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Geospatial Analysis of Spatial Patterns of U.S. Hospital Readmission Rates

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Abstract

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MS, Fudan University, 1991

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Health Services

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Abstract

Unplanned hospital readmission after a recent hospitalization is an indication of poor healthcare quality and a waste of healthcare resources. The Centers for Medicare and Medicaid Services (CMS) initiated the Hospital Readmission Reduction Program (HRRP) to improve healthcare quality and reduce costs; however, studies found the risk adjustment method used in calculating the standardized readmission rate was less accurate without hospital region or community factors. Accordingly, this cross-sectional quantitative study was designed to examine spatial patterns in hospital readmission rates following Andersen's behavioral model of health service utilization. This study was the first geospatial analysis on risk standardized hospital readmissions (RSRR) based on hospital geographic locations. Secondary data from the CMS was used in assessing the global and local geospatial cluster patterns using Global Moran's Index, Anselin local Moran's Index, and graphical analysis tool to identify cluster groups. The study found hospital-wide RSRR was significantly clustered across the country or at the local level. A total of 15 optimal cluster groups were identified with wide variability in cluster size. The hospital-wide and other seven CMS published RSRRs were significantly different among all clusters. The geographically bounded hospital RSRRs provided evidence in support of adding community or regional layer to risk adjustment of RSRR. The specific cluster groups with extremely high or low readmission rates can assist national and local policymakers and hospital administrators to identify specific targets to take actions. This research has social change implications for reducing hospital readmission rates and saving healthcare costs.

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Dedication

This dissertation is dedicated to my supportive and loving husband, Jing Wu, and my two incredible daughters Yiwen Wu and Lucy Wu. I appreciate the time, the patience, and the empathy so generously given as I studied and struggled to achieve this dream. I could not have done it without such love and support. I also dedicate this study to my mom, dad, sister, and brother in China. You encouraged me in all my endeavors in life. I was so grateful of growing up in an open and trusting family.

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

Introduction

Unplanned hospital readmission after a recent hospitalization is considered an indication of poor health care quality and a waste of healthcare resources. Hospital readmissions are an increasingly important problem for Medicare enrollees (Jencks, Williams, & Coleman, 2009). The Centers for Medicare and Medicaid Services (CMS) have begun penalizing hospitals with readmission rates above the national average. The expected readmission rate is calculated by adjusting the hospital readmission rate for patient demographics, comorbidities, and patient frailty (CMS, 2016a); however, the risk adjustment does not include community factors or consider the geographic location of the hospital. This type of risk-adjusted method has been criticized on the basis of overpunishing certain hospitals with excess readmission rates beyond hospital control.

Community factors are associated with geographic variation in readmission rates (Herrin et al., 2015). Geospatial analysis methods have been used to examine the relationship between location and pain management scores (Tighe, Fillingim, & Hurley, 2014), and Cui et al. (2015) has examined spatial clustering of hospital readmission rates at the patient level; however, no study has examined geospatial clustering of hospital readmission rates at the hospital level. The purpose of this study was to examine spatial patterns in hospital readmission rates. The results from the completed study may be useful to risk adjustment in the CMS Hospital Readmissions Reduction Program (HRRP) and, therefore, may help provide a more accurate understanding of the association between excess readmission rates and poor healthcare quality.

This chapter presented an overview of the present study, including the study background, problem statement, purpose, research questions, and hypotheses. The theoretical framework and the nature of the study were then discussed. This chapter also provided study definitions, assumptions, scope, limitations, and the expected significance of the study.

Background

The HRRP is a U.S. government effort to reduce healthcare cost and enhance the quality of hospital care. The Patient Protection and Affordable Care Act (ACA) (2010) established the path for the CMS to deduct payments to a hospital with risk-adjusted readmission rates above the national average. The program is tightened every year. In the fiscal year 2015 by increasing the reduction rate from up to 1% to 3% (CMS, 2016a). The applicable medical conditions were expanded over the years from pneumonia (PN), heart failure (HF), and acute myocardial infarction (AMI) to chronic obstructive pulmonary disease (COPD), elective total hip arthroplasty (THA) and total knee arthroplasty (TKA), and coronary artery bypass graft (CABG) surgery.

The penalty amount imposed on a hospital with an excessively high risk-adjusted readmission rate is based on how the calculated risk-adjusted expected readmission rate compares to the U.S. average. Horwitz et al. (2014), Keenan et al. (2008), Krumholz et al. (2011), and Lindenauer et al. (2011) presented methods for utilizing the Medicare claim database to evaluate quality of hospital care and risk standardization calculation methodologies for HF, AMI, PN, and hospital-wide readmissions.

Over the years, hospitals and researchers have criticized the current risk adjustment methods for not considering factors that are beyond hospital control. Lee et al. (2014) questioned which factors in hospital readmission were preventable. Unsuccessful experiences with reducing readmission rates efforts were observed by Altfeld et al. (2013), Linden and Butterworth (2014), and White et al. (2013). Shimizu et al. (2014) pointed that some readmissions are attributable to hospital resource constraints. Multiple authors (American Hospital Association [AHA], 2015; Jencks & Brock, 2013; Lipstein & Dunagan, 2014; Nagasako, Reidhead, Waterman & Dunagan, 2014; Oddone & Weinberger, 2012) have criticized the omission of socioeconomic status in current risk-standardized readmission rate (RSRR) methodology. Gu et al. (2014), Herrin et al. (2014), and Nuckols (2015) have noted that community factors, such as the quality or accessibility of outpatient and postoperative care, are associated with hospital readmission.

Hospital geographic location as another natural accessibility attribute has never been studied as an independent factor related to the hospital readmission rate. To address this knowledge gap, this research used the Geographic Information System (GIS) and related geospatial analysis to study potential hospital geographic location on hospital RSRR. Healthcare research has adopted GIS tools for many years, especially for accessing health needs, access, patient satisfaction, and education (Chaney and Rojas-Guyler, 2015; Fradelos et al., 2014; McLafferty, 2003; Tighe, Fillingim & Hurley, 2014). Similar to previous geospatial findings in the healthcare field, the results of this research provided an opportunity for a new view of the potential influential factor of geographic location on hospital readmission rates, and may improve the existing method of estimating the RSRR.

Problem Statement

In the U.S., about 20% of patients may be readmitted to the hospital in fewer than 30 days after their initial hospital discharge, resulting in an increase in healthcare spending of about $17 billion each year (Berenson, Paulus, & Kalman, 2012), and also raising concerns about the quality of hospital care. Starting in 2008, the CMS began to publish the RSRR on the publicly accessible Hospital Compare website. Section 3025 of the Patient Protection and ACA (2010) established the CMS Hospital HRRP as of fiscal year 2013. The objective of the HRRP was to reduce healthcare costs and improve the quality of hospital care by reducing unnecessary hospital readmissions (CMS, 2016a). Many factors were associated with and may potentially influence unnecessary hospital readmissions. The current RSRR adjusted the rate of hospital readmissions rates according to patient demographics, patient frailty, and comorbidities (CMS, 2016a). Despite the endorsement of the National Quality Forum (NQF) and evaluation by expert panels, the CMS RSRR estimation methodology remained subject to debate, because it did not take into account community factors or patient socioeconomic status (Atkinson, 2012; Gu et al., 2014; Oddone & Weinberger, 2012).

After years of implementation of HRRP, hospitals spent a substantial amount of resources to reduce their readmission rates. Some of their strategies worked, while others did not (Brown, Sox, & Goodman, 2014). Kind et al. (2014) studied a 5% sample of Medicare patient data and found a positive correlation between the socioeconomic location where patients lived and the hospital readmission rate. Herrin et al. (2015) studied Medicare published hospital readmission rates and observed that 58% of the variance in hospital readmission rates could be explained by hospital county location. Gu et al. (2014) took a more comprehensive approach and evaluated three models: patient level, hospital level, and both patient- and hospital-level indications. By adding vulnerable indicators to each model, they found that both patient-level and hospital-level indicators were associated with increasing the readmission rate. The NQF (2014) suggested the inclusion of various patient level sociodemographic factors in future standardized readmission rate adjustments after reevaluating the risk adjustment model. For the community factors, the NQF (2014) recommended conducting additional research to eliminate potential inaccuracies. To better understand the regional or community effect on the readmission rate, this study was designed to investigate the hospital geographical location pattern on hospital RSRR. Although the study did not investigate the specific regional or community factors associated with the RSRR, all regional factors are linked to geographic locations. The geographic location pattern could support the argument of the regional spatial effect. A similar GIS tool was applied by Tighe et al. (2014) in analyzing the correlation between hospital geographical location and hospital pain management score, another Medicare hospital quality measure.

Purpose of the Study

The study purpose was to examine spatial patterns in hospital readmission rates. Using the geospatial analysis tool, a method to identify the association between effect and location (Fradelos et al., 2014), RSRR across the continental United States were compared. If hospitals were clustered in their geospatial distribution, meaning that nearby hospitals had more similar readmission rates with distant hospitals, the next steps were to identify the local clusters, determine the number of regional cluster groups, and examine the differences in RSRR across the cluster groups. This exercise may find geographic trends supporting the hypothesis that hospital readmission rates are geospatially distributed, and therefore specific regional or community factors might contribute to this geospatial pattern.

Research Question and Hypotheses

Four research questions directed the conduct of this study:

RQ1: Are hospital-wide readmission rates geographically clustered by hospital location?

RQ2: Are there local geographic clusters of hospital-wide readmission rates?

RQ3: What is the optimal number of cluster groups for hospital-wide readmission rates across the continental U.S.?

RQ4: Are there differences in hospital readmission rates for various diseases or surgical types between cluster groups?

Research questions were tested using the following hypotheses, which were stated in the null and alternative forms.

$H1_0$: Hospital-wide readmission rates are randomly distributed by hospital location.

$H1_a$: Hospital-wide 30-Day readmission rates are geospatially clustered by hospital location.

$H2_0$: There are no local geographic clusters of hospital-wide readmission rates.

$H2_a$: There are local geographic clusters of hospital-wide readmission rates.

$H3_0$: There is no optimal number of cluster groups for hospital-wide readmission rates.

$H3_a$: There is an optimal number of cluster groups for hospital-wide readmission rates.

$H4_0$: Hospital readmission rates for various disease or surgical types are not different between cluster groups.

$H4_a$: Hospital readmission rates for various disease or surgical types are different between cluster groups.

Hypotheses 1 and 2 were tested using global Moran's Index and local Moran's Index and their corresponding p-values. The optimal number of cluster groups in RQ3 were identified with the peak pseudo F-statistic, which measured the between-cluster variance. The statistics test for hypothesis 4 was the Kruskal-Wallis test.

Theoretical Framework

The theoretical basis of this research project was the Andersen behavioral model of health service use. The model, initially developed in the late 1960s, described factors which enables or impedes health services usage. Since then, the model has been further cultivated and applied to a broad range of health services. In the most recent emerging model, Andersen (1995) connected four main health service components: population characteristics, health behavior, environment, and outcomes. Environment factors include the health care system and external environment. They influence health outcomes directly and also through population characteristics and population health behavior. Environmental influences on health services and outcomes within Andersen's behavioral model offer guidance in studying community and regional effects as well as the hospital geographic location on hospital readmission rates.

Nature of the Study

This study was cross-sectional quantitative research performed on Medicare hospital readmission data. This quantitative approach was necessary to test the study hypotheses and identify hospital geospatial patterns. The dependent variables were the hospital-wide readmission rate and other seven types of readmission involving PN, HF, AMI, COPD, THA and TKA, CABG, and Stroke. The independent variable was the hospital geographic location which was in the same data package as the Medicare Hospital Compare website.

The initial assessment focused on the existence of geographic location effect and whether hospital readmission rates were similar or diverse when the distance between two hospitals becomes closer. If the cluster relationship existed, the autocorrelation between hospital location and RSRR would be further evaluated by different ranges of interhospital distance. The local pattern of the hospital readmission rates and its neighborhood hospital performance were tested and indicated on the map. During the second approach, the number of hospital cluster groups was determined, and differences in readmission rates across cluster groups were also examined.

Definitions

30-Day unplanned hospital readmission: An unplanned admission to an acute care hospital within 30 days of discharge after a previous hospitalization for any causes related to medical conditions, including AMI, HF, PN, COPD, and stroke, as well as surgical procedures, including THA and TKA and CABG, and hospital-wide (CMS, 2016a).

Clustering: An analytical result in which nearby hospitals had risk-adjusted admission rates that are more similar to each other than those of distant hospitals. Clustering was one of the three major spatial organization patterns. Alternative patterns could be random or dispersed. In dispersed patterns, distant hospitals displayed similar readmission rates (Tighe et al., 2014).

Geocoding: A process of translating geographic data into GIS software-identifiable geographic properties (Passalent, Borsy, Landry & Cott., 2013). In this study, hospital street addresses were geocoded into latitude and longitude values.

Geographic Information System (GIS): A spatial data system. The spatial data were stored in digital format for display, analysis, and integration. In health care, researchers explored the correlation between geographic location and health activities to understand the trend or pattern (Fradelos, 2014).

Hospital readmission reduction program (HRRP): A program for reducing hospital Medicare IPPS for hospitals with excess readmission rates, in place since October 1, 2012. The program originated from an order in the Social Security Act (CMS, 2016a).

Hospital referral region (HRR): The aggregate of hospital service region that was defined by Medicare. Most Medicare patients are within the hospital service region. According to cardiovascular surgery and neurosurgery patterns, hospital service areas were regrouped to 306 hospital referral regions. HRR was defined as the region “where patients are referred for major cardiovascular surgical procedures and neuro surgery” (Dartmouth, 2016. para. 3). The region sometimes crosses state boundaries. HRR also has minimum population criteria (Dartmouth, 2016).

Inpatient Prospective Payment System (IPPS): The system by which Medicare pays for the acute hospital inpatient stay using a prospective rate according to the Diagnosis-Related Group (DRG). Based on the average resource usage, each DRG was assigned a payment weight (CMS, 2016b).

Medicare fee-for-service (FFS): The health service payment system which Medicare compensated healthcare providers by unit of services they provide to the Medicare enrollees (Barton, 2010; CMS, 2016c).

Risk standardized readmission rate (RSRR): An adjusted readmission rate using the national average readmission rate multiplied by the ratio of predicted versus expected readmission number for a specific hospital. The expected number of readmissions was calculated from the nation's performance with case-mix (patient combination) of the hospital under consideration. The predicted number of readmissions was an observed case-mix (AHRQ, 2016a).

Spatial autocorrelation: A similarity measure that compared a given variable from a set of samples and the spatial locations of these samples (Diniz-Filho, Bini, &

Hawkins, 2003). In this study, spatial autocorrelation measured hospital readmission rate similarities as a function of the distance between hospitals. In autocorrelation analysis, Moran's Index was the commonly used coefficient. The corresponding Z score and p-value were for statistical significance evaluation.

Assumptions

The study assumed that the Medicare readmission data published on the Hospital Compare website were high-quality, consistent data. The periodic data update did not significantly change the direction of the study findings. Hospital mergers and acquisitions cause minimal changes in hospital location and services. From a study design point of view, the study also assumed that the vast majority of hospital patients come from the local community. The regional location of the hospital represents the regional patient social demographics. Findings regarding geospatial clustering of readmission rates could link to the regional community effect, such as the social demographics or community healthcare facilities. As Tighe et al. (2014) described, there was no evidence that shows geographic difference separates from the regional socioeconomics or cultural difference.

Scope and Delimitations

The scope of this study was broad. Almost all Medicare FFS patient hospitals were evaluated, with the exception of the hospitals outside the continental United States or with fewer than 25 admissions per disease category. Due to the spatial disconnection with other continental hospitals, hospitals outside the continental United States were not evaluated using the hospital cluster effect. The other excluded hospitals were limited to those with readmission rates and confidence intervals that cannot be reliably compared with the national average and therefore, were not posted in the public domain (CMS, 2016d; QualityNet, 2016). The data to be used in the study was from all U.S. Medicare FFS hospitals; data from other institutions such as VA hospitals, children's hospitals, and other non-Medicare FFS hospitals may not be compatible for analysis.

Limitations

Publicly available hospital readmission data reflected the hospital-level readmission results. In some areas, especially metropolitan areas, patients could come from similar locations but with different socioeconomic backgrounds. It was also impossible to differentiate within-hospital patient variability using hospital-level aggregate data. This study was not designed to directly study the association between patient social demographics, geographic location, community healthcare resources, and hospital readmission in one place, but rather to focus on the hospital geographic location and corresponding readmission rates.

Significance of the Study

This research may contribute to closing the knowledge gap regarding how community or regional factors affect the hospital standardized readmission rate. The study was unique because evaluating hospital geographic location and hospital readmission rates has not been done previously. Most regional or community related readmission rate studies had focused on social demographic factors or hospital characteristics (see Herrin et al., 2015; Gu et al., 2014). One Canadian geospatial study on hospital readmission rates was based on patient geographical postal location (Cui et al., 2015). Since a hospital, as the healthcare provider, plays the major role in hospital care quality, it was necessary to evaluate hospital readmission from the hospital perspective. The correlation between hospital location and the hospital readmission rate had not been analyzed previously. If it can be shown that hospitals were penalized by excessive readmission rates outside of their control, the fairness and long-term sustainability of the HRRP are questionable. The positive change this study might bring to society was to enhance health policy and therefore to improve healthcare quality and efficiency.

