capita income, median household income and poverty rate, defined as the percent of the population living below the federal poverty level.

Rural/urban status

Two variables selected to reflect the rural/urban status of population locations are population density and the percent rural population. A ZCTA can be classified as urban, rural, or can contain both urban and rural areas. Hence, the percent rural population variable is the percentage of residents in a ZCTA living in a rural portion of that ZCTA. To understand what is meant by rural, the US Census identifies urban areas as "urbanized areas of 50,000 or more population and urban clusters of at least 2,500 and less than 50,000 population" (Bureau of the Census, 2011). Territories outside urban areas are classified as rural. Both population density and percent rural population data were extracted from SF1.

Racial/ethnic structure

The variables selected to reflect Racial/ethnic structure are percent black population, percent Hispanic population and percent minority population. These are defined as the percentage of residents of a ZCTA that are black, Hispanic, and other than non-Hispanic white, respectively. This data is obtained from SF1. While data for other minority populations are available in SF1, we separately consider only African American and Hispanic groups as they are identified as the primary minority populations in Arkansas (Hamilton, 2011). The percent minority variable is additionally considered to discover any potential effects related to the minority population as a whole instead of individual ethnic/race groups.

Primary care access

In addition to socio-economic characteristics, we include physician-to-population ratio to examine association between primary care access and home healthcare access. Physician-to-population ratio is used as a criterion to assess whether or not a location is a primary care health professional shortage area (U.S. Department of Health & Human Services, n.d.). Arkansas ranks 48th among 50 states with respect to this ratio (Association of American Medical Colleges, 2011). Physician-to-population ratio data were acquired from the 2010 Primary Care Service Area Data version 3.1 (HRSA, 2010). The 2010 Census Tract to PCSAv3.1 Crosswalk file provided by Health Resources and Services Administration (HRSA) Data Warehouse is used to map primary care service areas to ZCTAs.

Summary statistics for the above nine variables are provided in Table 15. These summary statistics are computed across the set of ZCTAs in the case study. It is interesting to note the median percent rural population across all ZCTAs in the state is 100% (the entire population of the ZCTA is in a rural area). It can also be observed that some ZCTAs have zero percent minority population while some have 100 percent.

4.4. Methods

This section describes the methods applied to understand disparities in home healthcare accessibility associated with independent variables such as socio-economic characteristics and primary care accessibility. We begin by introducing a test to examine the spatial auto-correlation of access scores and then explain the space-varying coefficient models to identify factors associated with access scores.

Table 15. Summary statistics of potential predictor variables for case study region

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
Black population (%)	12.61	1.02	19.99	0.00	100.00
Hispanic population (%)	3.47	2.00	4.96	0.00	40.99
Minority population (%)	18.77	8.76	20.12	0.00	100.00
Population density	5.36	1.01	15.28	0.02	130.75
Rural population (%)	84.09	100.00	30.35	0.00	100.00
Poverty rate (%)	20.22	18.00	12.21	0.00	83.00
Per capita income ($)	19,667	18,866	5,853	461	58,872
Median household income ($)	37,292	36,034	11,883	6,250	92,546
Physician-to-population ratio	0.00050	0.00046	0.00027	0.00000	0.00141

4.4.1. Examining Spatial Auto-correlation of Variables

According to Tobler's first law of geography, “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970). Spatial auto-correlation exists if nearby observations in space have related values. In this case, independence of observations, one of the ordinary least square (OLS) model assumptions, is violated and may result in inaccurate coefficient estimations. Hence, the initial assessment in our methodology is to examine the spatial auto-correlation of access scores by Univariate Moran’s I test (Moran, 1950). In the case of spatial auto-correlation, it is necessary to employ methods that account for this dependency.

Univariate Moran’s I Test

Univariate Moran’s I test is the most commonly applied test to measure spatial auto-correlation. In contrast to linear correlation, Univariate Moran’s I test measures the degree of the relationship between a variable and the spatial lag of the same variable (the *spatial lag* of a variable is the weighted average of neighboring values). The formula for Univariate Moran’s I Index is:

$$I = \frac{n}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}, \tag{17}$$

where n is the total number of observations (spatial units), x_i and x_j are the values of observations (e.g. access scores) at locations i and j, respectively, $\bar{x}$ is the mean of the observations and w_{ij} is the spatial weight between locations i and j. The spatial weight (w_{ij}) reflects the "nearness" of two locations and can be specified based on contiguity or distance. For the purposes of this study, we chose to compute spatial weights based on the straight-line Euclidean distance which is commonly used in accessibility research (Smoyer-Tomic, Hewko, & Hodgson, 2004).

Similar to the linear correlation coefficient, Univariate Moran's I correlation coefficient varies from -1 to +1. A correlation coefficient close to 1 implies a clustered pattern (e.g. high values are surrounded geographically by high values) and a correlation coefficient close to -1 implies a dispersed pattern (e.g. high values are surrounded by low values). A value of 0 indicates complete spatial randomness.

The null hypothesis for the Univariate Moran's I test is that observations are spatially independent; there is no spatial clustering. The significance of the Univariate Moran's I statistic against the null hypothesis can be tested by converting Moran's I values to *z*-scores. If the *p*-value of the test is statistically significant (*p*-value is smaller than the significance level α) then, the null hypothesis can be rejected. We applied the Univariate Moran's I test to examine the spatial auto-correlation of access scores for each service type in the case study region. In each case, the null hypothesis was rejected, indicating that spatial auto-correlation exists and models that account for spatial dependency are needed in order to explain variation in access. A detailed discussion of these results is given in Section 4.5.1.

4.4.2. Space-varying Coefficient Models

Varying coefficient models allow estimating the associations between response (access scores) and covariates (socio-demographic factors and primary care access) by accounting for the variation over time or across space or both time and space (Serban, 2011). Hence, unlike the traditional linear regression models, the regression coefficients are not required to be constant values and they can vary smoothly across a geographic area or a time period (Heier Stamm, 2010; Park, Mammen, Lee, & Lee, 2015). To account for the spatially-varying associations between home healthcare accessibility and the socio-demographic factors, we implement a space-varying coefficient model.

4.4.2.1. The Model

A space-varying coefficient model for a set of observed data $\left(Y_j, \{X_{rj}, r=1,\ldots,R\}\right)$ can be described using Equation (18):

$$\mathbb{E}\left[Y_j \middle| X\right] = \beta_0(l_j) + \beta_1(l_j)X_{1j} + \ldots + \beta_R(l_j)X_{Rj}, \tag{18}$$

where $Y_j = Y(l_j)$ is the dependent variable (accessibility score) and $X_{rj} = X_r(l_j)$ is a set of independent variables observed at location $l_j = (l_{j1,}l_{j2,}),\ j=1,\ldots,L$ (Heier Stamm, 2010; Serban, 2011). In the model, R is the number of independent variables and L is the number of geographical locations where data are observed. The smooth coefficient functions that may vary in space are represented by $\beta_r(l_j)$ for $r=1,\ldots,R$. Also, l_{j1} and l_{j2} denote the latitude and longitude of the locations (ZCTAs in our case).

4.4.2.2. Coefficient Estimation

In the literature, Bayesian methods (Assunção, 2003; Gelfand et al., 2003; Waller et al., 2007) and non-parametric methods (e.g. penalized splines (Ruppert, Wand, & Carroll, 2003)) have been proposed to estimate the unknown coefficient functions $\beta_r(l_j)$ for $r=1,\ldots,R$. We chose to use penalized splines because Bayesian approaches are computationally more expensive than non-parametric methods for large geographic regions (big data sets) (Heier Stamm et al., 2015; Hoeting, Davis, Merton, & Thompson, 2006). Penalized splines method is implemented using functions in the R statistical software library *mgcv* (Wood, 2006) to estimate the space-varying coefficients in our model. In the model, the space-varying coefficients are drawn from the Normal distribution.

4.4.2.3. Inference on Shape of Coefficients

Regression coefficients in a space-varying coefficient model can take various shapes. A non-constant (i.e., linear or non-linear) coefficient represents that the association between the dependent variable and the predictor varies over space. Hence, a non-constant coefficient indicates a varying association pattern and suggests that the corresponding predictor is significant. On the other hand, the predictors with a constant coefficient may not be statistically significant. Simultaneous confidence bands (Serban, 2011) are used to make inference on the shape and the statistical significance of coefficients. The inference is based on a 1- α confidence band for a two-sided hypothesis test with a significance level of α (Heier Stamm et al., 2015). For a non-constant predictor, if the lower bound of the confidence interval at a ZCTA is positive, then the coefficient at that ZCTA is identified as statistically significantly positive at a significance level of α. Similarly, if the upper bound of the confidence interval is negative, then the coefficient is identified as statistically significantly negative.

4.4.2.4. Implementation Stages

We implemented space-varying coefficient models by following the stages explained below. The implementation methodology is summarized in Figure 30.

Define a set of initial models. In Section 4.3, we have identified the following nine predictors:

- Income: *poverty rate* (Poverty), *per capita income* (PerCapInc), and *median household income* (MHInc)
- Racial/ethnic structure: *percent black population* (BlackP), *percent Hispanic population* (HispanicP), and *percent minority population* (MinorP)
- Rural/urban status: *percent rural population* (RuralP) and *population density* (PopDens)
- Primary care accessibility: *physician-to-population ratio* (P-to-P).

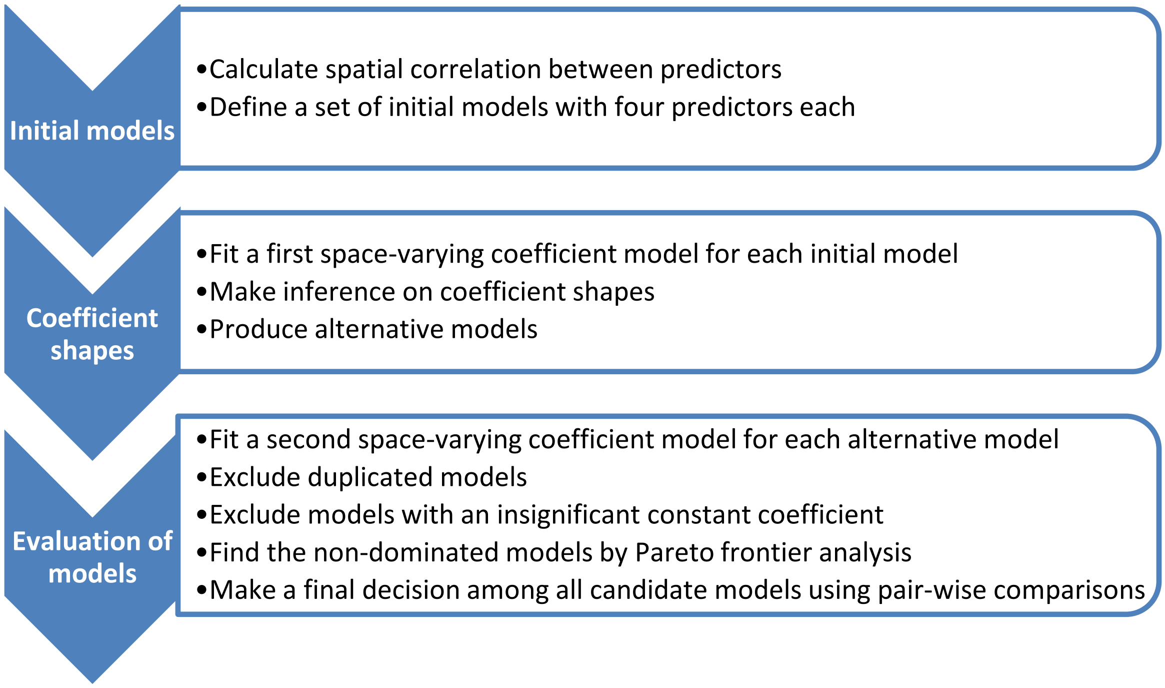


Figure 30. Implementation stages

We transform all predictors using the natural log-transformation to normalize the data and then standardize them to bring all values into the range [0, 1]. Doing so allows the relative importance of predictors in the same model to be compared based on coefficient ranges.

Due to the computational burden for estimating coefficients for a dataset consisting of 589 ZCTAs that also exhibits multicollinearity issues, we limit our consideration to models including at most four predictors. Moreover, including too many variables can avoid highlighting the meaningful effects of substantively important variables.

We refer to the models with four predictors as “initial models”. To determine the groups of predictors to include in each initial model, the spatial correlations (collinearity) between all pairs of the nine predictors were computed using the method developed by Jiang (2010). Using predictors that are highly collinear within the same regression model causes correlation among the regression coefficients and thereby understanding the individual impact of each factor can be impossible (Plant, 2012; D. Wheeler & Tiefelsdorf, 2005). Hence, a threshold value of 0.5 is used to determine whether a pair of predictors can be included in the same initial model. That is, we avoid using two variables in the same model if they have a spatial correlation of more than 0.5. The computed spatial correlations are given in Table 16. The spatial correlations above the allowable threshold are indicated in bold. Thus, pairs of variables associated with the bold indications do not appear together in the same initial models.

Table 16. Spatial correlations between independent variables (above threshold in bold)

	BlackP	**HispanicP**	**MinorP**	**PopDens**	**RuralP**	**Poverty**	**PerCapInc**	**MHInc**	**P-to-P**
BlackP	1								
HispanicP	0.379	1							
MinorP	**0.915**	0.403	1						
PopDens	0.177	**0.559**	0.087	1					
RuralP	-0.269	-0.342	-0.246	-0.736	1				
Poverty	0.375	0.407	0.347	0.083	-0.091	1			
PerCapInc	0.091	0.384	-0.006	**0.554**	**-0.511**	0.050	1		
MHInc	0.077	**0.600**	0.004	**0.685**	-0.453	-0.006	**0.831**	1	
P-to-P	0.238	0.148	0.155	0.244	-0.206	0.055	0.145	0.146	1

We also avoid including multiple variables that measure the same characteristic of a population location in the same model. For example, percent rural population and population density variables would not be allowed to appear together in an initial model because they both measure urban/rural status. One exception to this rule is with the variables for racial/ethnic structure. Variables for percent black population and percent Hispanic population are allowed to appear together in initial models. However, neither of these variables can appear together in a model with percent minority population, which accounts for all minorities including black and Hispanic. Table 17 provides a complete list of the initial models that were considered.