Summary

The CMS HRRP has been implemented since October 2012. RSRRs are calculated based on patient demographics and medical conditions without adjusting for patient socioeconomic factors or community factors. The current cross-sectional quantitative research used the geospatial analysis method to explore the potential association between hospital geographic location and hospital readmission rates. The CMS readmission reduction program and its background had been briefly reviewed in this chapter. In addition, the research purpose, problem statement, research questions and hypotheses, and planned secondary databases were presented, and the study assumptions, limitations, and potential social impact were discussed as an overview of the research. A detailed literature review summarizing current knowledge of the readmission reduction program is in Chapter 2, and related geospatial analysis methodology is in Chapter 3.

Chapter 2: Literature Review

Introduction

Hospital readmissions are an increasingly important problem among Medicare beneficiaries (Jencks et al., 2009), and community factors are associated with geographic variation in readmission rates (Herrin et al., 2015). Geospatial analysis methods have been used to examine the relationship between location and pain management scores (Tighe et al., 2014), and Cui et al. (2015) has examined spatial clustering of hospital readmission rates at the patient level; however, no studies have examined geospatial clustering of hospital readmission rates at the hospital level. The purpose of this study was to examine spatial patterns in hospital readmission rates. Results of the study might be useful to risk adjustment in the HRRP of the CMS.

This chapter presented a review of the Medicare HRRP, its rationale, risk-standardized method, current practice, and arguments on the risk factor selections. The chapter also provided explanations of the Andersen behavioral model and the geospatial method, which was applied to the study design and analysis. In addition, the literature search strategy used to identify sources for the review was described.

Literature Search Strategy

Different database and search strategies were utilized for the three literature review targets. SAGE journals were used to search for literature sources related to an appropriate theoretical framework. Academic Search Complete, Business Source Complete, Medline with full text, and Political Science Complete were used to search for readmission and related literature. The geospatial analysis literature search was performed using Science Direct. In addition, a related snowball search was used through the Google Scholar search engine. The two main literature search methods were the Boolean search and snowball search. Search terms and the number of literature results returned are summarized in Table 1.

Table 1

Literature Search Results (From 2012 to June 2016)

Database Name	Boolean Search Term	# Found
SAGE journals database	readmission and theory	1
Science direct	spatial regression models	188
Academic Search complete	TX geospatial AND TX readmission	18
Academic Search complete	TX geospatial AND TX hospital	877
Academic Search complete, business source complete, Medline with Full Text Political Science Complete	TX readmission AND TX penalty	1,929
EBSCO: CINAHL Plus Full Text	TX hospital readmission, from 2008	1,663
Academic Search Complete	DE "HOSPITALS -- Admission & discharge"	1,811

Note. Default search field for TX is all text field; DE is the heading for author-supplied keywords.

After reviewing these abstracts, over 100 articles related to the readmission penalty program were selected. In addition, 20 articles were collected through the snowball search. Similar literature search processes were applied to the geospatial research. With an additional 20 to 30 references found through the snowball search, a total of 88 related geospatial related sources were collected.

Theoretical Foundation

Andersen behavioral model of health service use was selected as the theoretical foundation of current research. This model described factors enabling or impeding the use of health services. With respect to readmission research, this model was about the factors related to hospital resource use. This model provided “measures of access of medical care” (Andersen, 1995, p. 4) and served both explanatory and predictive functions. The three types of influential factors were predisposing characteristics, needs, and enabling resources (Andersen, 1968). Predisposing factors included demographics, health beliefs, social structure including social network, and social interaction or culture. Andersen grouped personal and community related factors such as available sources of care, health insurance, income, and traveling and waiting time to access health services as enabling or impeding factors to use health services (Andersen, 1968). Quality of social relationships was a special type of community-driven enabling factor. Andersen believed that needs had social influences. Health education and cost of care could influence needs (Andersen, 1995). Patient traveling and waiting time related to hospital locations could be factors related to hospital readmission.

Although Andersen’s behavioral model had evolved since it was established , societal factors always existed as part of the model, directly or indirectly contributing to health access. Andersen (1968) introduced the concepts of equitable and inequitable access factors. Equitable factors included demographic characteristics and needs. Social structure, enabling resources, and health beliefs were identified as inequitable access factors. In the most recent model, these two factors were recategorized under population and environmental components (Andersen, 1995). In addition, the complete emerging model from Andersen also included health behavior and outcomes components. Culture factors, social interactions, and social networks were considered part of social structure (Andersen, 1995). Again, hospital geographic locations considered as enabling resources or environmental factors are possible factors influencing hospital readmission.

Andersen’s behavioral model also provided a theoretical framework for the study of hospital readmission. Existing studies (Wong et al., 2010; Chan & Wong, 2014) successfully used Andersen’s behavioral model to categorize different types of patient-level risk factors for hospital readmissions in Hong Kong and Singapore. Under the same theoretical model, the current research will focus on hospital location-related enabling or environmental factors to study their impact on hospital readmission rates.

Readmission Program Background and Current Practice

Medicare Hospital Payment

Health care spending in the U. S. is the highest in the world, while quality of health care is not. Spiro, Lee, and Emanuel (2012) reported that the average person spent $8,000 per year on health care, which was almost $3,000 more than the second leading country for health expenditures in the world. Despite maintaining the highest level of spending, key health indicators such as life expectancy or the prevalence of chronic conditions are not promising (Squires & Anderson, 2015). After Medicare and Medicaid programs were added to the Social Security Act in 1965, hospital patient bills became the largest portion of Medicare healthcare spending (see Figure 1). Since the early 1970s, the U.S federal government has exerted constant efforts to contain hospital spending.

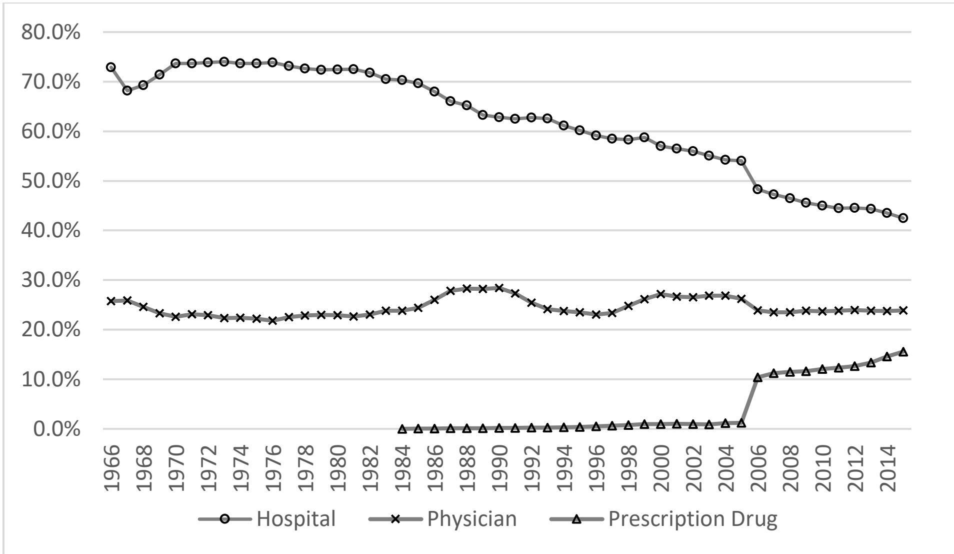

Figure 1. Percentage of selected expenditures in Medicare total personal spending over the year. Adapted from Medicare Expenditure. Retrieved from cms.gov (CMS, 2016e).

The U.S. government had developed multiple policies in an attempt to achieve healthcare cost containment. For FFS patients, when Medicare was first initiated, Medicare paid hospital bills representing the total capital and operating costs plus profit margin (Barton, 2010). Under the cost-based reimbursement system, all reasonable expenses would be fully reimbursed (Lave, 1989). Due to the lack of restriction, the hospital inpatient Medicare expenditures grew rapidly (see Figure 1) as hospitals increased spending on each patient. In order to reduce per-episode cost and improve healthcare efficiency, in 1983, Medicare rolled out the Inpatient Prospective Payment System (IPPS) (Barton, 2010). The IPPS payment model was based on the Diagnosis Related Group (DRG) system. According to the DRG system, hospitals only received a standardized single service fee for each hospitalization. Regardless how many diseases or symptoms were treated, only the one with the highest cost was reimbursed. Medicare pre-specified the payment amount for each DRG before the fiscal year started (Barton, 2010).

The IPPS effect in lowering the percent of Medicare hospital spending after year 1983 was displayed in Figure 1.

Although IPPS limited hospital expenditures per episode regardless of each episode's length or underlying costs to hospitals, it did not limit the number of hospital visits. Hospitals still could cause extra health care spending by increasing the frequency of hospital admissions. Under IPPS, payment was fixed per episode, with hospitals rewarded for efficiently delivering care and discharging the patient early (Beasely, 2015; Leatherman, et al., 2003). This payment system compensated hospitals for efficient treatment during each episode of care, but it paid for every episode of hospitalization, including readmission regardless of whether it was avoidable or not (Averill, Goldfield, & Hughes, 2013). Hospitals reducing readmission may reduce revenue with unfilled beds (Tilson & Hoffman, 2012). As such, Leatherman et al. (2013) commented that the current IPPS payment system rewarded doing more, and punished hospitals for lowering the admissions rates or improving the quality of care along with its efficiency. IPPS financially rewarded lower quality care. As one of the federal government's efforts to further improve quality of care, the ACA initiated readmission reduction program as part of the value-based reimbursement infrastructure (Tilson & Hoffman, 2012).

Hospital Readmission Reduction Program

The readmission reduction program reduced payment for hospitals with excessive readmission rates compared to the national average. With the readmission penalty program, hospitals were expected to reduce premature discharges that disregarded coexisting diseases and allowed short-term readmission to the hospital to collect a new payment. Tilson and Hoffmann (2012) noticed that readmissions generated a large amount of additional payments under the volume-based payment model. According to a CMS, 6.2% of hospitalized and discharged Medicare patients were readmitted as inpatients within 7 days. The readmission rates increased to 11.3% within 15 days, and 17.6% within 30 days. The cost of these additional hospitalizations was $15 billion as assessed by the Medicare Payment Advisory Commission (MedPAC, 2007). The total cost of 30-day hospital readmissions was about $44 billion annually, if non-Medicare population were also counted (Jencks et al., 2009).

Although the readmission rates varied across U.S. hospitals, hospital readmissions were often preventable. MedPAC (2007) estimated that 75% of readmissions were avoidable. The high incidence of unnecessary readmission rates has also lowered quality standard of hospital care (Rohit, 2013; Jencks et al., 2009). The most frequent readmissions listed by Jencks et at. (2009) including patient discharged for HF, PN, COPD, major hip or knee surgery, and other. Among those readmissions, the highest readmission came from HF patients (Heidenreich et al., 2011). It was believed that with better, safer inpatient care, and detailed communication on medications at discharge, avoidable readmissions would be significantly reduced MedPAC officials (2007).

Over the years, the U.S. government gradually rolled out the hospital readmission penalty program. Starting in 2008, CMS began to post the risk-standardized readmission rate on the Hospital Compare website. In 2010, Title III, Part III Section 3025 of the Patient Protection and Affordable Care Act (PPACA) further directed the CMS Hospital Readmission Reduction Program, beginning with the fiscal year of 2013. A hospital received a reduced DRG payment if its all-cause readmission rates on PN, HF, and AMI patients were greater than expected (“excessive”). The program was tightened every year. From an initial reduction of overall DRG payments by up to 1 % in fiscal year 2013, the program reduced overall DRG payments by 2% in 2014 and 3% in 2015 (Traynor, 2015). Over recent years, this program had expanded to cover other disease or surgical patients.

The HRRP started with a carefully selected target patient population. The initial round of three diseases, PN, HF, and AMI, had been designated as part of the initial implementation of HRRP due to their higher readmission rates (Jencks et al., 2009). The selected three conditions were common diseases in Medicare enrollees and were associated with sizable morbidity and mortality. Although outcomes of PN, HF, and AMI varied across U.S hospitals, readmissions for these conditions were often preventable by hospital (Cornett & Letimer, 2011; Jencks et al., 2009). The 30-day time window was chosen because it incorporated a large portion of readmissions after discharge and was short enough for a hospital and community to enhance patient care through changing the practice in hospital care and transitional care (MedPAC, 2007; Tilson & Hoffman, 2012).

The purpose of HRRP was to reduce healthcare costs and improve the quality of hospital care through eliminating unnecessary hospital readmissions (CMS, 2016a). Using financial tools to reduce readmission was part of pay-for-performance efforts. A good hospital practice should include an excellent transition care program even without the penalty program (Rohit, 2013).

Table 2

The Hospital Readmission Reduction Program (2013 -2017)

	Penalty fiscal year				
Parameter	2013	2014	2015	2016	2017
Performance measurement period	June 2008-July 2011	June 2008-July 2011	June 2008-July 2011	June 2008-July 2011	June 2008-July 2011
Maximum rate of penalty	1%	2%	3%	3%	3%
Average hospital payment adjustment	-0.27%	-0.25%	-0.49%	-0.48%	-0.58%
Percent of hospital penalized	64%	66%	78%	78%	79%
Percent of hospitals at max penalty	8%	0.6%	1.2%	1.1%	1.8%
CMS estimated total penalties, million	$290	$227	$428	$420	$528

Note. Adapted from "Aiming for Fewer Hospital U-turns: The Medicare Hospital Readmission Reduction Program" by C. Boccuti and G. Casillas, January 2016, Issue Brief, The Henry J. Kaiser Family Foundation. Reprinted with permission.

Current Practice

HRRP received the expected financial results over the initial program implementation period. According to a report from the Kaiser Family Foundation (see Table 2), Medicare reduced estimated hospital spending by a total of $1.9 billion from 2013 to 2017 (Boccuti & Casillas, 2016). After the first year of HRRP, Medicare inpatient discharge declined by 4.4%; about a hundred thousand fewer readmissions occurred in 2013 compared with 2012 for Medicare patients (Miller, 2015). From 2006 to 2013, the yearly readmissions rate was reduced about 17%. During the same time period, the average hospital occupancy rate dropped from 64% to 60% (Miller, 2015). This decrease occurred more rapidly in rural rather than urban hospitals.

Hospital Reducing Readmission Effort

Hospitals had been advised on different solutions for reducing readmission rates. According to Medicare Quality Improvement Organizations, improving the quality of pharmacy, documentation, post-discharge follow-up, patient self-management, patient support, and community infrastructure could reduce readmission rates (Tilson & Hoffman, 2012). Accordingly, CMS suggested hospitals only release clinically ready patients out through the hospital doors. In the meantime, Leatherman et. (2003) suggested hospitals should reduce the risk of hospital-acquired infections, reconcile medications, provide discharge education to patients and caregivers, and improve communication with community healthcare providers.

In addition to those offered solutions, hospitals identified additional readmission reasons and corresponding strategies through their own practices. Lagoe, Nanno, and Luziani (2013) found that the majority of readmissions were for diagnoses other than the one treated during the first hospital admission. This suggested that healthcare providers should manage a broad range of presenting diseases or other medical conditions within one hospital stay. Likewise, Hansen, Young, Hinami, Leung, and Williams (2011) concluded that most single interventions did not bring about significant reductions in readmission after reviewing quality improvement activities from various publications. They recommended a holistic effort with respect to predischarge, postdischarge, and bridge interventions. Additionally, Lee, Andrade, Mastey, Sun, and Hicks (2014) found it was beneficial to identify hospital-specific preventable factors to reduce readmission rates. Effectively reducing hospital readmission was not a simple task. Some excess readmissions might be beyond hospital control.

Over the years, some hospitals had experienced unsuccessful readmission reduction. After conducting a randomized trial, Altfeld et al. (2013) found no difference in readmission rates between the intervention group and the non-intervention group, despite the fact that patients who received the enhanced discharge planning intervention kept more postdischarge physician visits than non-intervention patients. Field, Ogarek, Garber, Reed, and Gurwitz (2015) found similar results in their observational study. Altfeld et al. (2013) observed limited influence from isolated single hospital interventions through a randomized study. They concluded that hospitals were unable to reduce readmission rates without community collaboration efforts. Similar unsuccessful intervention programs were reported by White, Garbez, Carrol, Brinker, and Howie-Esquival (2013) and Shimizu et al. (2014). Resource constraints and lack of community support are associated with higher hospital readmission rates. These factors are not under single hospital control.

Another factor related to the readmission reduction program is the cost of the intervention. It varies from hospital and intervention, ranging from $100 to over $1,000 per patient (Berenson, Paulus & Kalman, 2012; Bayati et al., 2014; Gardner et al., 2014). Gardner et al. (2014) compared total healthcare cost for patients with and without care transition intervention after hospital discharge. They reported a net cost-saving of $3,752 per patient after a 6-months post-discharge with a care transition program. Bayati et al. (2014), however, reported a net loss after an average of $1,300 per hospital HF post-discharge intervention program. It was not economically efficient to provide all patients with HF post-discharge intervention. They suggested profiling patients by their readmission risk, then only providing intervention to the patients at highest risk of readmission.

Criticism of HRRP

Since the rollout of the HRRP program, in addition to criticism from hospital administrators who experienced the unsuccessful efforts to reduce readmission rates or the higher cost of readmission intervention, other scholars have pointed out the defects of the current HRRP program. These issues included the sample data collection period, the 30-day post discharge time window of readmission, and the risk factors used for Medicare calculating the standard risk adjusted readmission rate.

The American Hospital Association noted that the three-year performance evaluation period for each HRRP adjustment did not reflect the progress of payment penalty year (AHA, 2015). For example, the readmission performance for FY 2017 payment penalty was based on actual Medicare claim data from July 2011 to June 2014. This means hospitals were penalized due to their historical record of poor quality, despite any recent gains from quality improvement efforts. Due to the long performance lag time, hospitals may still receive a readmission penalty even though the quality of care has been significantly improved (Lavenberg et al., 2014). For CMS, large numbers of hospitals did not have sufficient volume of readmission over a one-year period for evaluation (NQF, 2015, p. 13). With three-year cumulative data, the evaluation seemed to have a reasonable sample size.

Some scholars had criticized the 30-day timeframe based on lack of scientific justification and because it may include a period in which patient status was more strongly controlled by the patients' outside hospital activities. The critics suggested that readmission was largely influenced by the quality of outpatient service and the emergence of new health problems after 15 days (Lavenberg et al., 2014). Approximately one-third of 30-day readmissions occur within the first seven days, and more than half (55.7%) occur within the first 14 days (Dharmarajn et al., 2013; MedPAC, 2007). For CMS, readmissions remained frequent over the 30-day period. This time horizon was long enough to detect readmissions attributed to the index admission and also short enough to hold hospitals accountable for coordination over the long post-discharge period (CMS, 2016d; Lavenberg et al., 2014; Joynt & Jha, 2012).

Additionally, some scholars had criticized the program for the possibility that hospitals may shift readmission burdens to increase observation status. Reports had shown that annual hospital readmission rates are down, but hospital observation rates had increased (Gerhardt et al., 2014; Green, Leal, Sheehan, & Sobolik, 2015). As a hospital shifts inpatient status to outpatient, patients were forced to pay 20% of Medicare Part B. This was in reality a cost shift, not a cost saving.

Most scholars had criticized the current HRRP program for heavily penalizing safety net hospitals. Joynt and Jha (2013) studied CMS published HRRP data for FY 2013. They found large academic hospitals and safety net hospitals were among the most highly penalized in the list of hospitals receiving penalties through HRRP. This may be associated with the complex case mix in these hospitals with respect to the patients' clinical and socioeconomic status. Similarly, Cornett and Letimer (2011) pointed out that risk adjustment failed to take into account patients' frailty, race or ethnicity, Medicare and Medicaid dual eligibility status, limited English proficiency, social support structure, or geographic region. Public community facilities such as public transportation to the grocery store for proper dietary needs or community attributes including unemployment rates, median household income, percent of unmarried residents, and number of primary physicians (Herrin et al., 2015) also systematically influenced the quality of health care and possible readmission rates.

MedPAC acknowledged that the likelihood of hospital penalty correlated with the percent of low-income patients, suggesting that hospitals should be compared with similar peer institutions with similar rates of poor Medicare enrollees. Hospital readmission rates should be reported with both adjusted and unadjusted social economic status to avoid masking disparities on the quality of care (Miller, 2015).

Risk-Standardized Readmission Rate

The likelihood of a patient's readmission to a hospital after recent hospitalization depends on multiple influential factors. According to the updated Andersen behavioral model, a healthcare service event is affected by population characteristics, health behavior, environment, and outcomes (Andersen, 1995). As reported by MedPAC (2007), patients with multiple co-existing diseases had a higher incidence of readmissions. A similar pattern was observed by Lagoe et al. (2013). The conditions leading to readmission PN and HF patients in Syracuse area hospitals were different from their previous hospital admission disease. Evidence was also found that factors such as social support, health literacy, race, or community factors were associated with the readmission events (Joynt, Orav, & Jha, 2011; Hawkins, Jhund, McMurray, & Capewell, 2012). In order to fairly quantify a hospital's expected readmission rate, all related factors should be considered.

The purpose of HRRP was to enhance hospital care quality by penalizing excess readmission rates. The score reflected the quality of hospital practice. All other non-quality related factors need to be adjusted. NQF (2014) specified that their endorsed readmission measure was used in a "performance improvement and accountability application" (p. v). Medicare published RSRR was used to inform payers on acquiring care, and to assist consumers on selecting healthcare provider. For accurate scoring with appropriate adjustments, it was necessary to identify factors that are intrinsically related to readmission rate and cannot be altered by hospital performance.

Clinical Complexity

Clinical complexity was a medically accepted factor that may affect hospital readmission rate. The CMS RSRR calculation method adjusted the hospital readmissions by patient demographic factors, patient frailty, and comorbidities (CMS, 2016a). These methods were extensively validated and evaluated by Horwitz et al. (2014), Keenan et al. (2008), Krumholz et al. (2011), and Lindenauer et al. (2011). These authors validated the reliability of using claims data to measure hospital care quality and RSRR adjustment models for HF, AMI, PN, and all readmissions by comparing calculated expected readmission rates with actual rates recorded in claim and other clinical databases.

Keenan et al. (2008) evaluated the RSRR of HF program, endorsed by NQF (2015), for its scientific vigor and data source validity. They reported individual hospital HF risk-adjusted readmission model based on Medicare claim data. The results from their statistical regression model were validated by comparing model data with the results from a medical record database, which had more granulated clinical information than claims data (Keenan et al., 2008). The model adjusted risk for procedures and clinical comorbidities, as well as patient demographics. Decisions on the relevancy of clinical variables were determined by a team of five physicians. The initial model included a total of 189 clinical condition categories. Similarly, researchers also added procedures conducted in the hospital as adjustment factors (Keenan et al., 2008). The final RSRR model included one procedure variable, 34 clinical condition variables, and two demographic variables (Keenan et al., 2008).

Following similar model development methods, researchers developed models for other single diseases and one complex model for all clinical conditions. Krumholz et al. (2011) accomplished a risk-adjusted readmission model for AMI using the Medicare claim database, which they then validated with medical records from the Cooperative Cardiovascular Project. The final AMI model included two demographic variables, two procedure variables, and 25 clinical condition variables. This model also received an endorsement from NQF (Krumholz et al., 2011). Meanwhile, Lindenauer et al. (2011) published RSRR for pneumonia. After gaining experiences from single disease RSRR, Horwitz et al. (2014) published an adjustment model on hospital-wide 30-day unplanned readmission. This readmission rate included patients under all clinical conditions. It was targeting to profile whole hospital performance. The complicated model adjusted 74 clinical condition variables. Each discharge condition had its own model to differentiate the different level of readmission risk (Horwitz et al., 2014). Patient comorbidity conditions derived from medical claims data were included all RSRR models.

Patient-level Social Demographics

The CMS posted RSRR models only adjusted sample variability and patient risk. According to Krumholz et al. (2011), all other variations were “due to hospital quality” (p. 245); however, other researchers and societies did not accept this argument. The American Hospital Association (AHA, 2015), Jencks and Brock (2013), Lipstein and Dunagan (2014), Oddone, and Weinberger (2012) criticized the lack of socioeconomic status as an identified source of variation in current RSRR methodology. Cornett and Letimer (2011) pointed out that current risk adjustments failed to take into account race or ethnicity, patient frailty, limited English proficiency, Medicare and Medicaid dual eligibility status, social support structure, and geographic region.

Since the publication of HRRP, researchers had noticed different patterns for different types of hospitals. Joynt and Jha (2013) studied CMS published 2013 HRRP data, and found the safety net hospitals or large academic hospitals were among the most highly penalized hospitals. This may be associated with the complex case mix in these hospitals with respect to patients’ clinical and socioeconomic status. Patient factors such as educational level, employment status, and living alone could affect readmission outcome (Howie-Esquivel & Spicer, 2012). While excluding differences in hospital practice and hospital characteristics, a single urban hospital 30-day readmission study found patients living in high-poverty neighborhoods were 24% more likely to be readmitted (Hu, Gonsahn & Nerenz, 2014). Married patients were found to have lower readmission rates. Reporting consistent results, Kind et al. (2014) found the socioeconomic areas where patients live are associated with the hospital readmission rate after studying 5% sample of Medicare data.

Clinical quality could be measured through both outcome and process of care, according to Fiscella, Burstin, and Nerenz (2014). These authors believed that outcome measures such as mortality or readmission were “more strongly influenced by social risk” than the process of care. Krumholz and Bernheim (2014) explained the intention of creating a standardized readmission measure without clinical complications. The measure should not mask the disparity or create different quality standards for disadvantaged patients (NQF, 2014). Krumholz and Bernheim (2014) suggested not adding sociodemographic factors for two reasons: lack of available source and not wanting to mask potential lower quality due to the disparity of social economic status (SES).

In August 2014, a technical report from NQF described the necessity of adjusting patient-and community-level socioeconomic status in the quality measurement risk adjustment models. NQF (2014) recommended including patient-level socio-demographic factors, such as patient language, education, income, and others, in the forthcoming RSRR calculation model.

Community Factors

Similar to the patient level social economic status (SES), researchers found community settings also influenced readmission rates. These factors, such as public transportation, healthcare facility location, and grocery store distribution, were beyond hospital control. Based on Bikedeli et al. (2014) study findings, Krumholz and Bernheim (2014) stated that neighborhood SES may contribute more than individual SES.

Community factors matter to hospital readmission rates. About 50% of hospitalized patients did not visit any physician office visits between two hospitalizations (Jencks et al., 2009). Bikedeli et al. (2014) A 6-month HF readmission study conducted by Bikedeli et al. (2014) found that patient readmission was independently associated with neighborhood SES. Gu et al. (2014) took a thorough approach and tested models with hospital-level vulnerable indicators, patient-level vulnerable indicators or both. They found that both hospital-level and patient-level vulnerable indicators increased the readmission rates.

Compare to individual SES factors, community SES exerted more influential power on readmission rate. Herrin et al. (2015) studied CMS published RSRR data between July 1, 2007, and June 30, 2010 with hospital community data. They found that the county where a hospital was located could explain 58% of readmission variations. Herrin et al. (2015) also applied county-level variables such as average education level, employment status, living alone, income and others as proxies for individual sociodemographic status; in this way, it was possible for their model to identify independent county-level characteristics.

Although access to care had the strongest association with hospital readmission rates for AMI, HF, or PN, the correlation of this factor to readmission was controversial. Both positive (Sales et al., 2013) and negative associations (Oddone & Weinberger,

2012) between access to care and hospital readmission rates had been observed. Herrin et al. (2015) predicted lower readmission rate in the area with fewer specialists and more general practitioners per capita, but the correlation to the ratio of general practitioners and specialists was not linear. Both high and low ratios were associated with higher readmission rates (Herrin et al., 2015). Hospitals with more beds per capita tended to have higher readmission rates. The presence of more nursing home per capita can also reduce readmission rates (Herrin et al., 2015) or increase readmission rates, depending on the quality of nursing homes or related health policy (Konetzka, Polsky, & Werner, 2013).

Multiple community factors beyond hospital control were found to be related to hospital readmission rates. Hospitals with higher readmission rates may be located in an area with limited community support following a hospitalization. Patients living in that area may had less access to preventive health activity (Tilson & Hoffman, 2012). In facilitating preventive health habits, community support includes public transportation to the grocery store for proper dietary needs (Herrin et al., 2015), convenient access to primary care or hospital care, and controlling the number of primary care physicians, number of specialist physicians and number of hospital beds per capita.

Although prior work studied geographic variation such as community facilities (Herrin et al., 2015) or patient-level SES (Bikedeli et al., 2014; Gu et al., 2014), these studies had not covered geospatial details such as geographic location. Studies had shown that disorders such as infectious disease (Cartabia et al., 2012), heart disease (Semple et al., 2013), asthma (Keddem et al., 2015), or trauma (Newgard et al., 2011) could be highly associated with the geographical location; besides, population social demographics and community facilities were unevenly distributed across the geographic location. The planned research studied the location-related regional and community factors to evaluate the association with the hospital readmission rate.

Geospatial Analysis in HealthCare Research

Geographic information system (GIS) and corresponding spatial analysis had been applied in various healthcare-related researches. They were efficient tools for evaluating healthcare “needs, access, and availability” (McLafferty, 2003, p. 27). Kistemann, Dangendorf, and Schweikart (2002) interpreted GIS as both technology and science and referred GIS as Geographic Information Science. Besides being a map display instrument, GIS has contributed to solving spatial data problems. GIS-related spatial data management system involved data capture, storage, integration, analysis, and display (Fradelos et al., 2014; Kistemann et al., 2002). With the link between spatial data and other healthcare-related measurements, GIS provided healthcare decision-makers tools for solving a series of spatially related healthcare questions (Fradelos et al., 2014).

Overview

History. Geospatial analysis was a method to identify the association between effect and location (Fradelos et al., 2014). This method had been applied in healthcare research for nearly 200 years since John Snow introduced geospatial analysis in investigating a public health problem (Hempel, 2013). He was recognized with initiating map-supported spatial-temporal analysis into inductive causality research on the London cholera outbreak in 1854 (Kistemann et al., 2002). Since then, geospatial analysis had been applied in various healthcare-related fields (Chaney & Rojas-Guyler, 2015; McLafferty, 2003). During the 1960s and 1970s, scientists began to use cartographic data systematically with the Synagraphic Mapping System (SYMAP) (Fradelos et al., 2014). Its electronic feature of producing and printing a map was the first step for digitalizing map data. New programs built after SYMAP could visualize and analyze spatial data (Fradelos et al., 2014). Improvements in digitalized graphic display had occurred proportionally to progress in computer science. Today, there are various commercial and non-commercial GIS map tools available online or as standalone software packages (Fradelos et al.,2014; Sopan et al., 2012; Steiniger & Hunter, 2013). This made the geospatial analysis a convenient tool for researchers.

Function. Geospatial analysis was a unique tool for solving spatial data-related problems. This method of analysis linked geographic information with the event of interest by describing or making inferences about variables and their corresponding geographic location or neighboring area (Chaney & Rojas-Guyler, 2015). Geographic differences, proximity, and access were the common variables for understanding the healthcare-related variations from one place to another (Chaney & Rojas-Guyler, 2015). Compared to geographic analyses, geospatial analysis took a more generalized approach (Tighe et al., 2014) by excluding information from the different natural surface features, such as rivers, mountains, or forests. Geospatial analysis could only use certain features such as the distance or direction of an object to identify, explain, and account for spatial variation (Chaney & Rojas-Guyler, 2015). It was more powerful than non-spatial methods that did not directly link data to a geographic coordinate position or represent the influence of neighboring regions on individual observation (Chaney & Rojas-Guyler, 2015).

One important data element for geospatial analysis was spatial data, which had unique properties. First, spatial data could be presented on a geographic map (Clarke, McLafferty, & Tempalski, 1996). Spatial data were stored as grid or vector data or both even though the location itself was a nominal variable (Kistemann et al., 2002; Tighe et al., 2014). In geospatial analysis, spatial data could be represented through either area-based variables or distance-based variables (McLafferty, 2003). Area-based variables were expressed as predefined units, such as hospital referral region or county. Distance-based variables could be expressed as measures of distance or travel time, through straight-line or Euclidean distance (McLafferty, 2003). Both area-based and distance-based spatial data were used in healthcare research.

Unique in healthcare. Today, GIS had a wide spectrum of utility including health services (Fradelos et al., 2014; Chaney & Rojas-Guyler, 2015; McLafferty, 2003). In healthcare fields, because of the path of disease spread and location of healthcare facilities, it was necessary to adjust the method of geospatial analysis accordingly. Gesler (1986) encouraged researchers to be aware of the linkage between geography and health. These included disease pathogenesis or other biological processes.

Spatial Analysis Methods

In general, the process of spatial analysis was not different from other scientific research. It began with identifying the target problem, then verifying the spatial pattern through visualization method, and lastly applying statistical methods to test the study hypotheses, identify risk factors, or analyze phenomena (Kistemann et al., 2002). For spatially related healthcare data analysis, Clarke et al. (1996) specified three tasks: visualization of the data distribution through map overlay, exploratory analysis on overall and local distribution data patterns with statistic tests, and identification of risk factors with multiple regression models to improve knowledge of health care quality. The combination of all these spatial analysis tools in this study provided robust answers to health care questions.

Visualization and GIS software. Modern day mapping of spatial data relied on information technology. Various software packages supported the visualization and spatial data analysis. Steiniger and Hunter (2013) reviewed GIS software development history and provided an open-source GIS map software. They categorized three functional capability groups: viewer, editor, and analysis. ArcGIS was a broadly used software package that provides all three functions. Cui et al. (2015), Passalent, Borsy, Landry and Cott (2013), Tighe et al. (2014), and other researchers used ArcGIS map or analysis package to conduct healthcare-related research.

Spatial autocorrelation. After descriptive mapping and visualization, space-related distribution data analysis is separated into two steps: autocorrelation and cluster detection. Autocorrelation used geo-statistical methods to detect the distribution pattern of random, dispersed, or clustered (Chaney & Rojas-Guyler, 2015; Tighe et al., 2014). Clustered patterns showed similar measures within a proximity region. If the distant region had more common measures, the pattern was dispersed (Tighe et al., 2014). The measures could also be random across the whole region. Moran’s Black-White joins count measure was used to evaluate the existence of clustering (Gesler, 1986). Global Moran's index detected if there was an existing overall pattern for the measure (Penney, Rainham, Dummer, & Kirk, 2014; Tighe et al., 2014). Moran's index "is the weighted sum of the product of separate data observations, centered to the expected value of the observations, standardized to adjust for the variance of the observations, and normalized for the total sum of the weights" (Wartenberg, 1985, p.263). When Moran's index was close to +1, spatial data tends to cluster; if the value was negative, it was dispersed.