Table 17. Initial models with included independent variables

Initial Model	Predictors			
1	BlackP	HispanicP	Poverty	P-to-P
2	BlackP	HispanicP	PerCapInc	P-to-P
3	BlackP	HispanicP	Poverty	RuralP
4	BlackP	HispanicP	P-to-P	RuralP
5	BlackP	Poverty	P-to-P	PopDens
6	BlackP	Poverty	P-to-P	RuralP
7	BlackP	MHInc	P-to-P	RuralP
8	HispanicP	Poverty	P-to-P	RuralP
9	MinorP	Poverty	P-to-P	PopDens
10	MinorP	Poverty	P-to-P	RuralP
11	MinorP	MHInc	P-to-P	RuralP

Determine coefficient shapes of predictors. We fit a space-varying coefficient model for each initial model with four predictors. The output of this space-varying coefficient model is the confidence bands of smooth coefficient functions $(\beta_r(l))$. We determine the shape of the coefficients (constant, linear or non-linear) using confidence bands by applying the inference procedure proposed by (Serban, 2011).

For each model that includes one or more non-linear predictors and other predictors whose shape is constant or linear, we generate reduced models where each constant or linear predictor is either included as a constant or completely excluded. In other words, we produce reduced models by creating combinations of predictors whose shape is other than non-linear. Predictors with non-linear coefficients in the original model are included with non-linear coefficients in each of the corresponding reduced models. Hence, for an initial model with n constant and/or linear predictors we obtain 2^n different reduced models (these reduced models always contain the predictors with a non-linear coefficient). For example, suppose that in initial model 1, the variables BlackP and HispanicP are found to have non-linear coefficients, whereas Poverty has a linear coefficient and P-to-P has a constant coefficient. Then, the reduced models derived from initial model one would be as shown in Table 18. Note that BlackP and HispanicP appear in all four of the reduced models, because they have non-linear coefficients. In models 1.1 and 1.2, Poverty appears as a constant and does not appear at all in 1.3 and 1.4. Similarly, in models 1.1 and 1.3, P-to-P appears as a constant and does not appear at all in 1.2 and 1.4.

Table 18. An example of reduced models

Reduced Model ID	BlackP	HispanicP	Poverty	P-to-P
1.1	non-linear	non-linear	constant	constant
1.2	non-linear	non-linear	constant	N/A
1.3	non-linear	non-linear	N/A	constant
1.4	non-linear	non-linear	N/A	N/A

For each initial model, reduced models are produced in this fashion. The complete list of all reduced models constitutes what we refer to as “alternative models”. All alternative models are listed in Appendix G.

Evaluate the alternative models. Model selection among alternative models is done through several evaluation steps based on different criteria. We fit space-varying coefficient models for each alternative model and calculate two measures to use during model evaluation; Akaike Information Criteria (AIC) (Akaike, 1974) and spatial correlation between the response variable and the residuals (Jiang, 2010). AIC is used because it is a common measure of the trade-off between goodness of fit and model complexity (Johnson & Omland, 2004; Schunn & Wallach, 2005). The spatial correlation between the response variable and the residuals is used because it is “a measure of how much spatial dependence in the response variable is not explained by the model” (Heier Stamm et al., 2015). For both measures smaller values indicate a better model. Also, we provide *p*-values to test the significance of those predictors in the alternative models that are identified as having a constant coefficient. Recall it is not necessary to use *p*-values to test the significance of predictors having non-linear coefficients, because a non-linear coefficient indicates a varying association pattern and suggests that the corresponding predictor is significant. Below, we explain the model evaluation steps in our methodology.

1. In the first step of the model evaluation phase, we find and exclude the duplicated models from among all alternative models.
2. Next, we exclude all remaining alternative models that include at least one variable whose coefficient is constant but insignificant (*p*-value > 0.10).

3. In the following step, we compare all of the remaining alternative models having the same number of predictors based on Akaike Information Criteria (AIC) and absolute value of the correlation between the response and residuals. For both criteria, lower values indicate better models. This situation can be considered as a multi-objective decision process and hence a single model that simultaneously minimizes the AIC and absolute correlation may not exist. In multi-objective decision making, the Pareto optimal set is defined as the set of all trade-off solutions that are non-dominated (Abraham, Jain, & Goldberg, 2005). By using Pareto frontier analysis for the models with same number of predictors (for each possible number of predictors) we formally find the non-dominated model(s) and eliminate all dominated models for each number of predictors. In Appendix H Pareto frontiers are provided.

4. All non-dominated models are considered as “candidate models”. If there is only one candidate model for a particular service type, it is selected as the final model for that service type. If there is more than one candidate model, then we apply pair-wise comparisons, when possible. We compare the candidate models that have at least one predictor in common and check whether or not the additional predictor(s) included in the model with a larger number of predictors improve both AIC and correlation values. For example, suppose that there are two candidate models as shown below;

	AIC	**Correlation**	**1st Predictor**	**2nd Predictor**
Candidate Model 1:	2568.6	0.371	Poverty (non-linear)	N/A
Candidate Model 2:	2535.6	0.298	Poverty (non-linear)	HispanicP (constant)

Candidate Models 1 and 2 share the same predictor with a non-linear coefficient (e.g. Poverty). Because an additional predictor with a constant coefficient in Candidate Model 2 (e.g. HispanicP) improves both AIC and correlation, Candidate Model 2 is preferred over Candidate Model 1.

5. If multiple candidate models exist after pair-wise comparisons, we chose the model with greatest significance and/or magnitude of constant coefficients. All else being comparable, simpler models (those with fewer predictors) were preferred.

4.5. Results

In this section, we present the results of our implementation study.

4.5.1. Examining Spatial Auto-correlation of Variables

As described in Section 4.4.1, we applied Univariate Moran's I test to examining the spatial auto-correlation of access scores. Straight-line Euclidean distances were used to calculate the distances between two ZCTAs (d_{ij}). The spatial weights (W_{ij}) are then proportional to inverse distance $(d_{ij} = 1/w_{ij})$. Given that the values for all *z*-test statistics are greater than the critical value of 1.96 at a level of significance of 0.05, we reject the null hypothesis in favor of the alternative hypothesis that spatial auto-correlation exists in each set of access scores.

Table 19. Moran's I test results

Service Types	**Moran's I Index**	***z*-score**	***p*-value**
Skilled Nursing (SN)	0.365340	15.51	0.002
Physical Therapy (PT)	0.493931	22.00	0.005
Occupational Therapy (OT)	0.644209	29.39	0.002
Speech Pathology (SP)	0.635165	29.54	0.002
Medical Social (MS)	0.482794	20.48	0.005
Home Health Aide (HA)	0.691155	32.16	0.002

The Moran Scatterplots (Figure 31) illustrate the relationship between access values (x-axis) and spatially lagged access values (y-axis) using the variables in standardized form. The slope of the linear regression line through a scatterplot equals the associated Univariate Moran's I Index. Access scores of all service types have a positive spatial auto-correlation (these can be observed by the trendlines with positive slope in Figure 31). That means high values are surrounded geographically by high values and low values are surrounded geographically by low values. OT, SP, and HA display higher positive spatial auto-correlation than other service types. Significant spatial auto-correlations in the access scores of all service types indicate spatial dependency among observations and thereby inaccurate estimates may be obtained using linear regression models. Therefore, spatial regression models (e.g. space-varying coefficient models) are necessary to account for the spatial dependency in the data. SVC models can provide information on spatial relationships between variables.

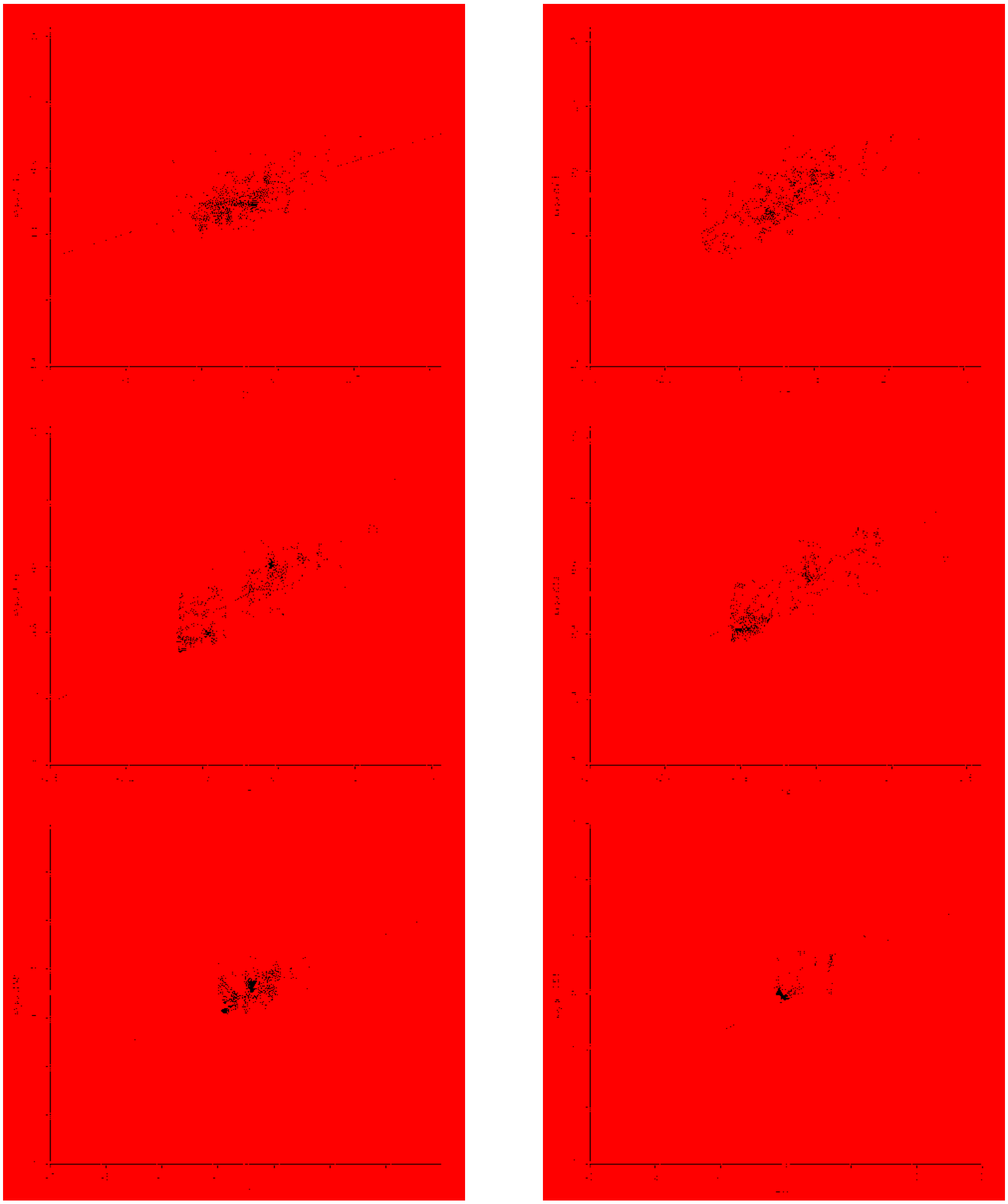


Figure 31. Moran’s I scatter plots

4.5.2. Space-varying coefficient models

We employ space-varying coefficient regression methods described in Section 5.4.2 to examine the association of predictors with accessibility of different home healthcare service types. None of the models selected as a result of the methodology include percent black population, percent minority population, population density, per capita income, median household income, or physician-to-population ratio as predictors. However, percent Hispanic population is associated with access scores for all service types and poverty rate and percent rural population are significant predictors for three service types.

Table 20 summarizes the selected explanatory models for each service type. NL denotes non-linear shape and C denotes constant shape. The numbers indicate the range of coefficient values.

Table 20. Shapes and coefficient values of predictors

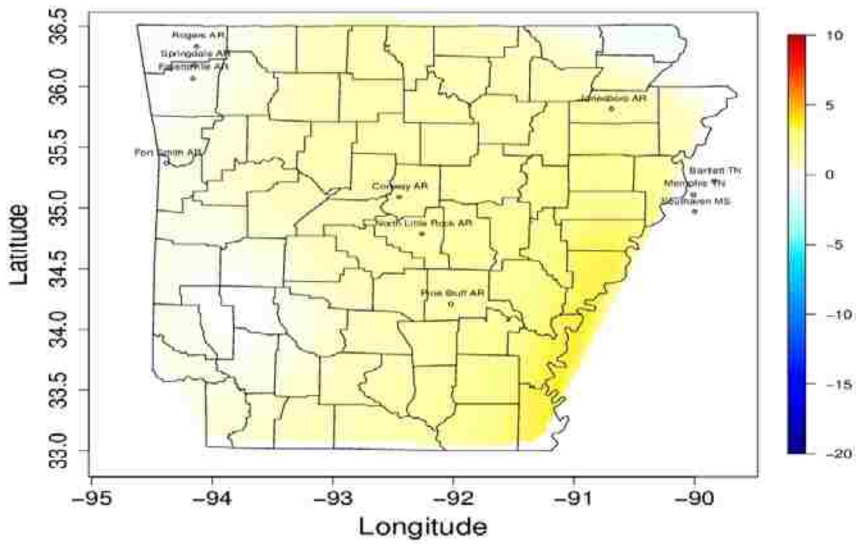
Service Type	**Hispanic population**	**Poverty rate**	**Rural population**
Skilled Nursing (SN)	NL [-1.23, 3.62]		
Physical Therapy (PT)	NL [-4.04, 3.50]	NL [-0.88, 7.30]	
Occupational Therapy (OT)	C* 2.25	NL [-5.55, 8.28]	NL [-15.78, 9.39]
Speech Pathology (SP)	NL [-5.10, 8.65]	NL [-0.34, 7.90]	NL [-19.94, 9.03]
Medical Social (MS)	C* 3.70		NL [-13.53, 2.32]
Home Health Aide (HA)	NL [-1.17, 4.44]		

NC: Non-linear shape, C: Constant shape
*corresponds to significance with *p*-value less than 0.01

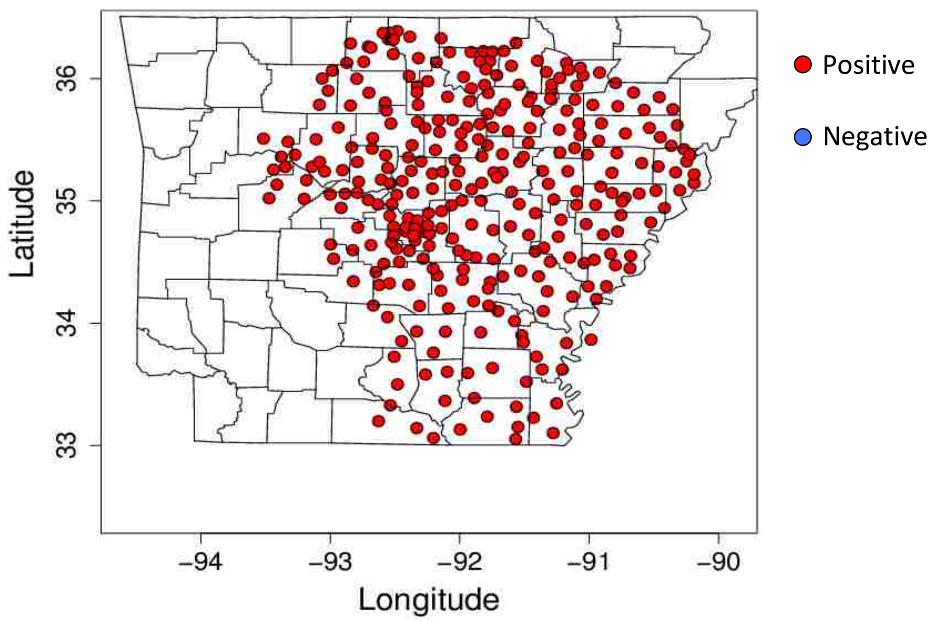
We mapped fitted coefficients for the predictors that have non-linear shape (association) across space in Figures 32 through 41 below. In the maps, the color red indicates positive regression coefficients whereas blue indicates negative regression coefficients. The color white indicates a zero regression coefficient. Please note that a common shading scale based on a range of [-20, 10] is used across all maps. The maximum positive coefficient (10) is always the darkest red whereas the minimum negative coefficient (-20) is always the darkest blue in the color scale. The common shading scale allows the comparison of maps separately and crosswise. In addition to coefficient maps, significance maps indicating statistically significant associations (either positive or negative) between access scores and the corresponding non-linear predictor are also provided. In these maps, a red dot indicates a ZCTA with a significant positive association whereas a blue dot indicates a ZCTA with a significant negative association. In the next section, those maps are presented along with a discussion of the associations between access values and the predictors in the final model for each service type.