Global Moran's index tested the null hypothesis of the global spatial pattern. Although global spatial autocorrelation was introduced more than a half century ago, a local correlation was started in the 1990s. There was a strong interest in knowing locally elevated risk (Marshall, 1991). In some cases, although global spatial testing did not show a significant pattern, local patterns could still exist (Ord & Getis, 1995). Clustering may exist in both time and space. Clustering may also be artefactual (Marshall, 1991). Similar to the global Moran's index, the local Moran's index discloses when and where local clustering occurs (Penney et al., 2013; Tighe et al., 2014). Although the global Moran's Index was initiated by Moran in 1948, the local spatial correlation was formulated in the 1990s (Getis & Ord, 1992; Anselin, 1995). Chaney and Rojas-Guyler (2015), Sharma (2014), and Tighe et al. (2014) provided examples of using Moran's I and Local Indicators of Spatial Association (LISA) (Anselin, 1995) to address global spatial autocorrelation and local spatial autocorrelation on a variety of healthcare-related topics. Compared to the surrounding regions, a significant local indicator LISA may indicate a local hot spot or local cluster (Anselin, 1995).

Application in Healthcare Related Fields

Spatial analysis had broad applications in healthcare related fields, given multiple linkages between spatial data, health data, and other risk factors (Kistemann et al., 2002; McLafferty, 2003). Epidemiologists drew maps to analyze the association between environment, location, and diseases (Clarke et al., 1996). Health promotion and education research adopted place analysis as their research tool (Chaney & Rojas-Guyler, 2015). Nykiforuk and Flaman (2011) demonstrated that spatial analysis could be used to study health outcomes surveillance, health services accessing and planning, community profiling and risk analysis. Gesler (1986) summarized the use of geospatial analysis in both disease type and health care delivery system.

Disease surveillance. The primary application of geospatial analysis in the healthcare world was on disease surveillance; because of special features linking the risk of diseases with the environment or community factors, disease patterns were associated with geographic distribution. Geospatial analysis could be useful for both commutable and non-commutable disease surveillance, to study disease pattern and causality. The first application of geospatial analysis was the investigation of a cholera outbreak in London (Fradelos et al., 2014). Modern disease surveillance automatically displays the disease incidence on the map to show the disease spread (CDC, 2016; Chen, Cunningham, Moore, & Tian, 2011). This accelerated the syndromic or infectious disease outbreak investigation. The geospatial tool also supported other disease surveillance systems. Surveillance systems for hepatitis C and intravenous drug use (Trooskin, Hadler, Louis, & Navarro, 2005), obesity rates (Penney et al., 2014), substance use (Guerrero, Kao, &

Perron 2013), and cancer distribution (Kulldorf, 1997) all use geospatial software to identify disease distributions and geographic clusters.

Epidemiologists had studied the statistics of disease clustering for many decades (Kulldorf & Nagarwalla, 1995). There was a trend to increase the use of spatial statistics in examining the geospatial pattern of health outcomes with advanced commercial software packages. (Chong et al., 2013).

Healthcare services and access. With the existing disease pattern, how the general public accesses healthcare facilities to obtain treatment is also geo-distributed. Healthcare service access was the public’s ability to use a given healthcare service (McLafferty, 2003). Geospatial analysis focused on geographical barriers to the access. Guerrero, Kao, and Perron (2013) studied travel distance to an outpatient substance disorder treatment center using spatial autocorrelation and network analysis. They identified the hot spot where large Latino population and farther street distance to the nearest treatment center provided evidence for the decision-making process in healthcare access (Fradelos et al., 2014). Other factors that may apply to geospatial analysis include environment risks and exposure to community members and mental health service location distribution. Air pollution and other environmental factors may be associated with cardiovascular diseases such as health and stroke deaths (Fradelos et al., 2014). Geospatial analysis was a valuable tool for evaluating the distribution of health services, to eliminate or minimize disparities, provide an optimized health services locally, and improve ease of traveling to reach those services (McLafferty, 2003).

Geospatial analyses and hospital readmissions. Geospatial analyses had been applied to the various fields of health policy-related research. It had supported healthcare planning (Chaney & Rojas-Guyler, 2015) and health services assessment (McLafertty, 2003). In the area of healthcare policy evaluation, Tighe et al. (2014) studied the correlation between hospital geographic locations and the hospital average pain management scores recorded in the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey (Tighe et al., 2014). HCAHPS is a quality measurement tool (CMS, 2014) similar to the risk-standardized readmission rate used by CMS to evaluate hospital healthcare quality. It is also linked to hospital payment. Using spatial autocorrelation analysis methods, Tighe et al. (2014) found the geographically clustered distribution of hospital pain management score in HCAHPS. This finding implied that hospital geographic location played a role in one of the CMS hospital quality measures.

Using the similar concept of the geographic location effect, Cui et al. (2015) studied correlations between Canadian patient hospital readmission data and patient resident locations together with other patient clinical and social demographic factors. They found the spatial cluster variation for the readmission rate across the study region; because all factors included in the Cui et al. study (2015) were patient-specific, including geospatial location, hospitals as healthcare providers were not part of the factors in the study. The role of hospital quality or hospital geographic locations in explaining geographic variation in readmission rates remains unknown. The study designed and planned in this dissertation research could potentially address this gap in the literature in geospatial analyses of hospital readmissions.

Summary

Hospital readmission imposes personal costs on patients and was financially expensive. Medicare penalized preventable readmission through reduced payments. U.S. hospitals were responding to these changes in Medicare reimbursement and working hard to reduce readmission rates. A proper algorithm to identify excess readmission assures the success of this program. Andersen's behavioral model had been used to guide previous hospital readmission research. Many factors had already been considered in current risk-adjusted methods for analyzing hospital readmission, although improvement was still sought. Geographic differences or regional differences affecting readmission represented possible candidates as adjustment factors. As a method of study for assessing healthcare services, geospatial analysis had been used by researchers for many decades.

Hospital geographic location had been studied in relation to one of the Medicare hospital quality measures (pain management scores) previously but not with respect to hospital readmission rate. Although a Canadian study evaluated geographic variation in hospital readmissions (Cui et al., 2015), that study was from the patient resident perspective. Geospatial analysis of readmission rates in the U.S. at the hospital level had not yet been studied. The present study targeted this knowledge gap and potentially provided an answer to this question.

Conclusions

Chapter 2 began with the introduction of Andersen's behavioral model, which supported the theoretical framework for analyzing and influencing the use of health services. The theory identified influential factors of a health care activity. It was impacted by disease status, social environment, knowledge, hardware and points to the potential regional or hospital location influence on hospital readmission rate.

Next, the literature review focused on the history of the hospital readmission penalty program and its current status as well as its financial and quality impact. The review then focused on the readmission reduction algorithm, explaining what factors were included and excluded in the risk adjustment methods. The results of the first few years of response from affected hospitals demonstrate mixed signals, reflecting both positive results and concerns. Improvement in the risk adjustment calculation, future changes in the algorithm, and the possibility of introducing regional factors were examined, based on a review of relevant publications.

Lastly, the review explored geospatial analysis, a method which was adopted in current research. In this review, the goal was to understand the methodology, its history, and its application, as well as to describe gaps in the literature. Because disease and healthcare nature were geographically related, geospatial analysis had been broadly used in disease surveillance, health access, service, and policy analysis. The method and technology for geospatial analysis had been improved over the recent years; thus, adoption of this method in current research was feasible.

Chapter 3 laid out the detailed research methodology used for the current study. A further description of data sources, method and research steps were presented. The detailed variables, analysis plan, and procedures were described to support the validity of using geospatial analysis of the regional impact of hospital readmission rate for this research.

Chapter 3: Research Method

Introduction

Hospital readmissions are an increasingly important problem among Medicare beneficiaries (Jencks et al., 2009), and community factors are associated with geographic variation in readmission rates (Herrin et al., 2015). Geospatial analysis methods were used to examine the relationship between location and pain management scores (Tighe et al., 2014), and prior research examined spatial clustering of hospital readmission rates at the patient-level (Cui et al., 2015); however, no studies examined geospatial clustering of hospital readmission rates at the hospital level. The purpose of this study was to examine spatial patterns in hospital risk adjusted readmission rates. Results of the study might be useful to risk adjustment in the HRRP of the Center for Medicare & Medicaid Services.

In this chapter, the study design, data source, and sample selection as well as the overall research question, hypotheses, analysis plan, study validity, and ethical procedures were described.

Research Design and Rationale

This research was a cross-sectional quantitative study. The target sample was U.S. hospitals participating in the Medicare FFS program. Hospital 30-Day Readmission and Death data for FY 2017 was used as the major data source. The independent variable for this study was the hospital RSRR, which was defined as the ratio of predicted readmission rate versus expected readmission rate multiplied by the U.S. average readmission rate.

The dependent variables for this study were the hospital geographical location and distances between hospitals. The reciprocal of the between-hospital distance and the corresponding hospital RSRR was used to create Moran's Index to evaluate whether hospital RSRR was geographically distributed in a cluster pattern across the nation or locally.

Geospatial analysis is a method of identifying the association between an effect and its relative location (Fradelos et al., 2014). It can explain, detect, and account for the spatial variation. Hospital street addresses were converted to latitude and longitude for the map display and interhospital distance calculation. Natural geographic surface features, such as existing rivers, mountains, forests, and roads were not considered.

Overall, the study analyses included two main steps. The first step was to evaluate how the hospital-wide RSRR was spatially organized across the continental United States. This step comprises three tests: The first test is to see if there was an overall geographic location effect using the Global Moran's Index. The second test is to seeif the global cluster pattern was significant, an incremental spatial correlation was performed to find out if the cluster was altered at the different threshold of the distances. The third test is to find the local indicators of spatial association with Anselin Local Moran's Index. Hospital RSRRs were marked on the heat map which displayed the different range of RSRRs at different markers. The second step required graphic analytic tools to determine the number of hospital regional cluster groups and test the differences in readmission rates across these groups.

Methodology

Study Population and Sample

The target sample hospitals included in the HRRP are over 4,000 U.S. acute care hospitals that participated in the Medicare FFS program. The FY 2017 estimated RSRR was calculated based on Medicare FFS patients discharged from July 1, 2011 to June 30, 2014. The readmission data together with death data published on the Hospital Compare website was updated every 12 months. Reported data included unplanned readmission after 30 days of discharge from a recent hospitalization for HF, AMI, PN, COPD, stroke, and surgical procedures including hip or knee replacement and CABG; hospital-wide readmissions were also reported. The data represented an all-inclusive sample with over 4,000 Medicare short-term acute care hospitals. The database did not consider hospitals when fewer than 25 cases were identified within that hospital (CMS, 2016d).

The study used hospital-wide readmission rates as the main dependent variable. Compared to other readmission rates, hospital-wide RSRR covers the largest number hospitals and is therefore the most representative.

Data Source and Quality

This study used secondary data published on the Medicare Hospital Compare website and the CMS website. These CMS-sponsored publicly available data were used for CMS reimbursement policy and consumer reference, as well as potential investigations. The CMS did not require permission to reuse these data (CMS, 2016d).

Hospital readmission data is refreshed annually. The readmission rates were calculated using CMS claim data 3 years before the reporting year. The data utilized in this research were published on April 2016. The source data for specific diseases or surgical types were recorded from July 1, 2011 to June 30, 2014.

Hospital-wide readmission rates were calculated based on Medicare patient readmissions from July 1, 2013 to June 30, 2014 because many more readmission events were available when all disease types are included. This provided the possibility of using the recent 1-year claim data for calculating hospital-wide RSRR. The CMS had contracted with an academic research center to perform the calculation of hospital RSRR. The methodology was approved by the NQF and has been previously published.

The RSRRs were reported by hospital and by diseases or surgery type. Depending on patients' different admitted disease or surgical type, the CMS (2016a) reported eight different RSRRs: hospital-wide RSRRs and RSRRs for patients whose primary hospital admission was for AMI, HF, CABG, COPD, pneumonia, hip and knee surgery, or stroke. Each disease or surgical type has its own RSRR reported on the CMS readmission data. The data also included the number of events and the time ranges covered by the data sources. More details on predicted or expected readmission rates were contained in the readmission reduction data, which were included in the same download package. For a hospital with total events of less than 25 or no event within a specific disease category, the readmission downloads were marked as "Data are not available." For 30-day hospital-wide readmission rates, about 7% of acute care hospitals either did not have data or the particular patients were too few to evaluate. Hospitals could be identified by CMS provider ID. This variable provided a link from hospital readmission rates to other CMS data indicating hospital geographic location and hospital referral region.

The readmission data published on the Hospital Compare website were consumer-oriented publicly available data created by the U.S. government. Reuse of this data does not require permission, although the CMS (2016d) stated that they appreciate an acknowledgment of the data source. The official Hospital Compare website provided comma-separated value (CSV) flat files which were available for download for the public (CMS, 2016d).

Research Questions and Hypotheses

Four research questions were addressed in this research. The four specific research questions and their corresponding null and alternative hypotheses were listed below.

RQ1: Are hospital-wide readmission rates geographically clustered by hospital location?

RQ2: Are there local geographic clusters of hospital-wide readmission rates?

RQ3: What is the optimal number of cluster groups for hospital-wide readmission rates across the continental U. S.?

RQ4: Are there differences in hospital readmission rates for various diseases or surgical types between cluster groups?

$H1_0$: Hospital-wide readmission rates are randomly distributed by hospital location.

$H1_a$: Hospital-wide 30-day readmission rates are geospatially clustered by hospital location.

$H2_0$: There are no local geographic clusters of hospital-wide readmission rates.

$H2_a$: There are local geographic clusters of hospital-wide readmission rates.

$H3_0$: There is no optimal number of cluster groups for hospital-wide readmission rates.

$H3_a$: There is an optimal number of cluster groups for hospital-wide readmission rates.

$H4_0$: Hospital readmission rates for various disease or surgical types are not different between cluster groups.

$H4_a$: Hospital readmission rates for various disease or surgical types are different between cluster groups.

Study Variables

This study used publicly available secondary data. Datasets were developed by CMS for hospital readmission reduction program (CMS, 2016a). The selected dataset, variables, and their applications for this research were listed in Table 3. The dependent variable for most research questions was the hospital-wide RSRR. Hospital RSRR was calculated as national average readmission rate (see Table 4) multiplied by hospital excess readmission ratio, i.e., the predicted readmission rate divided by the expected readmission rate. Another seven disease or surgery specified RSRRs were the dependent variables when evaluating the difference between cluster groups. The calculated distance between any two hospitals was the independent variables for geospatial analysis.

This research examined spatial patterns in hospital readmission rates. Hospital address was geocoded into longitude and latitude values. They were first set to the ArcGIS geographic coordinate system, then transformed to a Mercator projection for the accuracy of distance measurements. The between-hospital Euclidean, i.e. straight-line, distance was calculated regardless the natural features such as the mountain, or river.

Table 3

The Study Datasets and Relevant Variables

Dataset	Variable	Application
Readmission	2016 risk standardized hospital readmission rate for hospital-wide, AMI, HF, PN, COPD, CABG surgery, hip and knee surgery, stroke	Dependent variables
Hospital	Provider ID, Hospital Name, address, county, state, hospital type, with or without emergency service	For calculating the geospatial variables such as latitude, longitude, and distance between hospitals
HRR	Hospital Referral Region (HRR) level map data	As a reference layer on the map to compare the hospital RSRR distribution
Calculated	Distance between two hospitals	Use its inverse value for the weight in the Global Moran Index

Note. From Hospital Compare, CMS (CMS, 2016d); Dartmouth ATLAS Health (Dartmouth, 2016).

The HRR was defined based on the location of referrals for major cardiovascular surgery or neurosurgery (Dartmouth, 2017a). The geographical boundary of HRR was compared to the RSRR geographical distribution. The use of HRR geographical boundary data were “obtained from the Dartmouth Atlas, which was funded by the Robert Wood Johnson Foundation” (Dartmouth, 2017b). The RSRR was overlaid on the U.S map came from the ArcGIS. Geographic boundary of HRR generated by the Dartmouth ATLAS of Health Care was also used for map display (Dartmouth, 2016). In this context, HRR reflects the tertiary hospital market region. Each HRR had at least one major cardiovascular or neurosurgery hospital serving a population of at least 120,000 residents. There was a total of 306 HRRs in the nation (Dartmouth, 2016).

Given that the geospatial measure was based on the distance between hospitals, only hospitals located in the continental United States were included in this study. Total 84 hospitals located in Hawaii, Alaska, Puerto Rico, Virgin Island, Guam were excluded from this research.

Table 4

National Average Readmission Rate

Readmission category	National rate (%)	Number of hospital
Rate of readmission after discharge from hospital (hospital-wide)	15.2	4,593
Pneumonia 30-Day Readmission Rate	16.9	4,386
Heart failure 30-Day Readmission Rate	22	3,999
Rate of unplanned readmission for COPD patients	20.2	3,840
Rate of readmission after hip/knee surgery	4.8	2,819
Rate of unplanned readmission for stroke patients	12.7	2,762
Acute Myocardial Infarction 30-Day Readmission Rate	17	2,326
Rate of unplanned readmission after CABG	14.9	1,058

Note. From readmission and deaths – national (CMS, 2016d).

Data Analysis Plan

All descriptive statistical analyses used SAS (Raleigh, NC) version 9.3. The geospatial analysis and map display used ArcMap (Redlands, CA) version 10.4.1. Google App of Awesome table (France) was used for geocoding.

Descriptive statistics of RSRR. The hospital average RSRR by disease and surgery type were summarized for each state and HRR. The average distance between two hospitals was also summarized by state. The hospital-wide RSRR was displayed on U. S. map in five groups classified by the Jenks natural break algorithm.

Tests of global geographic clustering. The test of global spatial autocorrelation examined how hospital RSSR are distributed by location using the Global Moran's Index. It was calculated as (Moran, 1948; Rossen, Khan & Warner, 2014; Walder & Gotway, 2004)

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} z_i z_j}{\sum_{i=1}^{n} Z_i^2}$$

Where

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}$$

For this study, spatial weight ωij, was the inverse of the distance between hospital i and j. z_i and z_j are the excess RSRR for hospital i and j. It was the difference between hospital RSSR and national average. A total number of hospitals was n.

The Z score for the Global Moran's Index was calculated as

$$Z_I = \frac{(I - E[I])}{\sqrt{V[I]}}$$

Where

$$E[I] = -1/(n-1)$$

Under randomization or nonfree sampling assumption,

$$V[I] = \frac{A-B}{C} - \left(\frac{1}{n-1}\right)^2$$

$$A = n[(n^2 - 3n + 3)S_1 - nS_2 + 3S_0^2]$$

$$B = D[(n^2 - n)S_1 - 2nS_2 + 6S_0^2]$$

$$C = (n-1)(n-2)(n-3)S_0^2$$

$$D = \sum_{i=1}^{n} {z_i}^4 \Big/ \left(\sum_{i=1}^{n} {z_i}^2\right)^2$$

$$S_1 = \left(1/2\right) \sum_{i=1}^{n} \sum_{j=1}^{n} (\omega_{ij} + \omega_{ji})^2$$

$$S_2 = \sum_{i=1}^{n} \left(\sum_{j=1}^{n} \omega_{ij} + \sum_{j=1}^{n} \omega_{ji}\right)^2$$

With the normal distribution assumption, Z score and corresponding p-value were calculated to test the null hypothesis. The statistical significant clustering geographic pattern was claimed if the p-value was less than 0.05, and the Z score was positive.

The global spatial autocorrelation was further evaluated using incremental spatial autocorrelation test which repeats the correlation test at a set of neighborhood distances**.** At each distance setting, **t**he Global Moran's Index and corresponding z-scores were recalculated (Tighe et al., 2014). The results were displayed on the z-score versus distance chart. The planned intervals range started at the maximum distance of any hospital to its the nearest neighbor hospital. The incremental interval was 500 km with total of 10 intervals. The distance for the maximum Z values was selected as the reference range for testing of local geographic clustering.

Test of local geographic clustering. The Anselin local Moran's Index, also called local indicator of spatial association (LISA), was calculated. It was similar to the global Moran's Index but it counts individual hospital's contribution to the global Moran's Index (Anselin, 1995).

$$I_i = z_i \sum_{j=1}^{n} \omega_{ij} z_j$$

Its expected value and variance were calculated as:

$$E[I_i] = -\omega_i/(n-1)$$

$$V[I_i] = \frac{\omega_{i(2)}\,(n-b_2)}{(n-1)} + \frac{2\omega_{i(kh)}(2b_2-n)}{(n-1)(n-2)} - {\omega_i}^2 \left(\frac{1}{n-1}\right)^2$$

$$b_2 = m_4/{m_2}^2$$

$$m_2 = \sum_{i=1}^{n} {z_i}^2/n$$

$$m_4 = \sum_{i=1}^{n} {z_i}^4/n$$

And

$$\omega_i = \sum_{j=1}^{n} \omega_{ij}$$

$$\omega_{i(2)} = \sum_{j\neq i}^{n} {\omega_{ij}}^2$$

$$2\omega_{i(kh)} = \sum_{k\neq i}^{n} \sum_{h\neq i}^{n} \omega_{ik}\,\omega_{ih}$$

LISA decomposed the global Moran's Index into individual hospital's contribution. Based on hospital and its neighbor hospitals' local Moran's index and readmission rates, hospitals were classified into five categories: not statistically different (p-value ≥0.05) from its neighborhood hospitals; a high RSRR hospital surrounding with other high RSRR hospitals (hot spot); low RSRR hospital surrounding with low RSRR (cold spot); and two outliers, i.e. either high RSRR surrounding by low RSRR or low RSRR surrounding by higher RSRR. All hot spots, cold spots and outliers required p-value <0.05. The Z scores for both hot spot and cold spot were positive; Z score for outlier is negative. The results of these hospital categories were marked on the map.

Identify the number of RSRR cluster groups across the continental US. Using the minimal spanning tree method (Assunção, Neves, Câmara, & da Costa Freitas, 2006; Duque, Ramos, & Suriñach, 2007), hospitals was grouped into geographically connected homogeneity clusters. The edges weighted by the similarity between connecting hospitals were evaluated. Weaker connecting edges were "pruned" till the number of prespecified cluster groups were left. The tested cluster group will be 10, 6, and 4. The final optimal cluster group was selected at the peak pseudo F-statistics, a ratio representing the with-in group similarity and between-group variance (ESRI, 2017; Tighe et al., 2014). The results of hospital cluster groups were presented on the U. S. map.

Tests RSRR difference among the cluster groups. The RSRR differences among hospital cluster groups were tested using Kruskal-Wallis test, a nonparametric ANOVA test (SAS, 2013). Because different disease or surgical type RSRR had different number of available hospitals, each RSRRs were tested separately. The sequential testing order was based on the number of hospital with RSRR data, starting from hospital-wide RSRR which had the most number of hospitals. In addition, the pairwise RSRR differences for hospital-wide readmissions was tested using Dwass, Steel, Critchlow-Fligner multiple comparison analysis (SAS, 2013). P-value <0.05 was considered as the statistical difference.

Threats to Validity

This study focused on the hospital geographic location and the Medicare hospital-wide RSRR, i.e. all hospital inpatient admission patients were included in the evaluation of RSRR. This finding may not be generalized to the patients with specific diseases or surgical procedures, such as Medicare reported other RSRRs for AMI, HF, PN, stroke, COPD, or CABG or THA and TKA. To minimize this potential external validity threat, additional analyses were planned to explore the cluster pattern on each of these RSRRs. The cluster pattern differences among these disease or surgical patients will be compared.

The readmission data source was from Medicare FFS hospitals. Patients who do not participate in the Medicare program were not included in the analysis. Although Medicare patients composed the higher percent of US inpatient discharges (Tian, 2016), patients from the private payer, Medicaid also contribute a large amount of hospital inpatient discharges. These patients' readmission pattern might be different from the Medicare reported RSRR. This limitation could be further addressed by using more broad data sources, such as the national inpatient sample data from the Healthcare Cost and Utilization Project (HCUP) which "includes the largest collection of longitudinal hospital care data in the United States" (AHRQ, 2016b, para.1). It was worth noting that the HCUP reported 30-day readmission rates were not risk adjusted as the RSRR from CMS (Barrett, Raetzman, & Andrews, 2012).

This research measured the hospital RSRR by the hospital geographical location. It cannot separate this geographic factor from the other hospital or regional related factors such as hospital size, hospital type, or regional social demographic. Multiple studies had claimed the association of the hospital's types, patient social demographics were related to the hospital RSRR (Jencks & Brock, 2013; Joynt & Jha, 2013; Kind et al., 2014; Nagasako et al., 2014). To differentiate the impact of geographic location and other factors, it required further geospatially weighted multiple regression techniques. In this research, the hospital RSRR distribution was overlaid on hospital referral region to view the difference within a relative homogenous environment.

The primary statistical inference is the hospital-wide RSRR geospatial distribution based on Global Moran's Index. All other statistical tests provided additional support given the hospital-wide RSRR are geospatially clustered. There were no multiple comparisons and no threat to validity statistical conclusion.

Ethical Procedures

The research data were publicly available secondary data. The original data source was created by CMS. CMS allowed the reuse of data without requiring permission (Medicare.gov, 2016). The readmission data and community data were aggregated at the hospital level or the community level (i.e. HRR or State). The research process did not involve any use of individual personal information. Although ethical concerns related to this research were minimal, Institutional Review Board (IRB) approval was pursued for this investigation before data analysis. The reason for obtaining IRB approval was to protect the stakeholders who published the data and any community members who might be impacted by the research results (Walden University, 2016). The Walden University IRB reviewed and approved the study prior to inception (IRB approval number 04-25-17-0294939).

Summary

This study used published secondary data to conduct a cross-sectional study on hospital RSRR distribution across the nation and in various communities. The geospatial arrangement of RSRR across the United States was tested using the Global Moran's Index. It was further accessed with incremental spatial autocorrelation using similar Moran's Index calculation formulas by different distance thresholds. The study also used LISA, a local indicator of spatial association for detecting particular local hot or cold spot, i.e. the high or low RSRR hospital surrounded by high or low RSRR hospitals. Lastly, the study identified the number of regional cluster groups and compare their differences in readmission rates.

Chapter 3 described the quantitative research design, method, data sources, and analysis plan of this study, as well as methods for maintaining study validity and procedures related to ethical considerations. The data description and hospital readmission rates geospatial pattern results were presented in Chapter 4.

Chapter 4: Results

Introduction

The study evaluated the spatial patterns in hospital RSRRs. The patterns were studied at the global, local, and cluster group level. The analyses were focused on hospital-wide readmission rates. Other diseases and surgical specific readmission rates were also included in the exploration of their difference among states or clusters.

The four research questions were:

1. Are hospital-wide readmission rates geographically clustered by hospital location?

2. Are there local geographic clusters of hospital-wide readmission rates?

3. What is the optimal number of cluster groups for hospital-wide readmission rates across the continental U.S.?

4. Are there differences in hospital readmission rates for various diseases or surgical types between cluster groups?

This chapter included data collection, descriptive statistics, the analysis results of the four research questions, and additional analyses.

Data Collection

The analysis data set, readmission and deaths – hospital, was downloaded from the CMS. It was generated on April 19, 2016. The RSRRs reported in the analysis data were calculated using Medicare claims data between July 1, 2011 and June 30, 2014 except for the hospital wide readmission rate which used one-year Medicare claim data from July 1, 2013 to June 30, 2014 (CMS, 2016d).

The data used in this analysis included all CMS published hospitals in the continental U.S with non-missing hospital-wide readmission rates. A total of 4,772 hospitals were published in CMS 2016 readmission and deaths data. After excluding hospitals located in Hawaii, Alaska, Puerto Rico, Virgin Islands, Guam, and the Northern Mariana Islands, or hospitals with missing hospital-wide RSRR data, a total of 4,360 hospitals were included in the analysis from 48 states and the District of Columbia. (see Figure 2). All Veterans Administration (VA) Medical Centers (n = 129) were excluded due to missing hospital-wide RSRR.

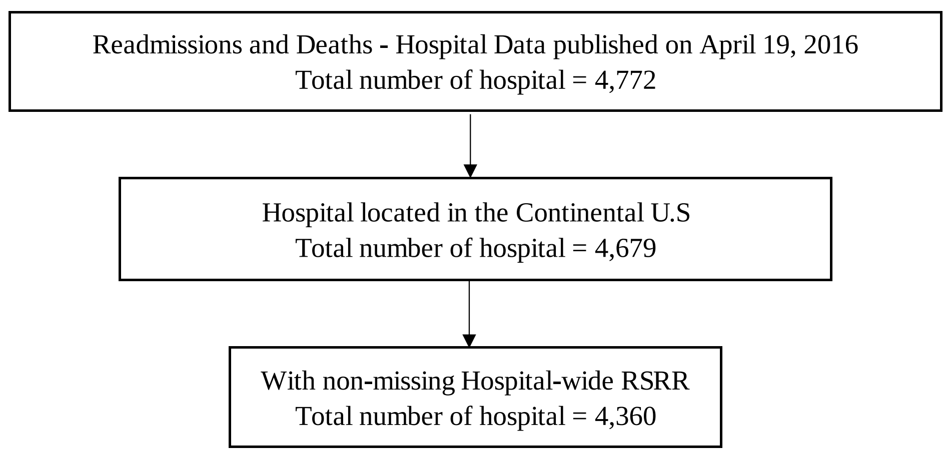

Figure 2. Hospital disposition.

The majority of the 4,360 analyzed hospitals were acute care hospitals (73.4%), and the remaining were critical access hospitals (26.6%). More than half of the hospitals were voluntary nonprofit hospitals (59.8%). Slightly less than a quarter of hospitals were run by various levels of government. The proportion of proprietary hospitals was 16.4%, and physician-owned or tribal (Native American) hospitals were less than 2 %. Almost all

Table 5

Summary of Hospital Characteristics

Parameter	All	Continental U.S.	Analyzed [1]
Total number of hospital, *N*	4,772	4,679	4,360
Total number of state or area [2], *N*	55	49	49
Hospital type, *n* (%)			
Acute Care - Veterans Administration	129(2.7)	128(2.7)	-
Acute Care Hospitals	3,368(70.6)	3,294(70.4)	3,202(73.4)
Children's	22(0.5)	22(0.5)	
Critical Access Hospitals	1,253(26.3)	1,235(26.4)	1,158(26.6)
Hospital ownership, *n* (%)			
Government – Federal	44(0.9)	40(0.9)	31(0.7)
Government - Hospital District or Authority	554(11.6)	554(11.8)	518(11.9)
Government – Local	406(8.5)	396(8.5)	386(8.9)
Government – State	60(1.3)	49(1.1)	44(1)
Government Federal (VA)	129(2.7)	128(2.7)	-
Physician	59(1.2)	59(1.3)	54(1.2)
Proprietary	784(16.4)	762(16.3)	717(16.4)
Tribal	6(0.1)	5(0.1)	5(0.1)
Voluntary non-profit – Church	352(7.4)	345(7.4)	341(7.8)
Voluntary non-profit – Other	465(9.7)	458(9.8)	450(10.3)
Voluntary non-profit – Private	1,913(40.1)	1,883(40.2)	1,814(41.6)
Emergency services, *n* (%)			
No	348(7.3)	345(7.4)	165(3.8)
Yes	4,424(92.7)	4,334(92.6)	4,195(96.2)
Distance to the nearest neighbor hospital (km)			
Average	-	-	25.4
Maximum	-	-	236

Note. From Hospital Compare, CMS (CMS, 2016d);

[1] Analyzed data include all hospitals on the continental U.S with non-missing hospital-wide RSRR.

[2] Area included District of Columbia, Puerto Rico, Virgin Island, Guam, and Northern Mariana Islands.

hospitals (96.2%) provided emergency services. A detailed summary of hospital characteristics is presented in Table 5.

Analysis Results

Descriptive Statistics

Hospital-wide RSRR distribution. A total of 4,360 hospitals were depicted on the U.S. map (see Figure 3) by five levels of Jenks Natural Breaks algorithm which maximized the similarity within groups and the difference among groups. The interval for the five levels of Jenks Natural Breaks are from 11.3% to 14.1%, 14.2% to 14.9%, 15.0% to 15.6%, 16.7% to 16.5%, and 16.6% to 19.8%. On the map, the darker circles represented the higher RSRR levels. The hospital-wide RSRR U.S. map showed a different pattern between the eastern and western halves of U. S. Hospital dots are crowded and darker in the eastern half and sparse and lighter in the western half which indicated that more hospitals and higher readmission rates were observed in the eastern half of the U.S. than the western half of the U.S.

The difference between the eastern half and the western half of the U.S. was also shown on the Hospital RSRR summary by Census region and district (see Table 6). The average hospital-wide RSRR for the West Census region (15%), Midwest Census region (15.1%), and West South Central Census division (15.1%) were lower than the national average (15.2%). The Northeast Census region (15.6%), the majority of the South region including the East South Central Census division (15.5%), and the South Atlantic Census division (15.4%) had an average hospital-wide RSRR greater than the national average

(15.2%). The variance of the hospital-wide RSRR is wider in the east of U.S. than in the west of U.S (See Table 6).