4.5.2.1. Skilled Nursing

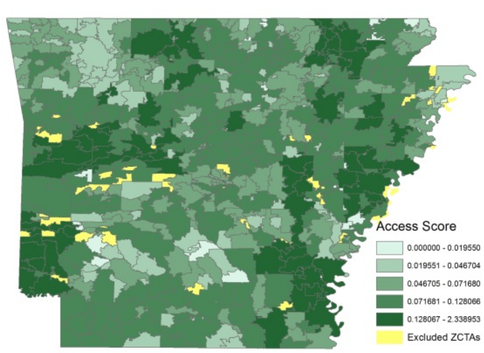
Percent Hispanic population is the only significant predictor for the skilled nursing model, and its association with access is spatially varying. Coefficient values across the case study region are presented in Figure 32a. In the Southeast and Central parts of the state, skilled nursing access increases in areas where percent Hispanic population increases (positive association). This seems to be largely tied to some areas with higher skilled nursing access relative to neighboring ZCTAS specifically along the Southeast border and also North and West of Little Rock. In the Northwest corner and inner Southwest, skilled nursing access decreases in areas where percent Hispanic population increases (negative association). This seems to be largely tied to some higher concentrations of Hispanic people in areas that have relatively very low access. The far Northeast of the state also exhibits a negative association. However, the Hispanic population in this area is low and access is relatively high.



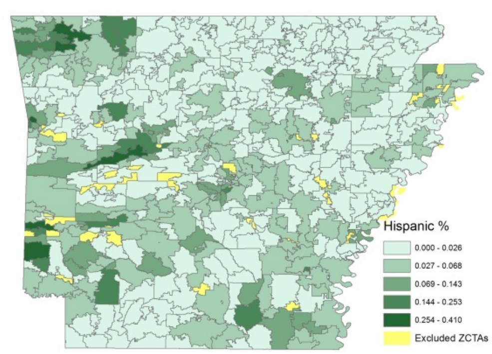
(a) Coefficient values of log(HispanicP)



(b) Significance map indicating statistically significant associations



(c) Access to skilled nursing



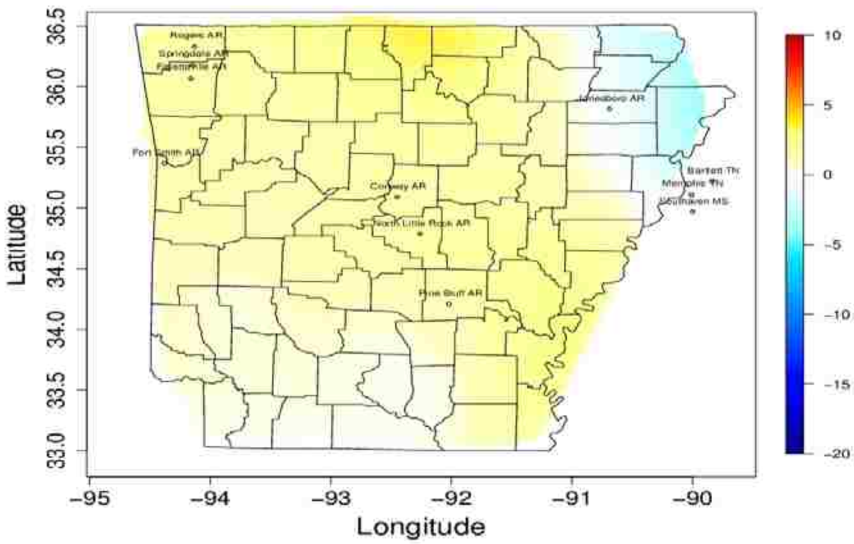
(d) Percent Hispanic population

Figure 32. Association between percent Hispanic population and skilled nursing accessibility

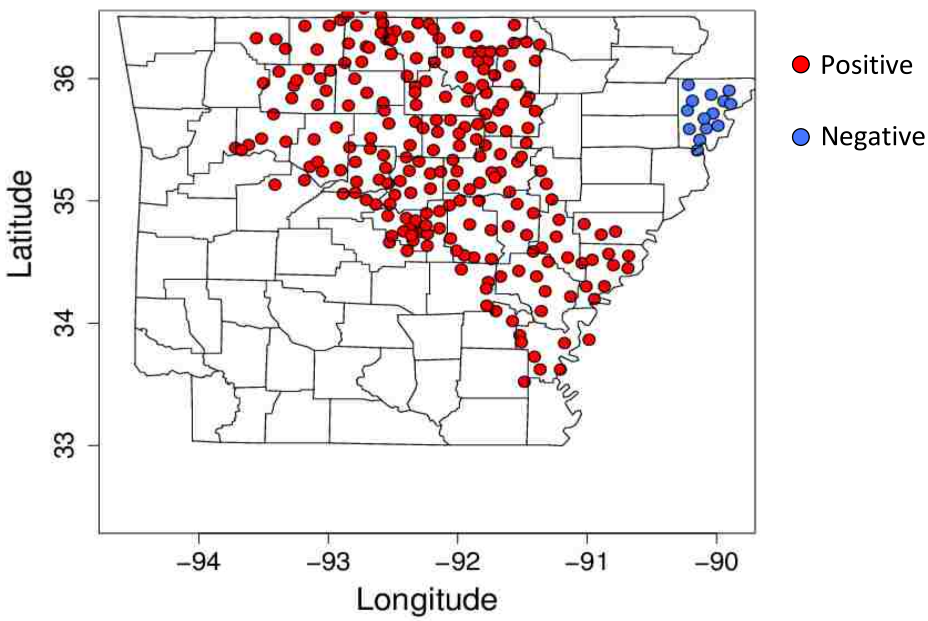
4.5.2.2. Physical Therapy

The percent Hispanic population has a non-linear relationship with physical therapy accessibility (Figure 33). Negative association is observed only in the Northeast corner where access to physical therapy decreases as percent Hispanic population increases. In this particular area, locations with relatively higher Hispanic population, at the border with Missouri and Tennessee, have relatively limited access. The relationship is moderately positive in the Southwest, where access and percent Hispanic population both increase. The relationship is more strongly positive in the rest of the state. In some areas (like Southeast), this appears linked to decreases in physical therapy access in locations with lower Hispanic populations. In others (like Northwest, Central and Central West), this occurs in areas of both high access and high Hispanic population.

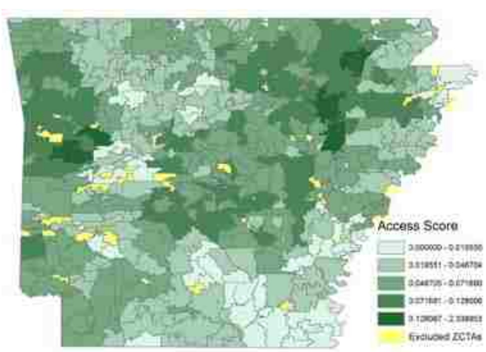
Poverty rate also has non-linear relationship with physical therapy accessibility, but this appears to be driven by strong positive association in Northeast corner and little association elsewhere (Figure 34). The coefficients vary in the range of values [-0.88, 7.30]. In the Northeast corner, many ZCTAs with lower poverty relative to proximal locations also have lower access, and those with higher poverty relative to neighbors have higher access.



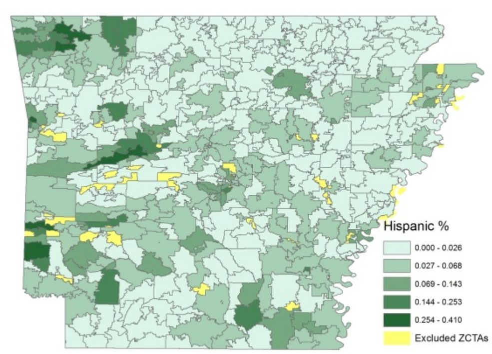
(a) Coefficient values of log(HispanicP), controlling for log(Poverty)



(b) Significance map indicating statistically significant associations

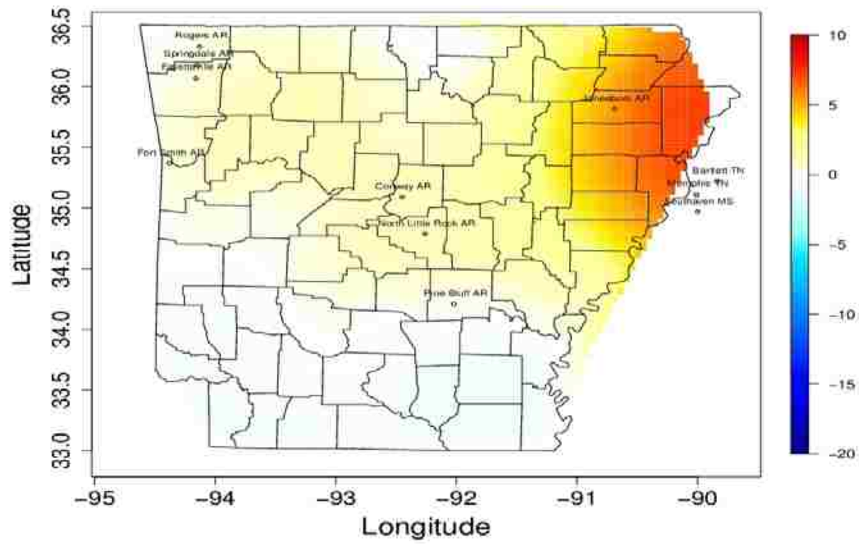


(c) Access to physical therapy

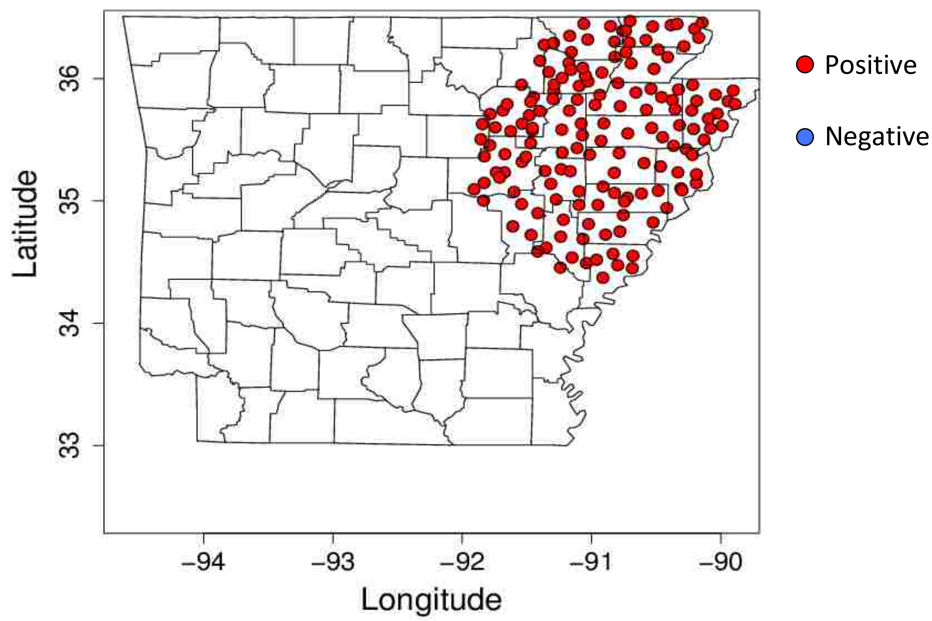


(d) Percent Hispanic population

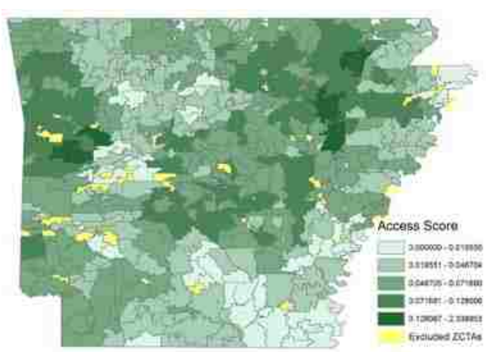
Figure 33. Association between percent Hispanic population and physical therapy accessibility



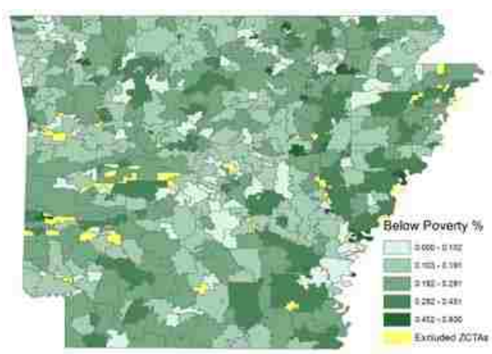
(a) Coefficient values of log(Poverty), controlling for log(HispanicP)