Table 6

Summary of Hospital-wide RSRR by Census Region and Division

Census region Census division	*n*	*Mean* (*SD*)	*Range*
Overall	4,360	15.2 (0.8)	(11.3, 19.8)
Northeast	559	15.6 (1.0)	(11.6, 19.7)
Middle Atlantic	386	15.7 (1.1)	(11.6, 19.7)
New England	173	15.3 (0.8)	(11.6, 17.1)
South	1,654	15.3 (0.8)	(11.3, 19.8)
East South Central	369	15.5 (0.8)	(12.8, 19.8)
South Atlantic	652	15.4 (0.9)	(12.0, 18.9)
West South Central	633	15.1 (0.8)	(11.3, 17.6)
Midwest	1,326	15.1 (0.8)	(11.9, 18.6)
East North Central	699	15.2 (0.8)	(11.9, 18.6)
West North Central	627	15.1 (0.6)	(12.0, 18.4)
West	821	15.0 (0.8)	(11.4, 18.8)
Pacific	457	15.0 (0.8)	(11.4, 18.4)
Mountain	364	15.0 (0.7)	(13.0, 18.8)

Hospital RSRR by disease and state. The hospital risk adjusted readmission summarized by state is presented in Appendix 1. All eight diseases and surgical specified RSRRs and their standard deviations by state were included. Within 4,360 hospitals with hospital-wide RSRR data, only 1,046 hospitals had non-missing coronary artery bypass graft (CABG) RSRRs. The number of hospitals with RSRRs was in-between for other disease or surgical patients. The highest readmission rate by patient type was the RSRR

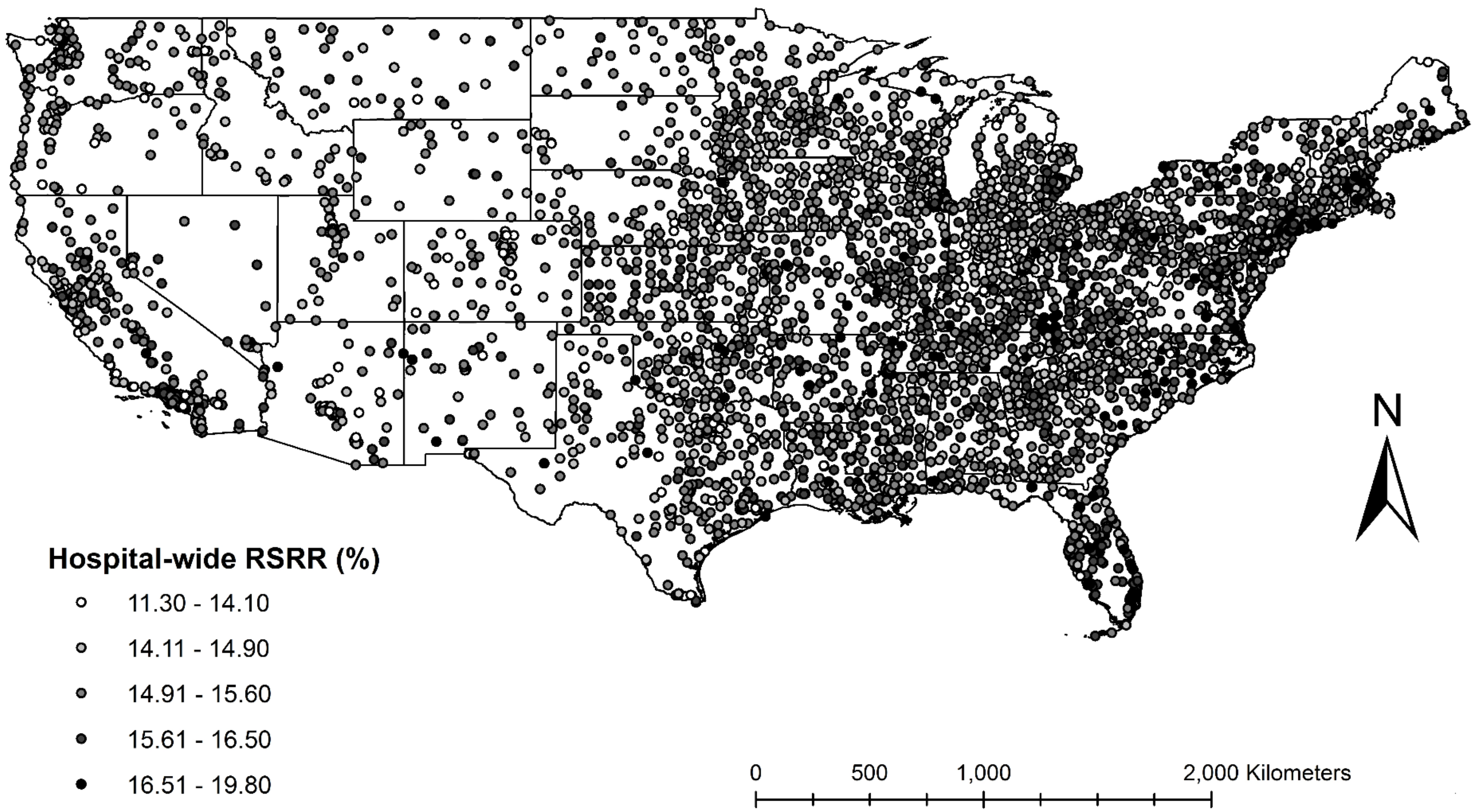

Figure 3. U.S map of hospital results for hospital-wide RSRRs. Each hospital in the continental U.S with available hospital-wide RSRR is indicated with a grey scaled dot. The categories shown were classified using the Jenks Natural Breaks algorithm.

for heart failure with an average readmission rate of 21%, followed by chronic obstructive pulmonary disease (COPD) (19.8%). The lowest RSRRs were for patients who had hip/knee angioplasty, with an average readmission rate of 4.9% and the lowest calculated variation (*SD* = 0.6).

For all states across the country, Texas (*n* = 339) and California (*n* = 316) have the most number of hospital data within each state. However, due to these states' large geographic area, and due to the uneven distribution across the state, the hospital distribution on the map (see Figure 3) still looks sparse compared to the eastern half of the U.S. map. In general, states tended to have similar RSRR patterns with respect to different diseases or surgical types. For example, Kentucky, New Jersey, Mississippi, Virginia, and West Virginia had higher RSRR compared to the national average on all eight RSRRs; and Oregon, Montana, Idaho, Connecticut, and New Mexico have lower RSRRs across different diseases and surgical types (see Figure 4). Only a few States had different readmission pattern for different diseases or surgery. For example, in the District of Columbia, the RSRR for CABG was much lower than the national average, while the other seven readmission rates (hospital-wide, HF, PN, AMI, stroke, COPD, and THA and TKA) were higher.

After hospitals were re-assigned according to their HRR, instead of by the hospital geographical address, the RSRR fluctuations were slightly smoothed compared to hospital RSRRs based on geographic location within states (see Figure 5).

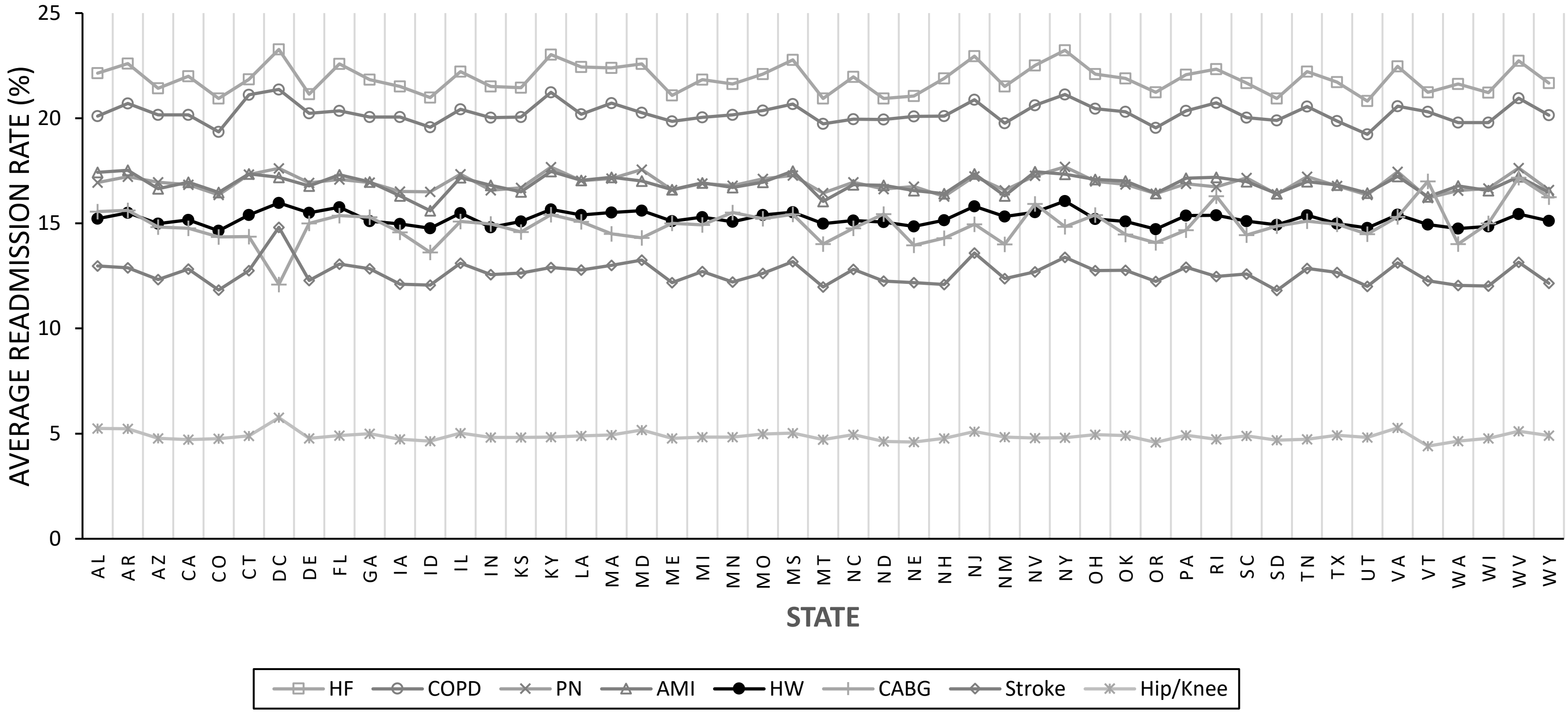

Figure 4. Eight hospital RSRRs by state of hospital located. Abbreviations: HF = heart failure, COPD = chronic obstructive pulmonary disease, PN = pneumonia, AMI = acute myocardial infarction, HW = hospital-wide, CABG = coronary artery bypass graft, Hip/Knee = total hip or knee arthroplasty.

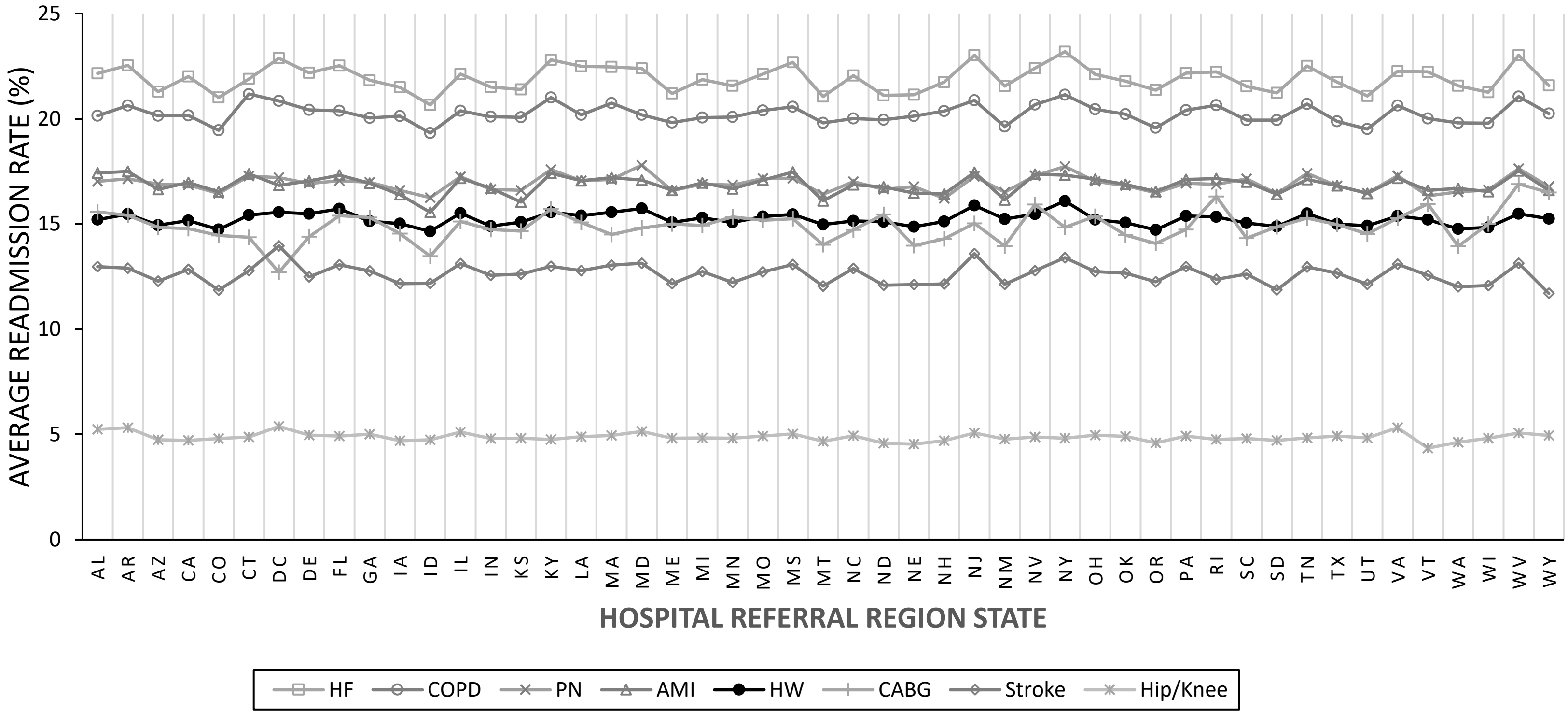

Figure 5. Eight hospital RSRRs by hospital referral region state. Abbreviations: HF = heart failure, COPD = chronic obstructive pulmonary disease, PN = pneumonia, AMI = acute myocardial infarction, HW = hospital-wide, CABG = coronary artery bypass graft, Hip/Knee = total hip or knee arthroplasty.

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Research Question 1: Global Cluster Pattern

The first research question for this study was: Are hospital-wide readmission rates geographically clustered by hospital location? The null hypothesis was that hospital-wide readmission rates are randomly distributed by hospital location. The alternative hypothesis was that hospital-wide 30-day readmission rates are geospatially clustered by hospital location.

The global Moran's index for hospital-wide RSRR was .23; the *Z*-score was 41.07, and the corresponding *p* value testing the significance of global cluster pattern was less than .0001. The null hypothesis was rejected, in favor of the alternative hypothesis. These results established the existence of global cluster on hospital-wide readmission rate across the country.

Table 7

Summary of Global Moran's Index

Parameter	Result
Moran's Index	.23
Expected Index	-.00023
Variance	0.000031
Z-score	41.07
P value	< .0001

Incremental spatial autocorrelation. The default Global Moran's Index was calculated with the minimum distance to ensure that every hospital had at least one neighbor. To test the robustness of the Global Moran's index, incremental spatial autocorrelation was performed with a series of distances for neighbor settings. This analysis started with the maximum computed hospital distance among all pairs of two nearest hospitals (236 km, see Table 2), and then increased the neighborhood distance range to include various numbers of neighbor hospitals. In this analysis, the range of distances from 250 km to 4,750 km at intervals of 500 km was tested. At all levels of intervals, the Moran's indices were always positive, with peak values at 2,250 km. The peak *Z*-score was 104.7 (see Table 8, Figure 6).

Table 8

Anselin Local Moran's Index for Hospital-wide RSRR

Distance (km)	Moran's index	Expected index	Variance	*Z*-score	*p* value
250	.135	- .000229	0.000008	48.41	< .0001
750	.072	- .000229	0.000001	74.03	< .0001
1,250	.047	- .000229	0.000000	80.63	< .0001
1,750	.035	- .000229	0.000000	87.79	< .0001
2,250	.031	- .000229	0.000000	104.67	< .0001
2,750	.020	- .000229	0.000000	93.89	< .0001
3,250	.016	- .000229	0.000000	98.98	< .0001
3,750	.012	- .000229	0.000000	95.68	< .0001
4,250	.009	- .000229	0.000000	93.42	< .0001
4,750	.006	- .000229	0.000000	88.95	< .0001

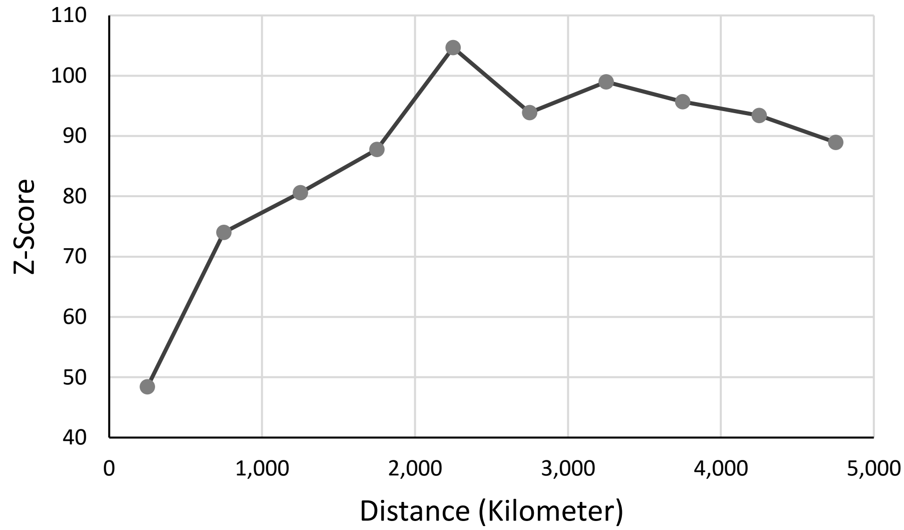

Figure 6. Incremental spatial autocorrelation by distance.

Research Question 2: Local Cluster Pattern

The second research question was: Are there local geographic clusters of hospital-wide readmission rates? The null hypothesis was that there are no local geographic clusters of hospital-wide readmission rates. The alternative hypothesis was that there are local geographic clusters of hospital-wide readmission rates.

With the peak Z-score neighbor distance (2,250 km, see Table 8), each hospital's contribution to the Global Moran's Index was calculated and classified according to its relative value compared to its neighbor hospitals. The five categories of the local pattern (high-high, low-low, low-high, high-low, and no significant difference for each hospital) were classified and displayed on the heat map (see Figure 7). At the hospital level, hospital-wide RSRRs were found to be geographically distributed using Anselin local Moran's index, also called local indicator of spatial association (LISA). Hospitals with high RSRR, marked by black dots, were clustered in Florida, in the Mid-Atlantic states, along with the Mississippi river, and Kentucky. The low RSRR-clustered hospitals, characterized in the black starts, were distributed in the West and Midwest census region such as Illinois, Michigan, and part of North Carolina and South Carolina. Low or high RSRR outliers, (meaning outliers in which a hospital's RSRR was lower or higher than its neighbor hospitals' RSRRs), marked in gray stars or dots were embedded within the region with high and low cluster region. The local cluster pattern (see Figure 7) also indicated hospitals were geographically clustered across the continental U.S.