(b) Significance map indicating statistically significant associations



(c) Access to physical therapy



(d) Poverty rate

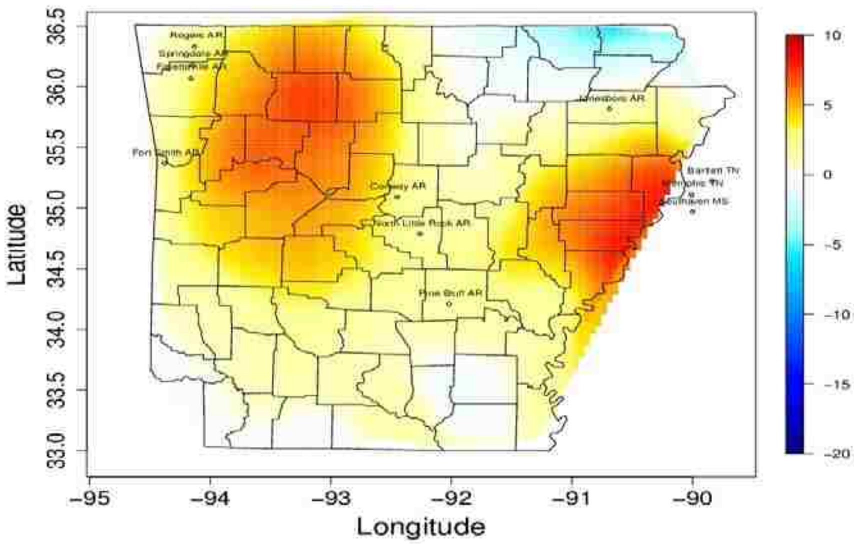
Figure 34. Association between poverty rate and physical therapy accessibility

4.5.2.3. Occupational Therapy

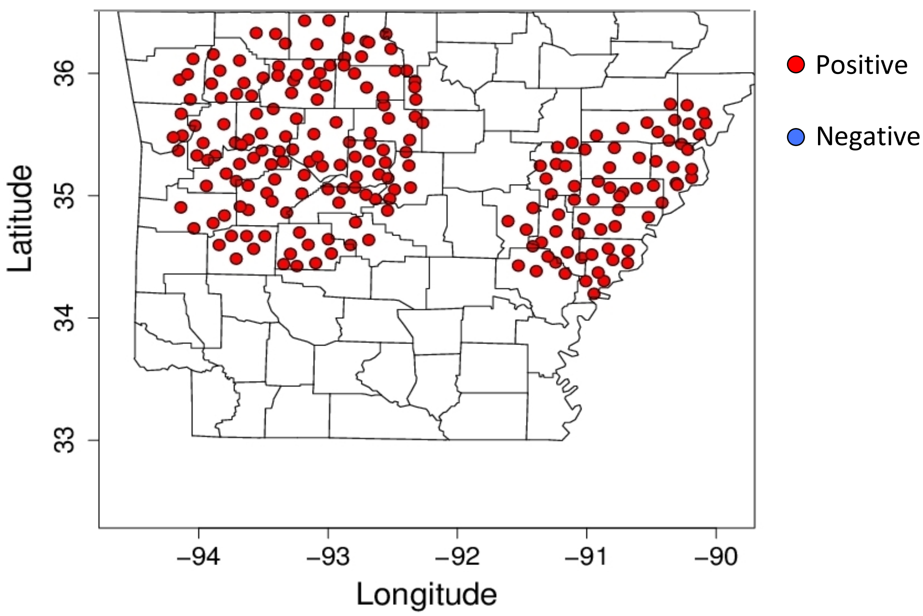
Percent Hispanic population has a significant positive association on occupational therapy accessibility across the state and its constant regression coefficient is estimated as 2.25 (p-value< 0.001). This means that as percent Hispanic population increases, occupational therapy accessibility is expected to increase. We observe that access tends to get better in western parts of the state, where Hispanic population concentrations are highest.

Poverty rate is shown to have a non-linear coefficient, meaning that the association is spatially varying across the study area. In the blue areas shown in Figure 35a, poverty rate is negatively associated with occupational therapy accessibility, while in the red areas the opposite is true. Access in Central East is slightly higher than in neighboring places and there is also a relatively higher poverty level in the Central East. However, in the Northeast and Southeast, access to occupational therapy decreases where the percentage of people living below the poverty level increases.

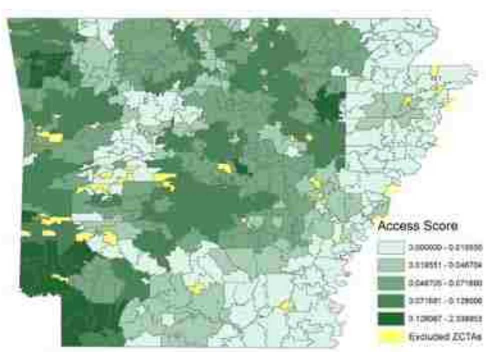
Percent rural population is another spatially varying factor for occupational therapy accessibility, and the coefficients have larger magnitude compared to the other two predictors. The relationship tends to be more positive in ZCTAs lying along the Northern border, and more negative in the South and East portions of the state. The association is very weak in major metropolitan areas such as Little Rock, Conway, and Fort Smith.



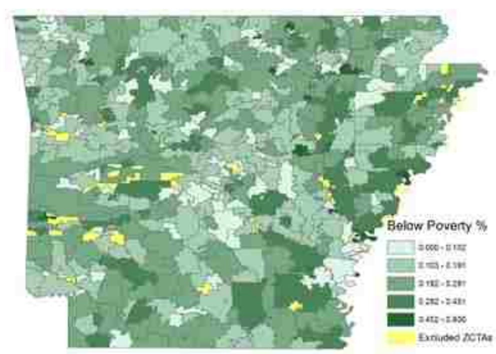
(a) Coefficient values of log(Poverty), controlling for log(HispanicP) and log(RuralP)



(b) Significance map indicating statistically significant associations

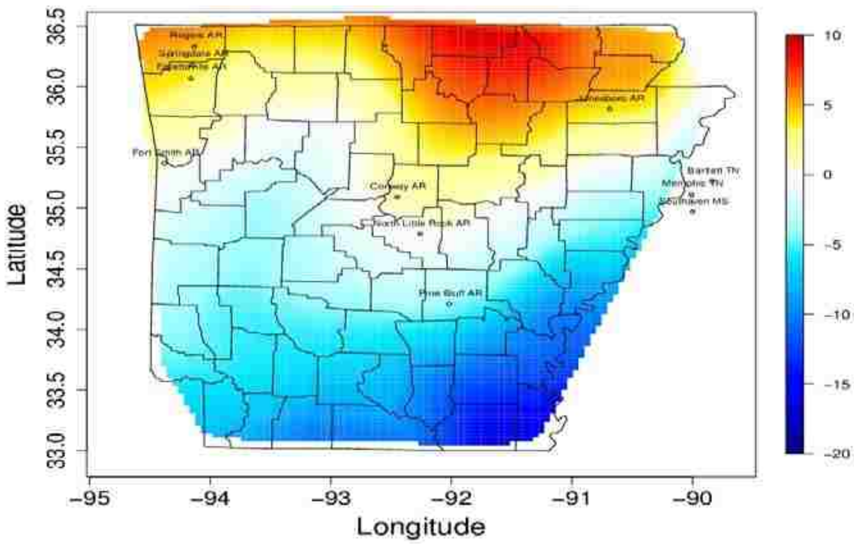


(c) Access to occupational therapy

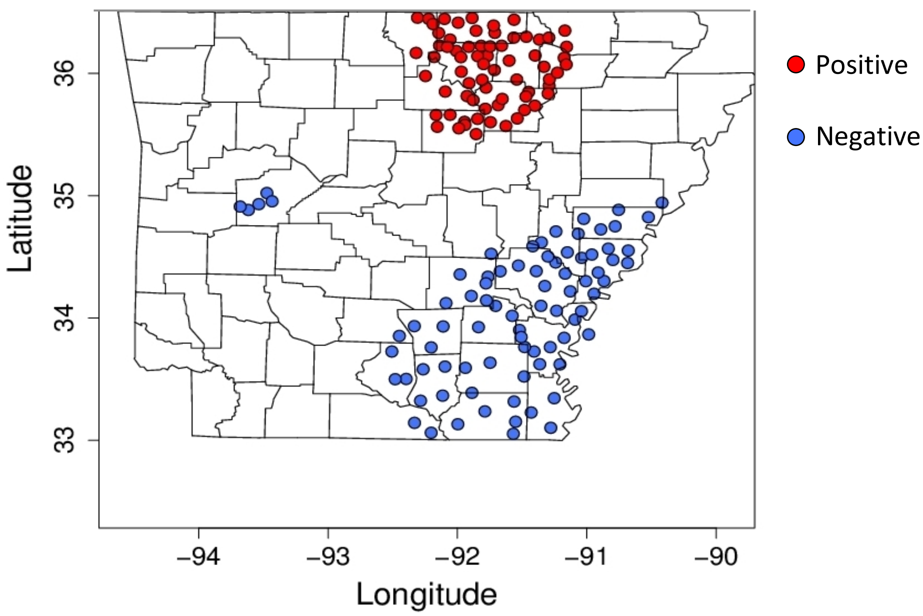


(d) Poverty rate

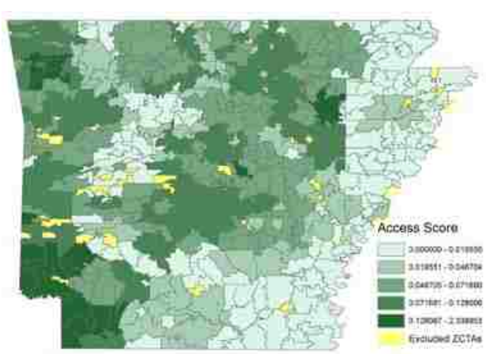
Figure 35. Association between poverty rate and occupational therapy accessibility



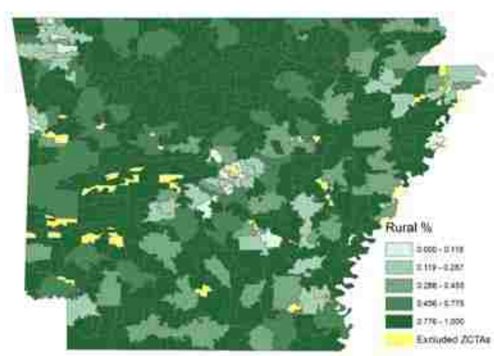
(a) Coefficient values of log(RuralP), controlling for log(HispanicP) and log(Poverty)



(b) Significance map indicating statistically significant associations



(c) Access to occupational therapy



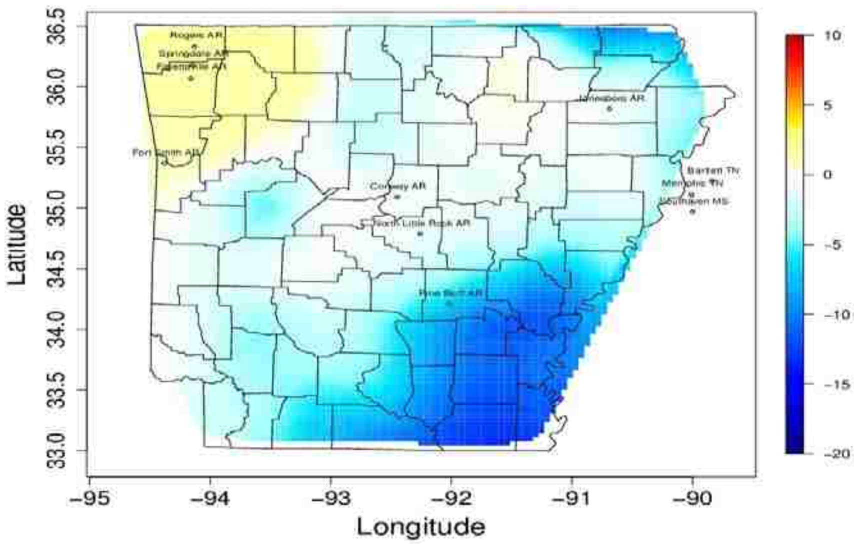
(d) Percent rural population

Figure 36. Association between percent rural population and occupational therapy accessibility

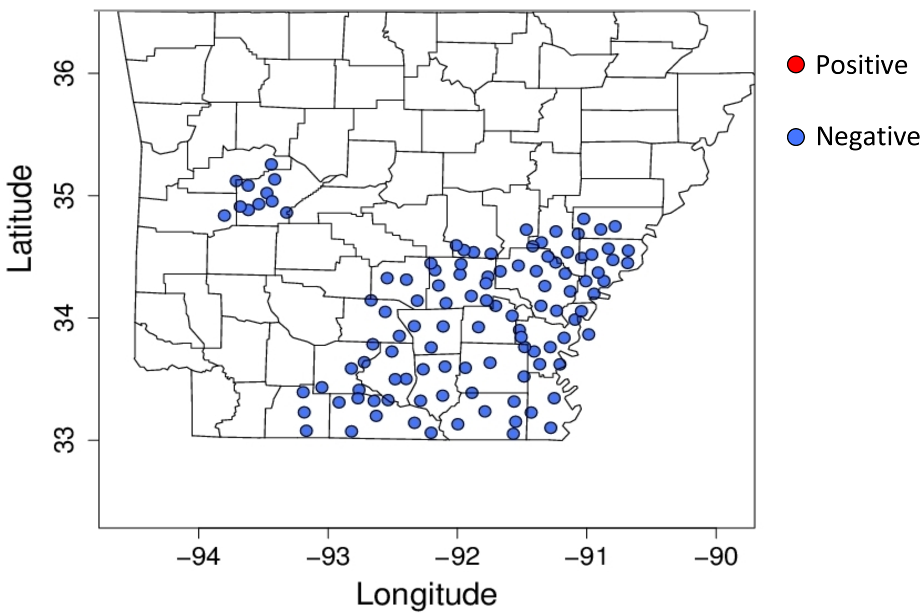
4.5.2.4. Medical Social

In the medical social model, percent Hispanic population is found to have a significant positive association with medical social accessibility across the state and the constant regression coefficient is 3.70 (p-value < 0.01).

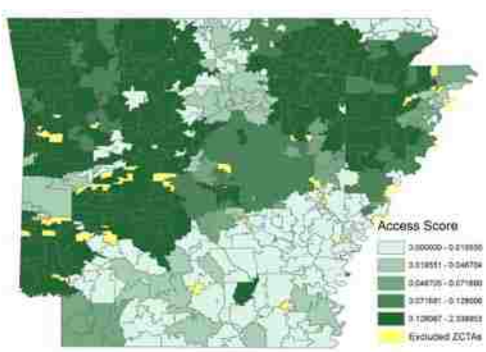
Percent rural population exhibits a non-linear pattern, with coefficients ranging from -13.53 to 2.32. There is a positive association between percent of rural population and medical social accessibility in ZCTAs located in Northwest areas of the state, meaning that access increases as rurality increases. Negative coefficients are found in the rest of the state and generally decrease as one moves south.



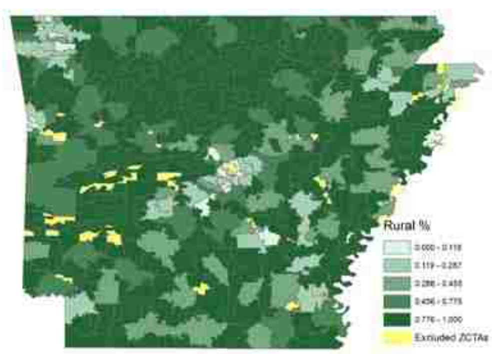
(a) Coefficient values of log(RuralP), controlling for log(HispanicP)



(b) Significance map indicating statistically significant associations



(c) Access to medical social



(d) Percent rural population

Figure 37. Association between percent rural population and medical social accessibility

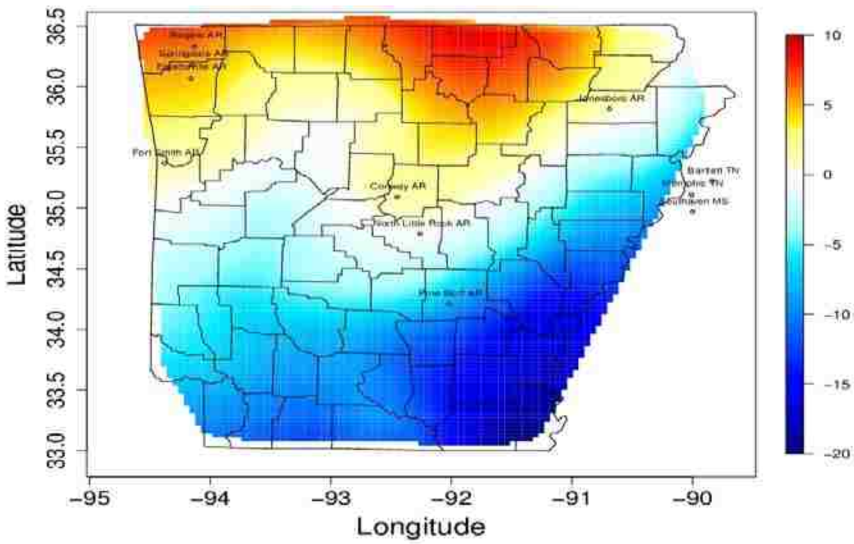
4.5.2.5. Speech Pathology

We find that three predictors, namely, percent rural population, percent Hispanic population, and percent of the population living below the federal poverty level, have spatially varying associations with speech pathology accessibility.

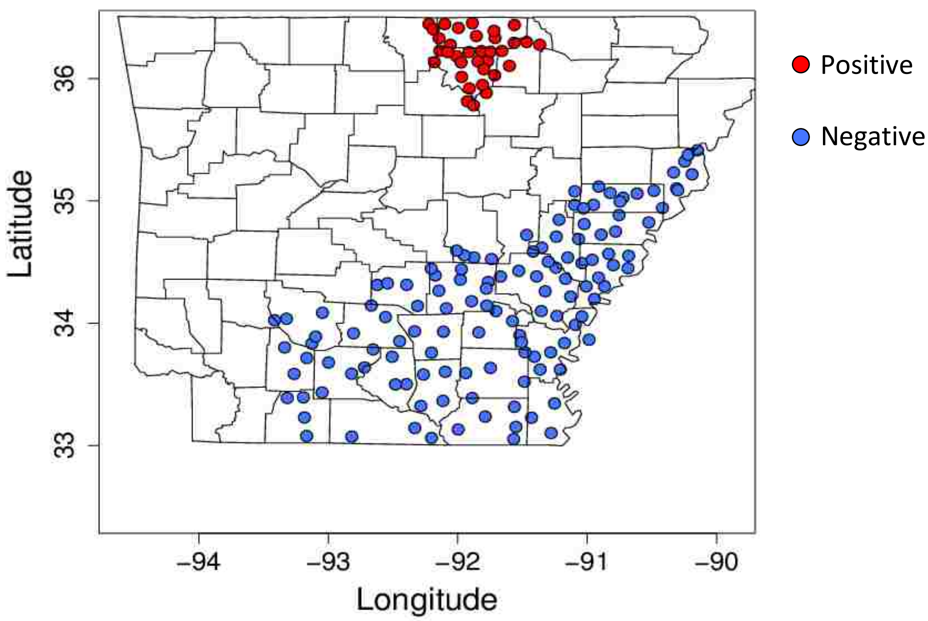
The coefficients corresponding to percent rural population exhibit both the largest magnitude and the largest range among the three factors in the model. The corresponding factor coefficients, varying between -19.94 and 9.03, are mapped in Figure 38a. There is a strong negative association between percent rural population and speech pathology accessibility in some ZCTAs (in blue), meaning that the access decreases as rurality increases. Other locations (in red), which are clustered in Northern part of the state, exhibit a positive association. This seems to be largely tied to some areas with higher access relative to neighboring ZCTAS specifically situated in Northern Arkansas.

The second factor shown to be significantly related to speech pathology accessibility is the percent Hispanic population and its coefficient function takes on values in the range [-5.10, 8.65]. Figure 39a illustrates that the magnitude of this factor is strongly positive in northwest Arkansas and moderately positive in Central and Southwest. In these areas, accessibility is better where Hispanic concentration is higher. On the other hand, negative association ZCTAs are present in Northeast and Southeast corners of the state. Negative association areas in Northeast and Southeast occur in places with higher percent Hispanic population and lower access.

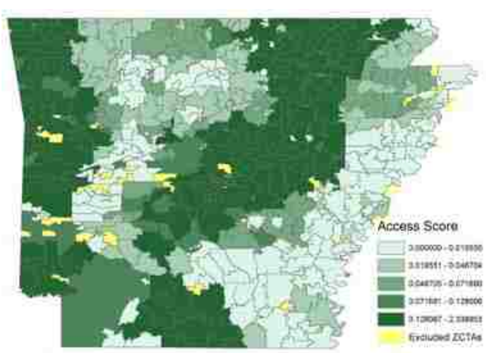
Poverty rate also has a non-linear relationship with speech pathology accessibility and the corresponding coefficients range from -0.34 to 7.90. The coefficient values of the poverty rate are illustrated in Figure 40a. The association between poverty rate and speech pathology accessibility is predominantly positive across the state.



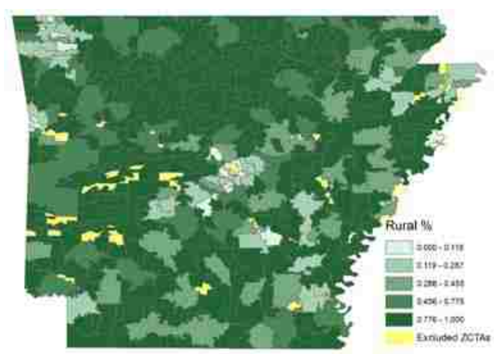
(a) Coefficient values of log(RuralP), controlling for log(HispanicP) and log(Poverty)



(b) Significance map indicating statistically significant associations

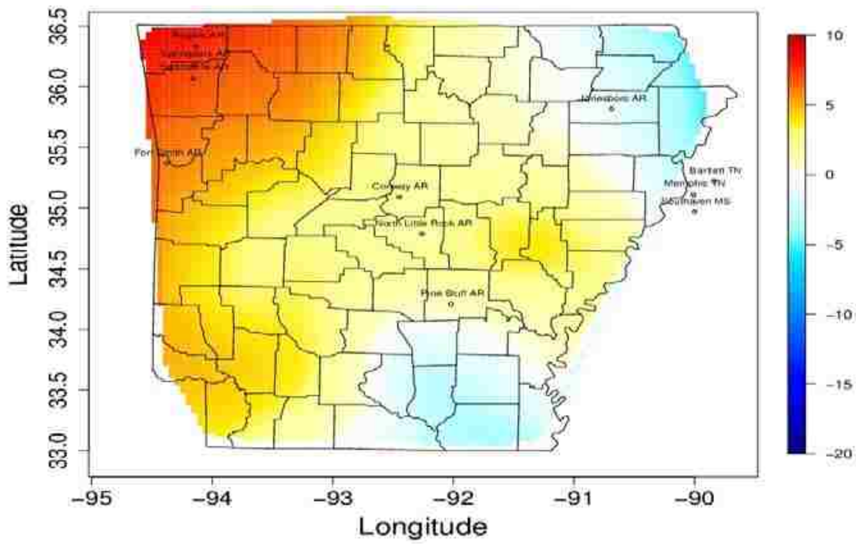


(c) Access to speech pathology

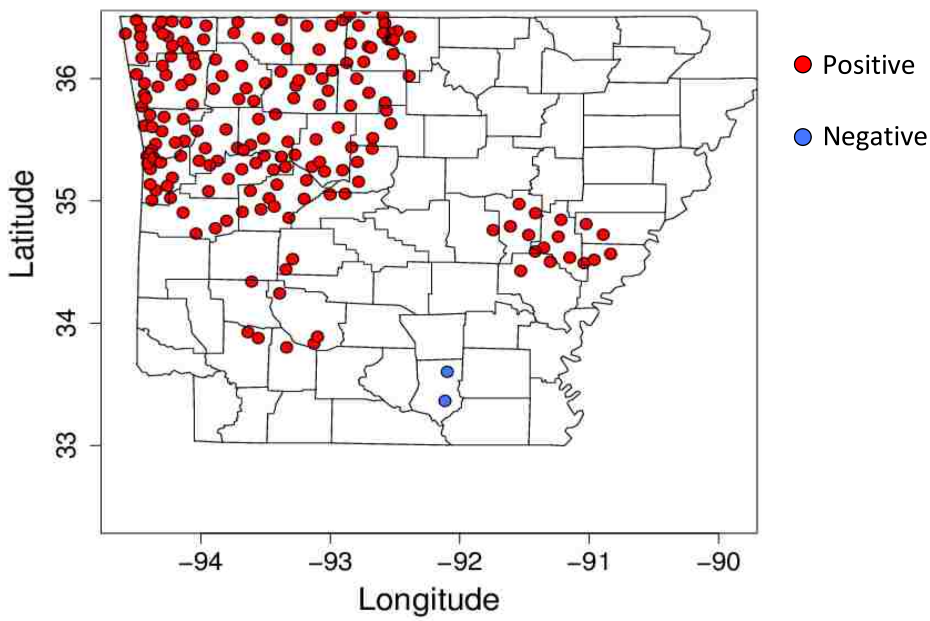


(d) Percent rural population

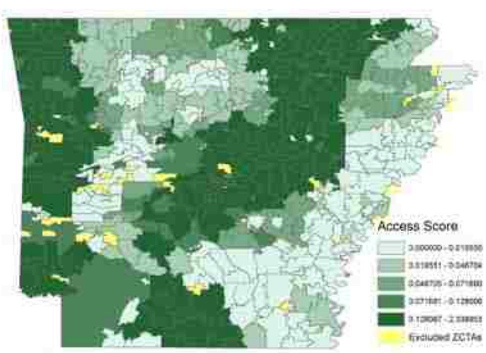
Figure 38. Association between percent rural population and speech pathology accessibility



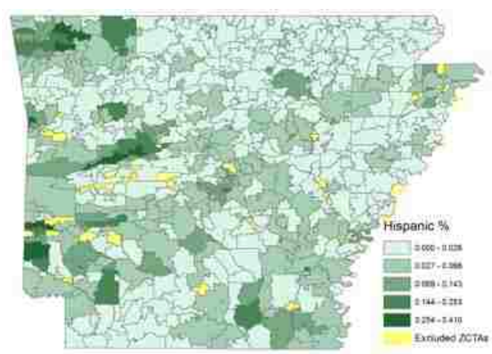
(a) Coefficient values of log(HispanicP), controlling for log(Poverty) and log(RuralP)



(b) Significance map indicating statistically significant associations

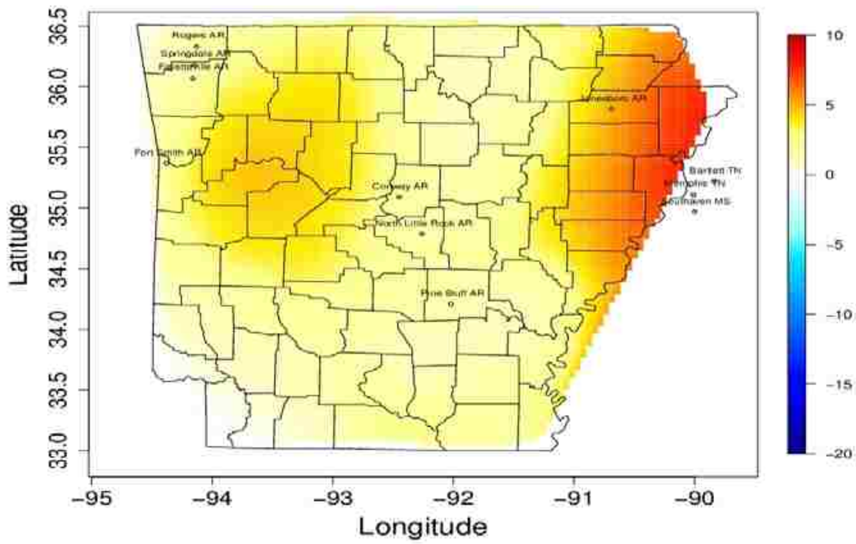


(c) Access to speech pathology

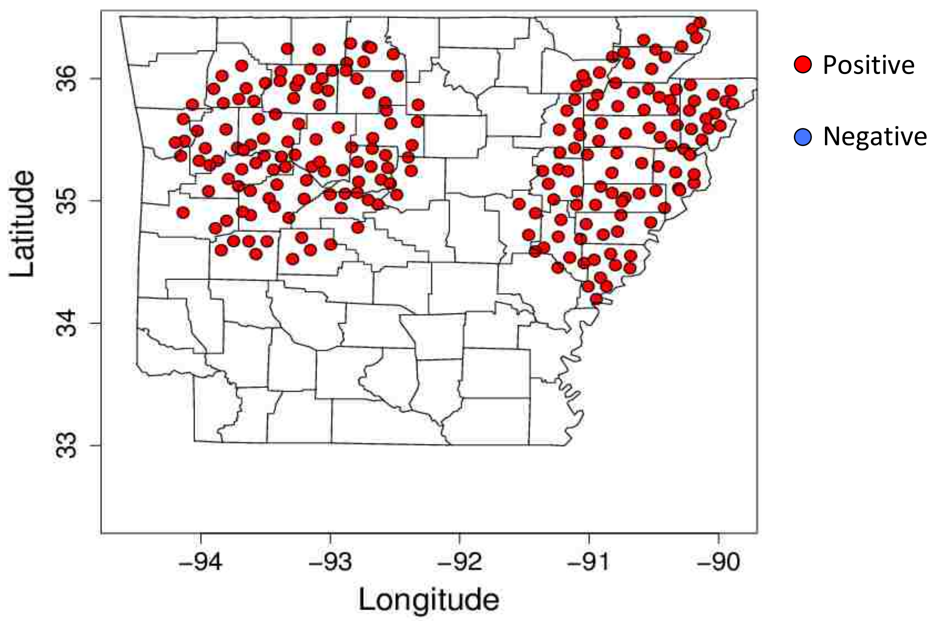


(d) Percent Hispanic population

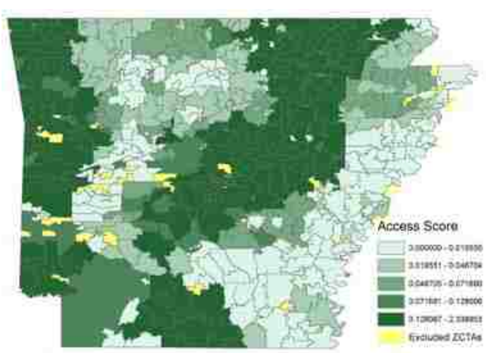
Figure 39. Association between percent Hispanic population and speech pathology accessibility