Research Question 3: Number of Cluster Groups Across the Nation

The third research question was: What is the optimal number of cluster groups for hospital-wide readmission rates across the continental U.S.? The null hypothesis was that there is no optimal number of cluster groups for hospital-wide readmission rates. The alternative hypothesis was that there is an optimal number of cluster groups for hospital-wide readmission rates.

Number of neighbor hospitals. Due to the computational limitation in finding the optimal cluster group, the applicable method of finding the optimal cluster group was to initially choose a specific number of hospitals as the neighbor, then compare the pseudo-F statistics to locate the optimal cluster groups under that neighbor hospital setting (ESRI, 2017). The number of neighbors was defined by the actual environment. Considering the number of accessible hospitals a patient could choose, the number of neighbor hospitals were tested from 3 to 8. Their corresponding optimal cluster groups were ranging from 2 to 15. After evaluating the size and geographical distributions of the

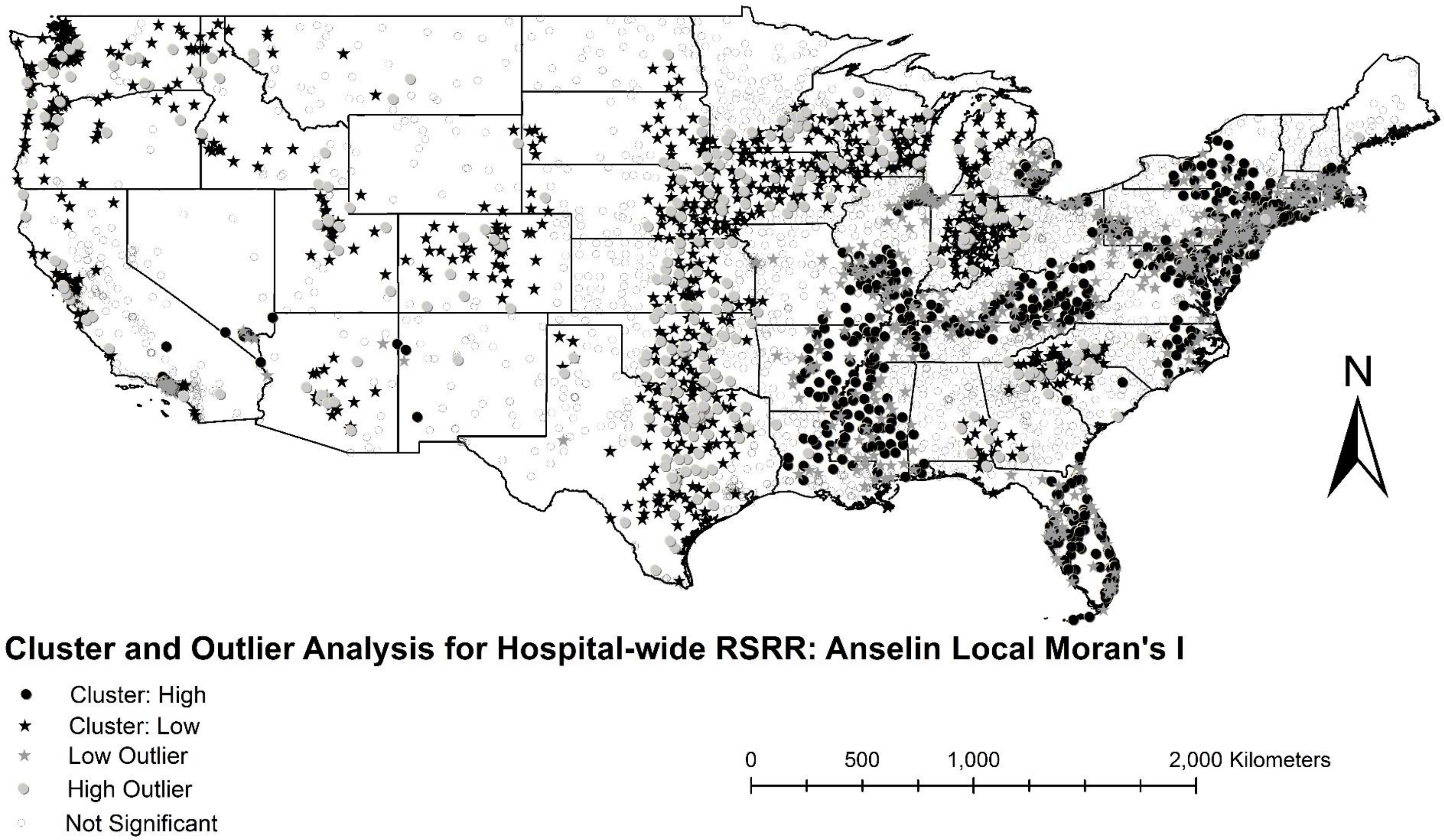

Figure 7. Hospital-wide RSRR cluster and outlier analysis of U.S. hospitals by Anselin local Moran’s Index.

six different sets of the cluster group, the neighbor setting of 7 was selected to find the optimal cluster groups.

Identify the optimal number of cluster groups. Spatial constraints were using the minimum spanning tree with edge removal method, pseudo *F*-statistics were calculated for group numbers from 2 to 20. The peak pseudo *F*-statistics which offered the optimal differentiation among groups was at a group number 15 (see Figure 8).

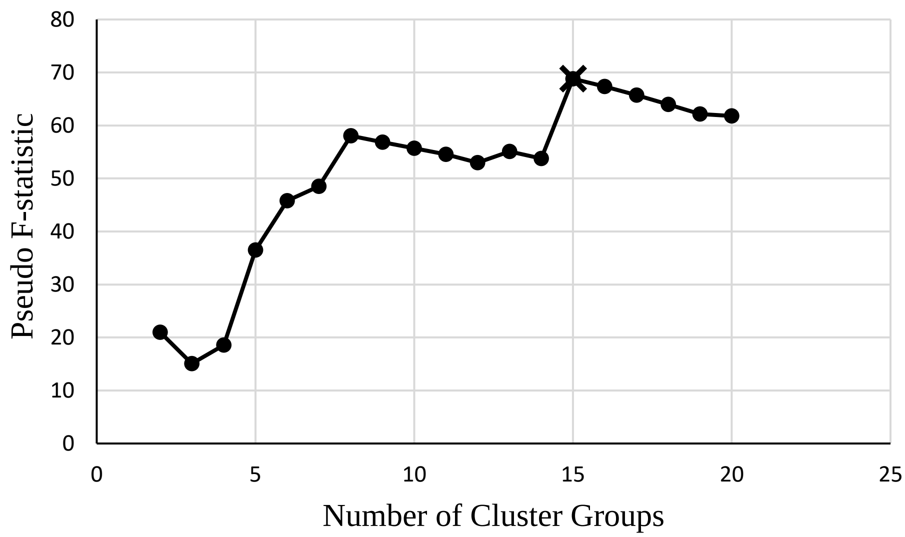

Figure 8. Pseudo F-statistic plot constructed using K-nearest neighbor's method with the number of neighbors set to seven.

Optimal cluster group. All 4,360 hospitals were depicted on the U.S. map in 15 different symbols according to their calculated cluster group (see Figure 9). The summary statistics of their hospital-wide risk adjusted readmission rates were provided in Table 9. The results show that hospital cluster patterns in the western half of the U.S. were less complicated than those in the eastern half of the U.S. (see Figure 9). Only three cluster groups (Group 5, 9, and 12) were observed in the western half. All of them had lower than national average hospital-wide RSRRs. Most of the West and Mid-West Census regions hospitals were included in the cluster Group 5. Their average hospital-wide RSRR (15.0%) was lower than the national average (15.2%). Cluster Group 9 was the second largest cluster group with low average hospital-wide RSRR (15.1%). It covered a large area of South Census region. More than half of the U.S hospitals (55%) were grouped into these two clusters. The northern part of the Midwest Census region was the cluster Group 12 with hospital-wide RSRR of 15.0%.

Cluster patterns were more complicated in the eastern half of the U.S. Most of the clusters' average hospital-wide RSRR were above the national average with the exception of two small cluster groups (Group 3 and 13) with extremely low RSRRs. They were located in Columbia, Missouri (Group 3, 14.4%), and Saginaw, Michigan (Group 13, 14.6%); however, around them were the clusters with higher RSRRs. They were Group 1 near Kansas City, Missouri; Group 4 at St. Louis, Group 8 at Arkansas, or Cluster 2 at Detroit. The average hospital-wide RSRR for cluster Group 1, 2, 4, and 8 were between 15.7 to 16.5% (see Table 9, Figure 9). The two largest cluster groups in the east of the U.S. were Group 6 and Group 15, which were located in the Northeast and in the northern part of the South Census region, respectively. In between, hospitals around New York City had higher RSRR. Cluster Group 14, with 20 hospitals located in New York City and its vicinity, had average hospital-wide RSRR of 17.5%. The eastern half of the U.S was also covered by a few eastern extensions of Group 9, Group 12, and some Group 5 hospitals.

The state of Florida included four different cluster groups (see Figure 10). Most Florida hospitals were in cluster Group 11 with above national average RSRR of 15.7%. The Florida panhandle hospitals with low hospital-wide RSRR were part of the large Southern cluster (Group 9). Two small cluster groups with extremely high hospital-wide RSRRs were Cluster Group 7 (17.7%) and Cluster Group 10 (18.0%). The seven hospitals in Cluster Group 7 were located in the central Miami hospital referral region (HRR). Their hospital-wide RSRRs were from 17.5 to 18.7%. Group 10 was the cluster with the highest average hospital-wide RSRR (18%) among all 15 cluster groups. It only had five hospitals, four hospitals in Orlando HRR, one hospital in neighbor Lakeland HRR.

Among all the 15 cluster groups, clusters with large number hospitals, (such as Group 5, 6, 9, 12, and 15), had similar average hospital-wide RSRRs. The extreme hospital RSRRs were those cluster groups with few hospitals such as Group 3, 7, 10, 13, or 14 where the number of hospitals was less than 50. Group 3 and Group 13 had extremely low RSRR (14.4 and 14.6%); Group 7, 10, and 14 had higher average RSRR (≥17.5%) (Table 9). Among a total of 15 cluster groups overall, two clusters (Groups 7 and Group 10) had the highest average RSRR (17.7%, and 18%) with seven and five geographically connected hospitals in each cluster, respectively.

Table 9

Summary Statistics of Hospital-wide RSRR for 15 Cluster Groups

ID	Location description	*n*	*Mean (SD)*	*Median*	*Range*
1	Kansas City	45	15.8 (0.6)	15.7	14.6 - 18.0
2	Detroit	24	16.7(0.6)	16.5	15.8 - 17.9
3	Columbia and Springfield	9	14.4(0.2)	14.3	14.1 - 14.7
4	St. Louis, Springfield, Springdale, and Jonesboro	61	15.8(0.7)	15.6	14.1 - 17.6
5	West and Midwest	1,447	15.0(0.8)	15.0	11.4 - 18.8
6	New England, western of Middle Atlantic, East North Central, East South Central, and South Atlantic	762	15.4(0.9)	15.4	11.6 - 19.8
7	Miami	7	17.7(0.4)	17.5	17.5 - 18.7
8	Arkansas	84	15.7(0.9)	15.7	11.8 - 17.5
9	West South Central and East South Central	953	15.1(0.7)	15.1	11.3 - 17.6
10	Orlando	5	18.0(0.8)	18.1	16.9 - 18.9
11	Florida	189	15.7(0.9)	15.6	13.4 - 18.0
12	Midwest States next to Canada	443	15.0(0.7)	15.0	12.4 - 17.5
13	Saginaw	19	14.6(0.5)	14.7	13.4 - 15.4
14	New York City	37	17.5(0.6)	17.5	16.5 - 19.1
15	Middle Atlantic and north of South Atlantic	275	15.5(0.9)	15.4	13.1 - 18.5

Note. Based on the cluster size, each cluster location was described according to the Census region, Census division, State, or the city of hospital referral region where most cluster hospitals were located.

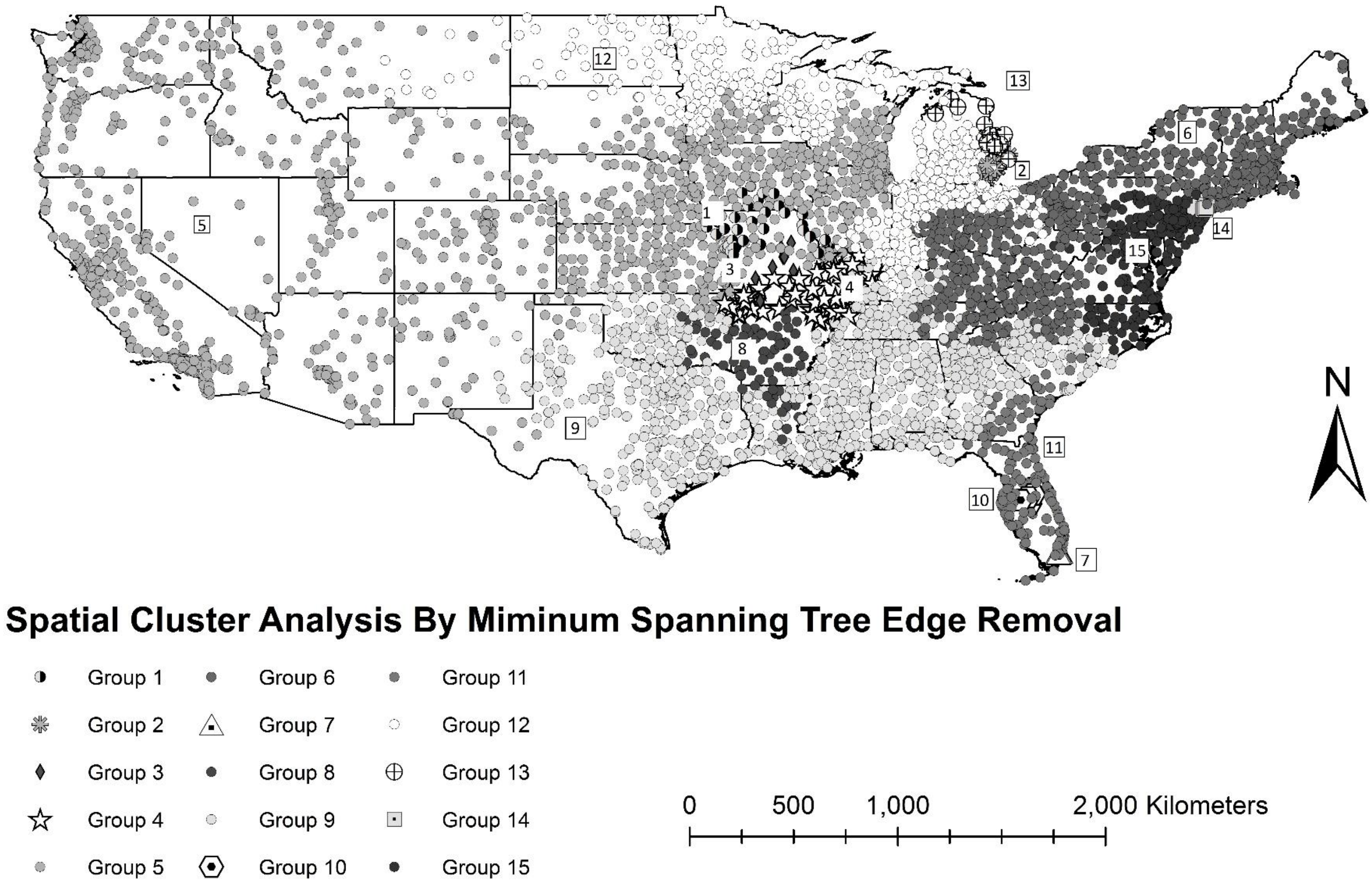

Figure 9. Fifteen cluster groups across the continental U.S. hospitals.