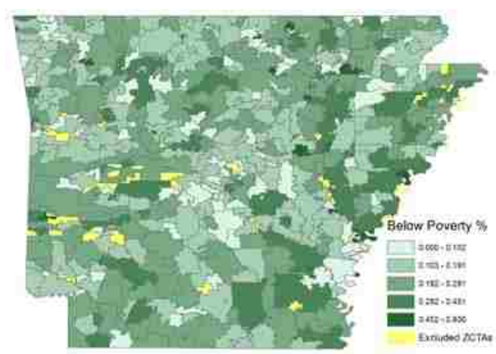
(a) Coefficient values of log(Poverty), controlling for log(HispanicP) and log(RuralP)



(b) Significance map indicating statistically significant associations



(c) Access to speech pathology

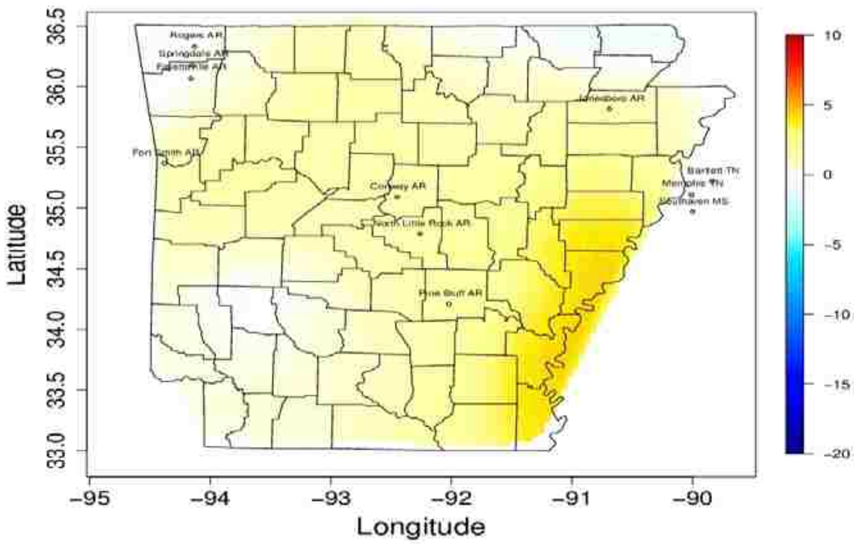


(d) Poverty rate

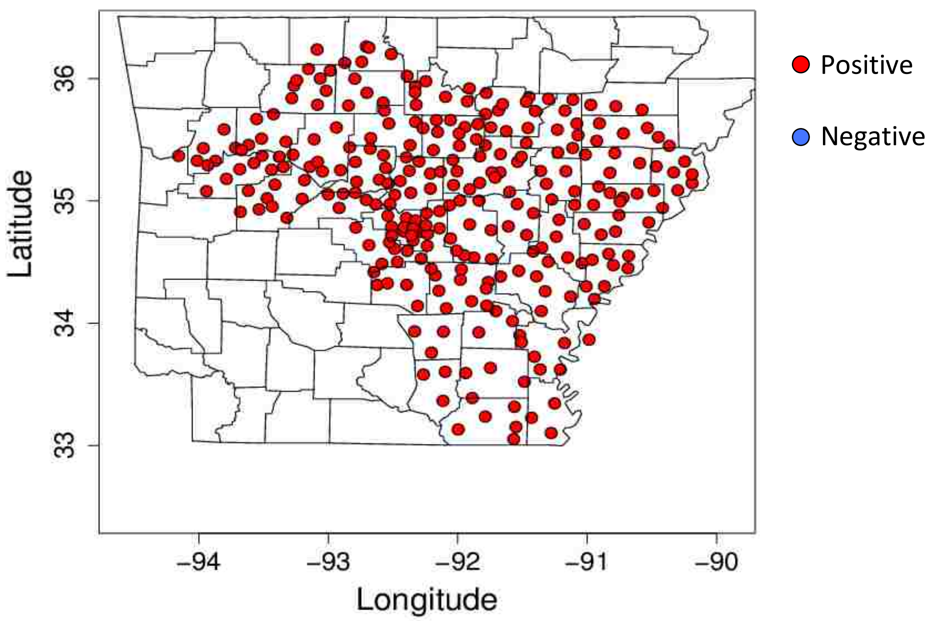
Figure 40. Association between poverty rate and speech pathology accessibility

4.5.2.6. Home Health Aide

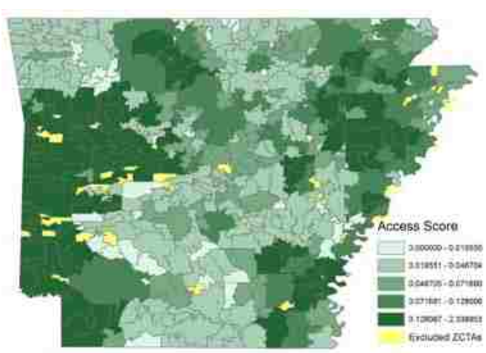
The percent population that is Hispanic is the only significant factor in home health aide model. Its association is spatially varying across the state and the coefficients take values between -1.17 and 4.44. Negative associations are clustered in inner Southwest, Northeast and Northwest corners of the state. In areas of negative association access to home health aide is lower where percent Hispanic population is higher. The relationship is strongly positive in the Southeast and moderately positive in the rest of the state.



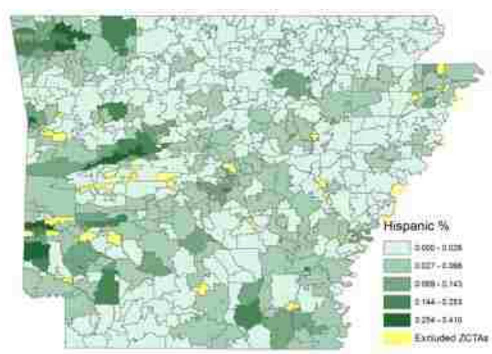
(a) Coefficient values of log(HispanicP)



(b) Significance map indicating statistically significant associations



(c) Access to speech pathology



(d) Percent Hispanic population

Figure 41. Association between percent Hispanic population and home health aide accessibility

The best-fitting space-varying coefficient models for all service types include percent Hispanic population. Percent Hispanic population has constant positive associations with occupational therapy and medical social accessibility. While the magnitude of this association is smaller than that of other predictors in the corresponding models, percent Hispanic population is still a significant factor for occupational therapy and medical social accessibility. Percent Hispanic population has spatially varying associations with other service types and the association is predominantly positive across state except the far northeast corner. We observe that percent Hispanic population is highly correlated with population density and median household income (see Table 16). In other words, ZCTAs with a higher Hispanic population rate tend to be metropolitan locations with higher income.

The percent of the population living below the poverty level is a statistically significant predictor of access to physical therapy, occupational therapy, and speech pathology services and the association varies spatially in each model. ZCTAs with strong positive associations are mainly clustered in the north and central west. Poverty rate is found to have positive correlations with all the variables reflecting minority population (see Table 16). ZCTAs with a higher poverty rate also tend to be areas with larger minority populations.

Percent rural population is significantly associated with access to occupational therapy, medical social, and speech pathology services. In each case, its association with access is spatially varying with strong negative associations in south. This indicates high portions of rural areas in southern portions of the state have relatively limited access to specific home healthcare services.

In our models, we do not control for a possible boundary impact (e.g. biased estimations on the state borders). However, we investigated whether or not a border effect exists in the models and concluded that associations between dependent variables (access scores) and predictors do not change when a potential border impact is controlled for. Please see Appendix I for details.

4.6. Conclusion

This chapter aimed to explore the associations between socio-economic factors and potential spatial access to six different home healthcare services in Arkansas. Access scores are calculated at the local level (in our case, for each ZIP code tabulation area, or ZCTA) using an adapted version of the two-step floating catchment area (2SFCA) method in Chapter 3. Univariate Moran's I test is applied to assess the similarity of accessibility among neighboring ZCTAs. The results of the test reveal strong positive spatial auto-correlation for access scores of each service type. In addition, covariate effects vary with location due spatial heterogeneity. That is, an estimate for the whole study area fails to explain associations at local level and thereby local estimates of associations are required. These suggest there is a need for spatial statistical method that incorporates spatial effects in the data and provides information on spatial relationships between variables.

To account for the spatially-varying relationships between home healthcare accessibility and the socio-demographic factors, we implement a space-varying coefficient model. We included several factors related to race/ethnicity, income, rurality, and primary care access. The model is then implemented in three main stages. First, we identify initial models by combining covariates that are not highly spatially correlated. Next, we make inference on the shape of coefficients and significance of explanatory factors. Finally, we select a best-fitting model for each service type using model selection criteria. According to the results, access to home healthcare services tends to be affected by proportion of Hispanic population, the percentage of people living below the federal poverty level, and the percentage of people living in rural areas in a ZCTA.

Space-varying coefficient models can quantify associations between home healthcare accessibility and the explanatory variables in each ZCTA. We visualize the spatial disparities of access to different home healthcare services and reveal the population characteristics that are significantly associated with access. The results indicate inhomogeneous spatial patterns of associations in the case study area. For spatially varying coefficients, an important output of this analysis includes positive (respectively, negative) significance maps that illustrate ZCTAs that have a statistically significant positive (negative) association between accessibility and the predictor variable. The presence of a large number of such points indicates potential inequities.

This study has a number of limitations. First, the quality and the completeness of the input data can improve the reliability of the model outputs. The results of this study still could be influenced by the missing FTE data problem in Chapter 3. Also, we consider only limited types of population characteristics as explanatory variables in our models. Other important variables that can be associated with home healthcare accessibility can be home ownership, houses without basic amenities, population without a high-school diploma, etc (Wang & Luo, 2005). However, the possible impacts of these variables were not examined due to the lack of ZCTA level data for these variables. Lastly, we examine potential accessibility of home healthcare services, not realized.

Despite the limitations just discussed, the findings can serve as a complementary guideline for public healthcare policy. The home healthcare market has demonstrated responsiveness to past policy interventions. However, collecting and verifying comprehensive data at the local level are required before basing policy on these results. Accurate results with better data have the potential to inform policies that will positively impact individuals' access to care. The following actions can be considered by public policy designers aiming to ensure equitable home healthcare access for all patients: (i) examine the accessibility of each home healthcare service independently since supply of and demand for these services in a region may vary, (ii) coordinate and promote data collection efforts at local level across state by collaborating with providers and professional associations, and (ii) design government interventions that address significant disparities in home healthcare accessibility from the aspects of race/ethnicity structure, income, and rural/urban status at the local level.

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Appendix G: Alternative Models

Table G.1. Alternative models for skilled nursing

ID	BlackP	HispanicP	Poverty	P-to-P
1.1	*p* = 0.42	NL	*p* = 0	*p* = 0.69
1.2	N/A	NL	*p* = 0	*p* = 0.73
1.3	*p* = 0.15	NL	N/A	*p* = 0.69
1.4	*p* = 0.44	NL	*p* = 0	N/A
1.5	N/A	NL	N/A	*p* = 0.77
1.6	N/A	NL	*p* = 0	N/A
1.7	*p* = 0.16	NL	N/A	N/A
1.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**PerCapInc**	**P-to-P**
2.1	*p* = 0.15	NL	*p* = 0.17	*p* = 0.77
2.2	N/A	NL	*p* = 0.18	*p* = 0.85
2.3	*p* = 0.15	NL	N/A	*p* = 0.69
2.4	*p* = 0.15	NL	*p* = 0.16	N/A
2.5	N/A	NL	N/A	*p* = 0.77
2.6	N/A	NL	*p* = 0.17	N/A
2.7	*p* = 0.16	NL	N/A	N/A
2.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**RuralP**
3.1	*p* = 0.47	NL	*p* = 0	*p* = 0.66
3.2	N/A	NL	*p* = 0	*p* = 0.6
3.3	*p* = 0.18	NL	N/A	*p* = 0.63
3.4	*p* = 0.44	NL	*p* = 0	N/A
3.5	N/A	NL	N/A	*p* = 0.52
3.6	N/A	NL	*p* = 0	N/A
3.7	*p* = 0.16	NL	N/A	N/A
3.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**P-to-P**	**RuralP**
4.1	*p* = 0.17	NL	*p* = 0.67	*p* = 0.61
4.2	N/A	NL	*p* = 0.73	*p* = 0.51
4.3	*p* = 0.18	NL	N/A	*p* = 0.63
4.4	*p* = 0.15	NL	*p* = 0.69	N/A
4.5	N/A	NL	N/A	*p* = 0.52
4.6	N/A	NL	*p* = 0.77	N/A
4.7	*p* = 0.16	NL	N/A	N/A
4.8	N/A	NL	N/A	N/A
ID	**BlackP**	**Poverty**	**P-to-P**	**PopDens**
5.1	*p* = 0.35	*p* = 0	*p* = 0.45	*p* = 0.09
ID	**BlackP**	**Poverty**	**P-to-P**	**RuralP**
6.1	*p* = 0.19	*p* = 0	*p* = 0.55	*p* = 0.61
ID	**BlackP**	**MHInc**	**P-to-P**	**RuralP**
7.1	*p* = 0.02	*p* = 0.63	*p* = 0.52	*p* = 0.57

Table G.1. Alternative models for skilled nursing (Cont.)

ID	**HispanicP**	**Poverty**	**P-to-P**	**RuralP**
8.1	*p* = 0	*p* = 0	*p* = 0.63	*p* = 0.64
ID	**MinorP**	**Poverty**	**P-to-P**	**PopDens**
9.1	*p* = 0.55	*p* = 0	*p* = 0.47	*p* = 0.04
ID	**MinorP**	**Poverty**	**P-to-P**	**RuralP**
10.1	*p* = 0.74	*p* = 0	*p* = 0.61	*p* = 0.47
ID	**MinorP**	**MHInc**	**P-to-P**	**RuralP**
11.1	*p* = 0.35	*p* = 0.52	*p* = 0.61	*p* = 0.47

Table G.2. Alternative models for physical therapy

ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
1.1	*p* = 0.38	NL	NL	*p* = 0.47
1.2	N/A	NL	NL	*p* = 0.5
1.3	*p* = 0.4	NL	NL	N/A
1.4	N/A	NL	NL	N/A
ID	**BlackP**	**HispanicP**	**PerCapInc**	**P-to-P**
2.1	*p* = 0.14	*p* = 0	*p* = 0.03	*p* = 0.52
ID	**BlackP**	**HispanicP**	**Poverty**	**RuralP**
3.1	*p* = 0.43	NL	NL	*p* = 0.62
3.2	N/A	NL	NL	*p* = 0.57
3.3	*p* = 0.4	NL	NL	N/A
3.4	N/A	NL	NL	N/A
ID	**BlackP**	**HispanicP**	**P-to-P**	**RuralP**
4.1	*p* = 0.19	*p* = 0	*p* = 0.39	*p* = 0.46
ID	**BlackP**	**Poverty**	**P-to-P**	**PopDens**
5.1	*p* = 0.41	*p* = 0	*p* = 0.2	*p* = 0
ID	**BlackP**	**Poverty**	**P-to-P**	**RuralP**
6.1	*p* = 0.12	*p* = 0	*p* = 0.35	*p* = 0.41
ID	**BlackP**	**MHInc**	**P-to-P**	**RuralP**
7.1	*p* = 0	*p* = 0.54	*p* = 0.32	*p* = 0.39
ID	**HispanicP**	**Poverty**	**P-to-P**	**RuralP**
8.1	NL	NL	*p* = 0.47	*p* = 0.54
8.2	NL	NL	N/A	*p* = 0.57
8.3	NL	NL	*p* = 0.5	N/A
8.4	NL	NL	N/A	N/A
ID	**MinorP**	**Poverty**	**P-to-P**	**PopDens**
9.1	*p* = 0.15	*p* = 0	*p* = 0.21	*p* = 0
ID	**MinorP**	**Poverty**	**P-to-P**	**RuralP**
10.1	*p* = 0.38	*p* = 0	*p* = 0.41	*p* = 0.26
ID	**MinorP**	**MHInc**	**P-to-P**	**RuralP**
11.1	*p* = 0.57	*p* = 0.45	*p* = 0.41	*p* = 0.27

Table G.3. Alternative models for occupational therapy

ID	BlackP	HispanicP	Poverty	P-to-P
1.1	$p = 0.6$	$p = 0$	NL	$p = 0.83$
1.2	N/A	$p = 0$	NL	$p = 0.82$
1.3	$p = 0.15$	N/A	NL	$p = 0.9$
1.4	$p = 0.6$	$p = 0$	NL	N/A
1.5	N/A	N/A	NL	$p = 0.93$
1.6	N/A	$p = 0$	NL	N/A
1.7	$p = 0.15$	N/A	NL	N/A
1.8	N/A	N/A	NL	N/A
ID	**BlackP**	**HispanicP**	**PerCapInc**	**P-to-P**
2.1	$p = 0.19$	$p = 0$	$p = 0.63$	$p = 0.76$
ID	**BlackP**	**HispanicP**	**Poverty**	**RuralP**
3.1	$p = 0.53$	$p = 0$	NL	NL
3.2	N/A	$p = 0$	NL	NL
3.3	$p = 0.14$	N/A	NL	NL
3.4	N/A	N/A	NL	NL
ID	**BlackP**	**HispanicP**	**P-to-P**	**RuralP**
4.1	$p = 0.29$	$p = 0$	$p = 0.91$	NL
4.2	N/A	$p = 0$	$p = 0.87$	NL
4.3	$p = 0.02$	N/A	$p = 0.79$	NL
4.4	$p = 0.28$	$p = 0$	N/A	NL
4.5	N/A	N/A	$p = 0.85$	NL
4.6	N/A	$p = 0$	N/A	NL
4.7	$p = 0.02$	N/A	N/A	NL
4.8	N/A	N/A	N/A	NL
ID	**BlackP**	**Poverty**	**P-to-P**	**PopDens**
5.1	$p = 0.3$	NL	$p = 0.76$	$p = 0.03$
5.2	N/A	NL	$p = 0.77$	$p = 0.02$
5.3	$p = 0.3$	NL	N/A	$p = 0.03$
5.4	$p = 0.15$	NL	$p = 0.9$	N/A
5.5	N/A	NL	N/A	$p = 0.02$
5.6	N/A	NL	$p = 0.93$	N/A
5.7	$p = 0.15$	NL	N/A	N/A
5.8	N/A	NL	N/A	N/A
ID	**BlackP**	**Poverty**	**P-to-P**	**RuralP**
6.1	$p = 0.14$	NL	$p = 0.94$	NL
6.2	N/A	NL	$p = 0.96$	NL
6.3	$p = 0.14$	NL	N/A	NL
6.4	N/A	NL	N/A	NL

Table G.3. Alternative models for occupational therapy (Cont.)

ID	BlackP	MHInc	P-to-P	RuralP
7.1	$p = 0.02$	$p = 0.88$	$p = 0.78$	NL
7.2	N/A	$p = 0.88$	$p = 0.84$	NL
7.3	$p = 0.02$	N/A	$p = 0.79$	NL
7.4	$p = 0.02$	$p = 0.89$	N/A	NL
7.5	N/A	N/A	$p = 0.85$	NL
7.6	N/A	$p = 0.88$	N/A	NL
7.7	$p = 0.02$	N/A	N/A	NL
7.8	N/A	N/A	N/A	NL
ID	**HispanicP**	**Poverty**	**P-to-P**	**RuralP**
8.1	$p = 0$	NL	$p = 0.78$	NL
8.2	N/A	NL	$p = 0.96$	NL
8.3	$p = 0$	NL	N/A	NL
8.4	N/A	NL	N/A	NL
ID	**MinorP**	**Poverty**	**P-to-P**	**PopDens**
9.1	$p = 0.67$	NL	$p = 0.78$	$p = 0.02$
9.2	N/A	NL	$p = 0.77$	$p = 0.02$
9.3	$p = 0.66$	NL	N/A	$p = 0.02$
9.4	$p = 0.42$	NL	$p = 0.95$	N/A
9.5	N/A	NL	N/A	$p = 0.02$
9.6	N/A	NL	$p = 0.93$	N/A
9.7	$p = 0.42$	NL	N/A	N/A
9.8	N/A	NL	N/A	N/A
ID	**MinorP**	**Poverty**	**P-to-P**	**RuralP**
10.1	$p = 0.41$	NL	$p = 0.98$	NL
10.2	N/A	NL	$p = 0.96$	NL
10.3	$p = 0.41$	NL	N/A	NL
10.4	N/A	NL	N/A	NL
ID	**MinorP**	**MHInc**	**P-to-P**	**RuralP**
11.1	$p = 0.01$	$p = 0.71$	$p = 0.87$	NL
11.2	N/A	$p = 0.88$	$p = 0.84$	NL
11.3	$p = 0.01$	N/A	$p = 0.88$	NL
11.4	$p = 0.01$	$p = 0.71$	N/A	NL
11.5	N/A	N/A	$p = 0.85$	NL
11.6	N/A	$p = 0.88$	N/A	NL
11.7	$p = 0.01$	N/A	N/A	NL
11.8	N/A	N/A	N/A	NL

Table G.4. Alternative models for medical social

ID	BlackP	HispanicP	Poverty	P-to-P
1.1	*p* = 0.04	*p* = 0	NL	*p* = 0.83
1.2	N/A	*p* = 0	NL	*p* = 0.77
1.3	*p* = 0	N/A	NL	*p* = 0.96
1.4	*p* = 0.04	*p* = 0	NL	N/A
1.5	N/A	N/A	NL	*p* = 0.95
1.6	N/A	*p* = 0	NL	N/A
1.7	*p* = 0	N/A	NL	N/A
1.8	N/A	N/A	NL	N/A
ID	**BlackP**	**HispanicP**	**PerCapInc**	**P-to-P**
2.1	*p* = 0	*p* = 0	*p* = 0.62	*p* = 0.88
ID	**BlackP**	**HispanicP**	**Poverty**	**RuralP**
3.1	*p* = 0.08	*p* = 0	*p* = 0	NL
3.2	N/A	*p* = 0	*p* = 0	NL
3.3	*p* = 0.01	N/A	*p* = 0	NL
3.4	*p* = 0.01	*p* = 0	N/A	NL
3.5	N/A	N/A	*p* = 0	NL
3.6	N/A	*p* = 0	N/A	NL
3.7	*p* = 0	N/A	N/A	NL
3.8	N/A	N/A	N/A	NL
ID	**BlackP**	**HispanicP**	**P-to-P**	**RuralP**
4.1	*p* = 0.01	*p* = 0	*p* = 0.99	NL
4.2	N/A	*p* = 0	*p* = 0.9	NL
4.3	*p* = 0	N/A	*p* = 0.74	NL
4.4	*p* = 0.01	*p* = 0	N/A	NL
4.5	N/A	N/A	*p* = 0.84	NL
4.6	N/A	*p* = 0	N/A	NL
4.7	*p* = 0	N/A	N/A	NL
4.8	N/A	N/A	N/A	NL
ID	**BlackP**	**Poverty**	**P-to-P**	**PopDens**
5.1	*p* = 0.02	NL	*p* = 0.73	*p* = 0
5.2	N/A	NL	*p* = 0.75	*p* = 0
5.3	*p* = 0.02	NL	N/A	*p* = 0
5.4	*p* = 0	NL	*p* = 0.96	N/A
5.5	N/A	NL	N/A	*p* = 0
5.6	N/A	NL	*p* = 0.95	N/A
5.7	*p* = 0	NL	N/A	N/A
5.8	N/A	NL	N/A	N/A

Table G.4. Alternative models for medical social (Cont.)

ID	BlackP	Poverty	P-to-P	RuralP
6.1	*p* = 0.01	*p* = 0	*p* = 0.73	NL
6.2	N/A	*p* = 0	*p* = 0.8	NL
6.3	*p* = 0	N/A	*p* = 0.74	NL
6.4	*p* = 0.01	*p* = 0	N/A	NL
6.5	N/A	N/A	*p* = 0.84	NL
6.6	N/A	*p* = 0	N/A	NL
6.7	*p* = 0	N/A	N/A	NL
6.8	N/A	N/A	N/A	NL
ID	**BlackP**	**MHInc**	**P-to-P**	**RuralP**
7.1	*p* = 0	*p* = 0.97	*p* = 0.74	NL
7.2	N/A	*p* = 0.99	*p* = 0.84	NL
7.3	*p* = 0	N/A	*p* = 0.74	NL
7.4	*p* = 0	*p* = 0.97	N/A	NL
7.5	N/A	N/A	*p* = 0.84	NL
7.6	N/A	*p* = 0.98	N/A	NL
7.7	*p* = 0	N/A	N/A	NL
7.8	N/A	N/A	N/A	NL
ID	**HispanicP**	**Poverty**	**P-to-P**	**RuralP**
8.1	*p* = 0	*p* = 0	*p* = 0.97	NL
8.2	N/A	*p* = 0	*p* = 0.8	NL
8.3	*p* = 0	N/A	*p* = 0.9	NL
8.4	*p* = 0	*p* = 0	N/A	NL
8.5	N/A	N/A	*p* = 0.84	NL
8.6	N/A	*p* = 0	N/A	NL
8.7	*p* = 0	N/A	N/A	NL
8.8	N/A	N/A	N/A	NL
ID	**MinorP**	**Poverty**	**P-to-P**	**PopDens**
9.1	*p* = 0.05	NL	*p* = 0.79	*p* = 0
9.2	N/A	NL	*p* = 0.75	*p* = 0
9.3	*p* = 0.05	NL	N/A	*p* = 0
9.4	*p* = 0.01	NL	*p* = 0.93	N/A
9.5	N/A	NL	N/A	*p* = 0
9.6	N/A	NL	*p* = 0.95	N/A
9.7	*p* = 0.01	NL	N/A	N/A
9.8	N/A	NL	N/A	N/A
ID	**MinorP**	**Poverty**	**P-to-P**	**RuralP**
10.1	*p* = 0.01	*p* = 0	*p* = 0.84	NL
10.2	N/A	*p* = 0	*p* = 0.8	NL
10.3	*p* = 0	N/A	*p* = 0.89	NL
10.4	*p* = 0.01	*p* = 0	N/A	NL
10.5	N/A	N/A	*p* = 0.84	NL
10.6	N/A	*p* = 0	N/A	NL
10.7	*p* = 0	N/A	N/A	NL
10.8	N/A	N/A	N/A	NL

Table G.4. Alternative models for medical social (Cont.)

ID	MinorP	MHInc	P-to-P	RuralP
11.1	$p = 0$	$p = 0.72$	$p = 0.88$	NL
11.2	N/A	$p = 0.99$	$p = 0.84$	NL
11.3	$p = 0$	N/A	$p = 0.89$	NL
11.4	$p = 0$	$p = 0.72$	N/A	NL
11.5	N/A	N/A	$p = 0.84$	NL
11.6	N/A	$p = 0.98$	N/A	NL
11.7	$p = 0$	N/A	N/A	NL
11.8	N/A	N/A	N/A	NL

Table G.5. Alternative models for speech pathology

ID	BlackP	HispanicP	Poverty	P-to-P
1.1	$p = 0.76$	NL	NL	$p = 0.4$
1.2	N/A	NL	NL	$p = 0.39$
1.3	$p = 0.73$	NL	NL	N/A
1.4	N/A	NL	NL	N/A
ID	**BlackP**	**HispanicP**	**PerCapInc**	**P-to-P**
2.1	$p = 0.31$	NL	NL	$p = 0.31$
2.2	N/A	NL	NL	$p = 0.28$
2.3	$p = 0.28$	NL	NL	N/A
2.4	N/A	NL	NL	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
3.1	N/A	NL	NL	NL
3.2	$p = 0.74$	NL	NL	NL
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
4.1	$p = 0.36$	NL	$p = 0.41$	NL
4.2	N/A	NL	$p = 0.39$	NL
4.3	$p = 0.34$	NL	N/A	NL
4.4	N/A	NL	N/A	NL
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
5.1	$p = 0.53$	NL	$p = 0.9$	$p = 0$
5.2	N/A	NL	$p = 0.89$	$p = 0$
5.3	$p = 0.53$	NL	N/A	$p = 0$
5.4	$p = 0.17$	NL	$p = 0.66$	N/A
5.5	N/A	NL	N/A	$p = 0$
5.6	N/A	NL	$p = 0.62$	N/A
5.7	$p = 0.17$	NL	N/A	N/A
5.8	N/A	NL	N/A	N/A

Table G.5. Alternative models for speech pathology (Cont.)

ID	BlackP	HispanicP	Poverty	P-to-P
6.1	*p* = 0.33	*p* = 0	*p* = 0.71	NL
6.2	N/A	*p* = 0	*p* = 0.68	NL
6.3	*p* = 0.03	N/A	*p* = 0.73	NL
6.4	*p* = 0.32	*p* = 0	N/A	NL
6.5	N/A	N/A	*p* = 0.67	NL
6.6	N/A	*p* = 0	N/A	NL
6.7	*p* = 0.03	N/A	N/A	NL
6.8	N/A	N/A	N/A	NL
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
7.1	*p* = 0.03	*p* = 0.32	*p* = 0.74	NL
7.2	N/A	*p* = 0.32	*p* = 0.69	NL
7.3	*p* = 0.03	N/A	*p* = 0.73	NL
7.4	*p* = 0.03	*p* = 0.32	N/A	NL
7.5	N/A	N/A	*p* = 0.67	NL
7.6	N/A	*p* = 0.32	N/A	NL
7.7	*p* = 0.03	N/A	N/A	NL
7.8	N/A	N/A	N/A	NL
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
8.1	NL	NL	N/A	NL
8.2	NL	NL	*p* = 0	NL
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
9.4	*p* = 0.32	NL	*p* = 0.86	*p* = 0
9.5	N/A	NL	*p* = 0.89	*p* = 0
9.6	*p* = 0.32	NL	N/A	*p* = 0
9.7	*p* = 0.1	NL	*p* = 0.6	N/A
9.8	N/A	NL	N/A	*p* = 0
9.9	N/A	NL	*p* = 0.62	N/A
9.10	*p* = 0.1	NL	N/A	N/A
9.11	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
10.1	*p* = 0.13	*p* = 0	*p* = 0.66	NL
10.2	N/A	*p* = 0	*p* = 0.68	NL
10.3	*p* = 0	N/A	*p* = 0.63	NL
10.4	*p* = 0.13	*p* = 0	N/A	NL
10.5	N/A	N/A	*p* = 0.67	NL
10.6	N/A	*p* = 0	N/A	NL
10.7	*p* = 0	N/A	N/A	NL
10.8	N/A	N/A	N/A	NL

Table G.5. Alternative models for speech pathology (Cont.)

ID	BlackP	HispanicP	Poverty	P-to-P
11.1	$p = 0$	$p = 0.2$	$p = 0.65$	NL
11.2	N/A	$p = 0.32$	$p = 0.69$	NL
11.3	$p = 0$	N/A	$p = 0.63$	NL
11.4	$p = 0$	$p = 0.2$	N/A	NL
11.5	N/A	N/A	$p = 0.67$	NL
11.6	N/A	$p = 0.32$	N/A	NL
11.7	$p = 0$	N/A	N/A	NL
11.8	N/A	N/A	N/A	NL

Table G.6. Alternative models for home health aide

ID	BlackP	HispanicP	Poverty	P-to-P
1.1	$p = 0.18$	NL	$p = 0$	$p = 0.33$
1.2	N/A	NL	$p = 0$	$p = 0.37$
1.3	$p = 0.05$	NL	N/A	$p = 0.35$
1.4	$p = 0.2$	NL	$p = 0$	N/A
1.5	N/A	NL	N/A	$p = 0.41$
1.6	N/A	NL	$p = 0$	N/A
1.7	$p = 0.05$	NL	N/A	N/A
1.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
2.1	$p = 0.05$	NL	$p = 0.14$	$p = 0.41$
2.2	N/A	NL	$p = 0.14$	$p = 0.48$
2.3	$p = 0.05$	NL	N/A	$p = 0.35$
2.4	$p = 0.05$	NL	$p = 0.12$	N/A
2.5	N/A	NL	N/A	$p = 0.41$
2.6	N/A	NL	$p = 0.12$	N/A
2.7	$p = 0.05$	NL	N/A	N/A
2.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
3.1	$p = 0.2$	NL	$p = 0$	$p = 0.97$
3.2	N/A	NL	$p = 0$	$p = 0.92$
3.3	$p = 0.06$	NL	N/A	$p = 0.96$
3.4	$p = 0.2$	NL	$p = 0$	N/A
3.5	N/A	NL	N/A	$p = 0.82$
3.6	N/A	NL	$p = 0$	N/A
3.7	$p = 0.05$	NL	N/A	N/A
3.8	N/A	NL	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
4.1	$p = 0.1$	$p = 0$	$p = 0.28$	$p = 0.95$

Table G.6. Alternative models for home health aide (Cont.)

ID	BlackP	HispanicP	Poverty	P-to-P
5.1	$p = 0.12$	$p = 0$	$p = 0.17$	$p = 0.2$
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
6.1	$p = 0.06$	$p = 0$	$p = 0.22$	$p = 0.91$
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
7.1	$p = 0$	$p = 0.99$	$p = 0.21$	$p = 0.85$
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
8.1	NL	$p = 0$	$p = 0.36$	$p = 0.87$
8.2	NL	N/A	$p = 0.4$	$p = 0.77$
8.3	NL	$p = 0$	N/A	$p = 0.92$
8.4	NL	$p = 0$	$p = 0.37$	N/A
8.5	NL	N/A	N/A	$p = 0.82$
8.6	NL	N/A	$p = 0.41$	N/A
8.7	NL	$p = 0$	N/A	N/A
8.8	NL	N/A	N/A	N/A
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
9.1	$p = 0.97$	$p = 0$	$p = 0.19$	$p = 0.1$
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
10.1	$p = 0.79$	$p = 0$	$p = 0.25$	$p = 0.78$
ID	**BlackP**	**HispanicP**	**Poverty**	**P-to-P**
11.1	$p = 0.14$	$p = 0.85$	$p = 0.27$	$p = 0.74$

Appendix H: Pareto Frontiers

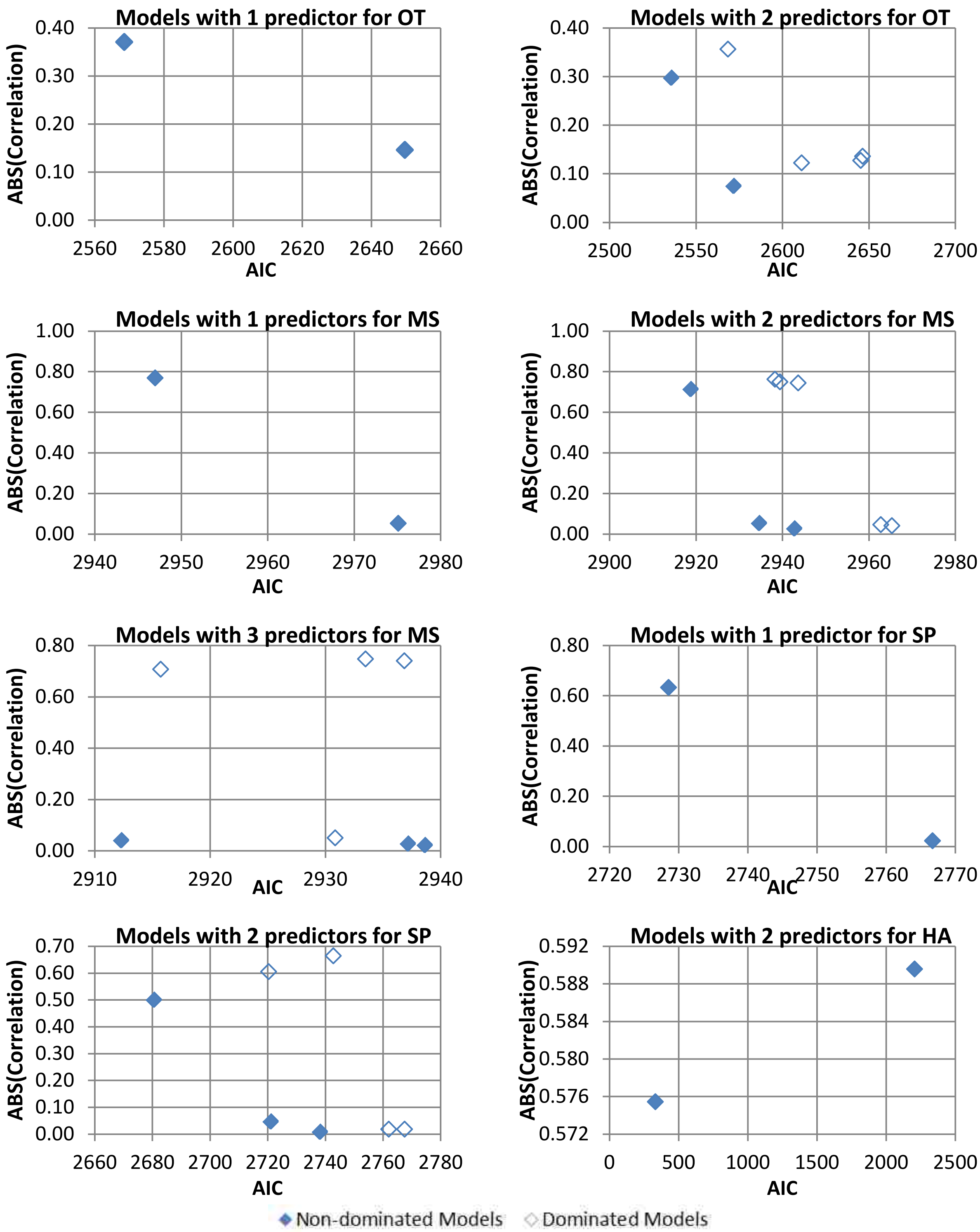

Figure H.1. Non-dominated and dominated models

Appendix I: Analyzing the Border Impact

A new binary variable, which takes the value of 1 if the ZCTA is located in the border and 0 otherwise, is used to examine the possible border impact. This variable (border variable, X_b) is included to the original best-fitting models with either constant and non-linear shape, separately. The results are provided in Table I.1. If X_b is introduced as a constant predictor, the *p*-values indicate that this variable is not statistically significant in any of the models. If X_b is introduced as a non-linear predictor, the ranges of the corresponding coefficients are very small. Also, when we examine the coefficient ranges and association patterns of other predictors in the model, we do not see dramatic differences compared to original model results. Hence, we conclude that associations between dependent variables (access scores) and predictors do not change when a potential border impact is controlled.

Table I.1. Models with a border variable

Provider Type	Models	AIC	Correlation	HispanicP	Poverty	RuralP	X_b
Skilled nursing	Original model	2210.0	0.284	[-1.23, 3.62]			
	Original model with a NL X_b	2216.1	0.271	[-0.98, 3.50]			[-0.36, 0.55]
	Original model with a C X_b	2211.7	0.285	[-1.24, 3.61]			0.026 (p = 0.904)
Physical therapy	Original model	2287.0	0.153	[-4.04, 3.50]	[-0.88, 7.30]		
	Original model with a NL X_b	2291.3	0.167	[-4.15, 3.48]	[-0.82, 7.15]		[-0.37, 0.91]
	Original model with a C X_b	2286.5	0.151	[-4.16, 3.51]	[-0.92, 7.28]		0.185 (p = 0.458)
Occupational therapy	Original model	2540.7	0.079	2.25 (p<0.01)	[-5.55, 8.28]	[-15.78, 9.39]	
	Original model with a NL X_b	2546.6	0.082	2.23 (p<0.01)	[-5.50, 8.22]	[-15.77, 9.42]	[-0.12, 0.18]
	Original model with a C X_b	2542.6	0.079	2.24 (p<0.01)	[-5.55, 8.27]	[-15.77, 9.40]	0.016 (p = 0.962)
Speech pathology	Original model	2677.5	0.109	[-5.10, 8.65]	[-0.34, 7.90]	[-19.94, 9.03]	
	Original model with a NL X_b	2681.1	0.106	[-5.14, 8.90]	[-0.26, 7.85]	[-20.21, 9.34]	[-0.42, 0.51]
	Original model with a C X_b	2679.2	0.109	[-5.16, 8.76]	[-0.39, 7.84]	[-19.89, 9.11]	0.143 (p = 0.69)
Medical social	Original model	2934.6	-0.055	3.70 (p<0.01)		[-13.53, 2.32]	
	Original model with a NL X_b	2939.7	-0.056	3.67 (p<0.01)		[-13.31, 2.25]	[-0.03, 0.43]
	Original model with a C X_b	2936.1	-0.056	3.68 (p<0.01)		[-13.39, 2.27]	0.151 (p = 0.734)
Home health aide	Original model	2218.3	0.572	[-1.17, 4.44]			
	Original model with a NL X_b	2222.7	0.561	[-1.17, 4.40]			[-0.175, 0.355]
	Original model with a C X_b	2220.0	0.572	[-1.18, 4.42]			0.03 (p = 0.895)

5. Conclusion

The availability, quality and efficiency of home healthcare services will likely have important roles in meeting the increasing demand for long-term care in this century. A key factor for a better home healthcare industry is utilizing strategic approaches supported by quantitative tools. This dissertation examines two main issues in the US home healthcare system: telehealth diffusion and spatial accessibility. The main objective of the research is to analyze these topics through developing and employing intuitive solution methods from a comprehensive systems perspective.

Home telehealth is an emerging technology that has the potential to increase efficiency and health outcomes. However, the utilization of this technology has been limited primarily due to lack of reimbursement and lack of evidence on its impacts. In this dissertation, we study the factors impacting home telehealth diffusion among agencies and develop a system dynamics model to demonstrate the impacts of home telehealth on healthcare utilization and overall healthcare cost. Next, we study potential spatial accessibility of home healthcare services. A new measure that simultaneously considers both staffing levels and eligible populations is developed and demonstrated via a case study using the state of Arkansas. To the best of our knowledge, no previous measure has proposed to quantify the potential spatial accessibility of home healthcare services within a geographic region. The results of the case study reveal disparities across the study area for each home healthcare service type. Finally, to better understand the spatial accessibility of home healthcare services, we investigate associations between population characteristics and access using space-varying coefficient models. The findings indicate statistically significant associations between access and predictor variables across the state.

The primary limitation in all chapters is collecting the required data for the models. We rely on secondary data sources to populate our models. In chapter 2, there is uncertainty in the system dynamics model inputs of diffusion rates, telehealth's impact on healthcare visits and telehealth nurse capacity. We overcome these challenges by conducting comprehensive literature reviews and sensitivity analyses. In chapters 3 and 4, unavailable cost reports from some agencies and questions around the accuracy of self-reported data in the cost reports of other agencies may influence model outputs on certain parts of the state.

As future work, independent from the ideas proposed after each chapter, the impact of home telehealth utilization on access to home healthcare services can be examined. Distance and location are considered as barriers against accessing healthcare services. However, telehealth technology provides opportunities to the lower the impact of the distribution of healthcare resources and traveling barriers on patient's access to care. Hence, the concept of accessibility evaluation can be broadened to consider telehealth utilization.