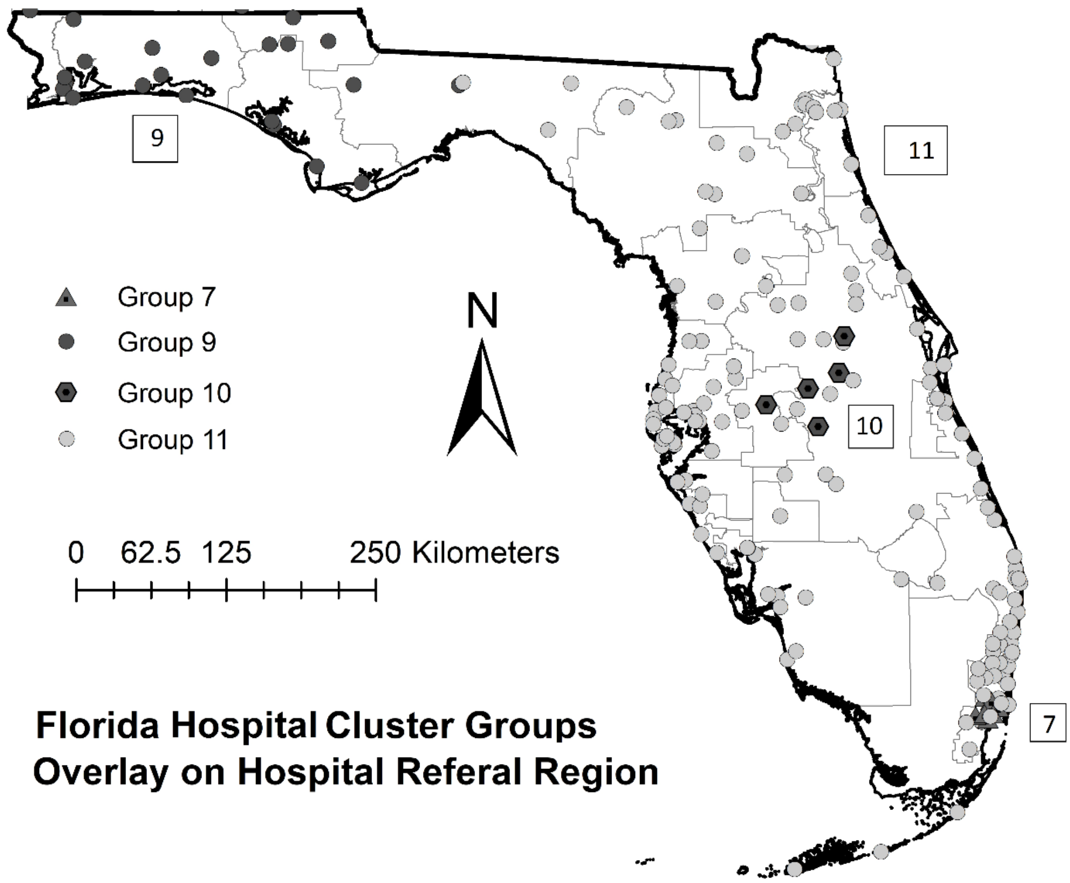

Figure 10. Florida hospital groups overlay on hospital referral regions.

Research Question 4: Group difference

The fourth research question was: Are there differences in hospital readmission rates for various diseases or surgical types between cluster groups? The null hypothesis was that hospital readmission rates for various disease or surgical types are not different between cluster groups. The alternative hypothesis was that hospital readmission rates for various disease or surgical types are different between cluster groups.

Table 10

Average Hospital RSRRs by Disease and Surgery Type for 15 Cluster Groups

Group ID	Statistics	HW	PN	HF	AMI	COPD	Hip/ knee	CABG	Stroke
All	Mean	15.2	17	22	17	20.3	4.9	15	12.8
	n	4,360	4,022	3,697	2,188	3,658	2,735	1,044	2,678
1	Mean	15.8	17.3	22.2	17.2	21	5.1	14.8	12.7
	n	45	45	43	23	42	31	14	23
2	Mean	16.7	18	23.6	17.5	21	5.1	15.3	14.2
	n	24	24	23	23	23	23	12	23
3	Mean	14.4	16.1	21.8	16.6	19.7	4.8	15.1	12.1
	n	9	9	9	9	9	9	5	9
4	Mean	15.8	17.6	22.6	17.3	20.7	5	15.5	13.2
	n	61	58	54	25	56	31	15	33
5	Mean	15	16.7	21.6	16.8	20	4.8	14.7	12.5
	n	1,447	1,289	1,114	622	1,073	869	328	779
6	Mean	15.4	17.2	22.3	17.1	20.6	4.9	15	12.9
	n	762	741	718	484	732	545	172	561
7	Mean	17.7	18.5	25	18	20.7	5	14.8	13.4
	n	7	7	7	6	7	5	1	6
8	Mean	15.7	17.4	22.9	17.6	20.7	5.2	15.6	12.9
	n	84	82	73	27	76	28	17	44
9	Mean	15.1	16.9	21.9	17	20.1	4.9	15.1	12.8
	n	953	850	795	402	792	511	227	533
10	Mean	18	17.9	24.8	19.1	22.7	4.9	16.7	14.6
	n	5	5	5	5	5	4	3	5
11	Mean	15.7	17.1	22.5	17.3	20.4	5	15.3	13
	n	189	185	181	143	181	152	73	155
12	Mean	15	16.7	21.5	16.7	20.1	4.8	15.1	12.4
	n	443	412	360	153	347	260	83	218
13	Mean	14.6	16.6	20.9	16.5	19.5	4.7	14.8	11.7
	n	19	17	15	8	17	12	5	11
14	Mean	17.5	18.6	24.9	18	22	4.9	15.4	14.1
	n	37	37	37	33	37	19	9	35
15	Mean	15.5	17.2	22.4	17.1	20.5	5.1	14.8	13.2
	n	275	261	263	225	261	236	80	243

Notes. Abbreviations: HW = hospital-wide, PN = pneumonia, HF = heart failure, AMI = acute myocardial infarction, COPD = chronic obstructive pulmonary disease, Hip/Knee = total hip or knee arthroplasty. CABG = coronary artery bypass graft,

Differences across all cluster groups. Since there are only less than a quarter of hospitals with RSRR for all disease or surgery types, only hospital-wide RSRR was used to identify the cluster groups. Table 10 and Figure 11 present the average hospital RSRR by different disease or surgery types for 15 cluster groups. The high or low RSRRs were consistent across different disease or surgical type for each of the cluster group. Kruskal-Wallis test showed that differences across all 15 cluster groups were statistically significant for hospital-wide RSRR as well as the seven Medicare reported disease or surgical types. The *p* values were $< .0001$ for all types of RSRRs except for CABG surgical patients ($p = .0064$) (see Table 11).

Table 11

Kruskal-Wallis Test of Hospital RSRRs Difference Across All 15 Cluster Groups

Hospital RSRR by disease or surgical type	*p* value
Rate of readmission after discharge from hospital (hospital-wide)	< .0001
Pneumonia (PN) 30-Day Readmission Rate	< .0001
Heart failure (HF) 30-Day Readmission Rate	< .0001
Acute Myocardial Infarction (AMI) 30-Day Readmission Rate	< .0001
Rate of unplanned readmission for stroke patients	< .0001
Rate of unplanned readmission for CABG	.0064
Rate of unplanned readmission for chronic obstructive pulmonary disease (COPD) patients	< .0001
Rate of readmission after hip/knee arthroplasty	< .0001

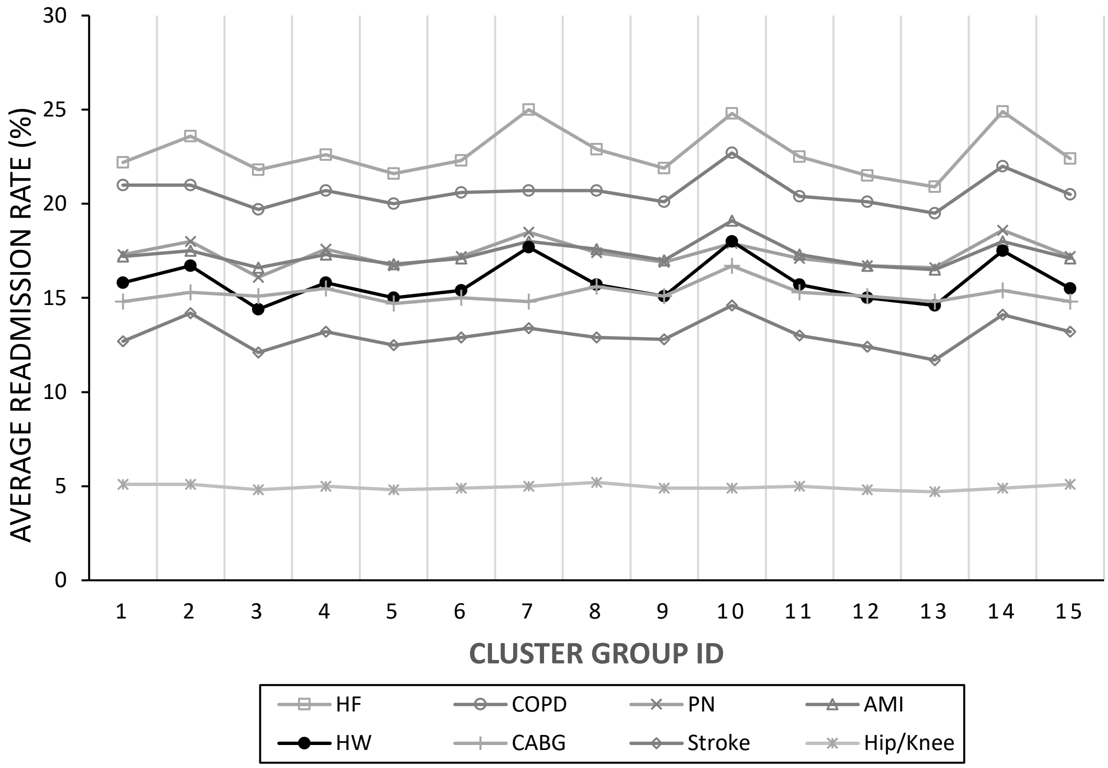

Figure 11. Eight hospital RSRRs by optimal cluster groups. Abbreviations: HF = heart failure, COPD = chronic obstructive pulmonary disease, PN = pneumonia, AMI = acute myocardial infarction, HW = hospital-wide, CABG = coronary artery bypass graft, Hip/Knee = total hip or knee arthroplasty.

Difference between pairwise cluster groups. The Dwass, Steel, Critchlow-Fligner (DSCF) test was conducted to compare pairwise RSRR differences (see Table 12). Most cluster groups (79 out of 105 pairs) had significantly different average hospital-wide RSRR compared to their neighbor hospitals cluster group. For example, Cluster Group 8 located in West South Central Census division, the DSCF test *p* values were significant when compared to the surrounding cluster Group 9 ($p < .0001$) and adjacent cluster Group 5 or Group 3 ($p < .0001$). The similar RSRR pairs usually happened for the

Table 12

P Values for Pairwise Comparison of Hospital-wide RSRR Between Cluster Groups

Group ID	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	<.0001	<.001	1.000	<.0001	.010	.004	1.000	<.0001	.029	.996	<.0001	<.0001	<.0001	.318
2		.001	<.0001	<.0001	<.0001	.046	<.0001	<.0001	.148	<.0001	<.0001	<.0001	<.001	<.0001
3			<.001	.054	.002	.054	<.001	.014	.149	.001	.023	.984	<.001	.009
4				<.0001	.025	.002	1.000	<.0001	.029	1.000	<.0001	<.0001	<.0001	.474
5					<.0001	.001	<.0001	.053	.011	<.0001	1.000	.441	<.0001	<.0001
6						.001	.033	<.0001	.015	.011	<.0001	.002	<.0001	.999
7							.001	.001	1.000	.002	.001	.010	.998	.001
8								<.0001	.025	1.000	<.0001	<.0001	<.0001	.552
9									.010	<.0001	.796	.105	<.0001	<.0001
10										.021	.011	.051	.987	.018
11											<.0001	<.0001	<.0001	.616
12												.310	<.0001	<.0001
13													<.0001	.003
14														<.0001

Note. *p* values were calculated using the Dwass, Steel, Critchlow-Fligner multiple comparison test.

two clusters were not geographically connected, for example, Group 8 versus Group 1 located in Kansas City, Missouri area, or Group 11 and Group 15 which located in the Florida and East Coast. There was also an exception such as the Group 8 and its neighbor Group 4 which located in St. Louis and South Missouri. Their hospital-wide RSRR were at the similar range (15.7% vs. 15.6%) (see Figure 9).

The insignificant RSRR differences more often occurred between two large adjacent cluster groups. Group 5, which was the largest cluster group located in the West and Mid-West Census regions, had almost the same average hospital RSRR (15%) compared to its two large neighbor clusters: Group 9 (15.1%) in the South Census region and Group 12 (15%) in the North Census region. Their DSCF test *p* values were not significant. A similar pattern was observed in the East region. The two adjacent large clusters, Group 6 which was located in the Northeast and East Central Census division, and Group 15 which was located in the Atlantic region, had similar hospital-wide RSRRs of 15.4% and 15.5%.

Summary

This quantitative cross-sectional study evaluated the geospatial pattern of hospital risk adjusted readmission rate in the continental United States. The research questions focused on the global and local cluster patterns of the hospital-wide readmission rate to identify the cluster groups across the nation, and lastly, evaluated the difference between each pair of the cluster group. As expected, the study found hospital-wide RSRR was significantly clustered, not dispersed across the continental U.S or at the local level. A total of 15 optimal cluster groups were identified. The hospital-wide and other seven

CMS published RSRRs were significantly different among all clusters. Most geographically connected clusters had significantly different hospital-wide RSRRs.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

Risk standardized hospital readmission is a hospital health care quality measure. The CMS used this measure to adjust the hospital Medicare payment under the HRRP (CMS, 2016a). The calculation of risk adjustment was criticized for lack of consideration of risk factors beyond the hospital's control (Herrin et al., 2015; Howie-Esquivel & Spicer, 2012; Joynt & Jha, 2013; Kind et al., 2014). This study was designed to evaluate hospital geographic location and hospital-wide readmission rates. The purpose of the study was to examine geospatial clustering of hospital readmission rates, which can provide preliminary evidence of a geographic regional effect on hospital readmissions.

The study used secondary data from Medicare hospital readmission data for the fiscal year 2017. It included 4,772 hospitals. After excluding hospitals outside the continental U.S. or hospitals missing a hospital-wide readmission rate, the total number of analyzed hospitals was 4,360. These hospitals were from 49 states and the District of Columbia, and the majority were short-term acute hospitals. Almost all hospitals provided emergency services.

The first research question of the study assessed the global hospital readmission pattern, specifically: Is there a global cluster pattern of hospital-wide RSRRs across the continental U.S? The positive Global Moran's Index (.23), and large Z score (41.07) showed that hospital-wide RSRRs were geographically clustered and distributed (p value $< .0001$). Furthermore, the cluster pattern was sustained regardless of the neighbor range setting (from 250 km to 4,750 km) with the peak z-score at 2,250 km.

The second research question was focused on the local pattern and was: Are there local geographic clusters of hospital wide readmission rates? Using each hospital's Anselin local Moran's Index and hospital-wide readmission rates for individual hospitals and neighbor hospitals, the hospitals were classified into one of five categories: hot spot or cold spot, high outlier or low outlier, or not significantly different from its neighbor hospitals. The result (see Figure 7) showed that most hot spots were distributed in the eastern half of the U.S. and that most cold spots were located in the western half of the continent. The hot spots had low outliers nearby. Similarly, but vice versa, the cold spots had high outliers within a short distance. Both eastern and western halves of the U.S. had hospitals which were not significantly different from their neighbor hospitals regarding hospital-wide RSRRs.

The third research question was trying to identify the cluster groups across the whole continental U.S. and was: What is the optimal number of cluster groups for hospital-wide readmission rates across the continental U.S? Using the graph analytic approaches, 15 groups were identified as the final optimal cluster groups across the U.S. with the peak pseudo F-statistic of 68.8. Among 15 cluster groups, the lowest group average hospital-wide RSRR was 14.3%, and the highest was 18.1%. These extremely low or high RSRR regions could be specific targets for policymakers to learn lessons and improve the efficiency of reducing readmission rates.

The fourth research question evaluated hospital-wide RSRR difference across all clusters groups and was: Are there differences in hospital readmission rates for various diseases or surgical types among cluster groups? Although the cluster groups were identified using the hospital-wide RSRR, all other seven RSRRs for HF, AMI, PN, COPD, stroke, hip/knee arthroplasty, and CABG showed significant differences across all cluster groups. The *p* values according to the non-parametric Kruskal-Wallis test were all < .0001, except for CABG RSRR (*p* = .0064). In addition to the differences across all cluster groups, the pair-wise hospital-wide RSRRs cluster was tested using DSCF multiple comparison analysis. Most pairwise hospital groups were significantly different, especially where they were geographically connected.

Interpretation of the Findings

The purpose of this study was to evaluate the geospatial distribution of hospital readmission rates. The series of evaluations included visual browsing of a graphical display on the map, summary descriptive statistics, Global Moran's Index statistic, Anselin local Moran's Index, optimal cluster groups identified through minimum spanning tree method, and statistical tests of the RSRR differences.

Descriptive Statistics of RSRR

The fluctuation of state average RSRRs was consistent with the overall RSRR by disease or surgical type. Diseases or surgical types with higher readmission rates, such as heart failure or COPD had more variation of RSRR in range. The lower readmission rates, such as for total hip or knee arthroplasty RSRRs, had less variation by state with one exception for CABG surgical patients. The variation of CABG patient RSRRs were wider than the seven other types of readmission rates. This result might be related to the small number of hospitals providing CABG surgery or cardiac surgery (Neupane, Arora,

& Rudolph, 2017). Local health authorities should be aware of these states with unusual patterns and variation.

Summarizing hospitals based on their physical locations may not fully reflect the patient sources data. As an alternative, this study also evaluated the hospital RSRR by hospital referral region, which reassigned hospitals by state according to their service area. The variation in RSRR was slightly reduced when summarized by HRR state (see Figure 5). Because HRR criteria considered cardiovascular surgery and neurosurgery hospital location pattern, it balanced the patient risk from one service area to another service area. However, because only the hospitals located near the state border could be assigned to a different state between geographical state and HRR state, the difference by state and by HRR State RSRR pattern was very limited. HRR was designed for comparing Medicare utilization and expenditures (Dartmouth, 2016a). Using HRR to regroup hospitals could be a quick method to explore the readmission pattern of healthcare utilization although this analysis was beyond the scope of this study.

The overall hospital-wide RSRR showed different patterns between the eastern and western halves of the continental U.S. More hospitals were clustered in the eastern half compared to the western half. There were small regions depicted with a darker color in the figures generated for analysis, which indicated higher RSRRs. Due to the limitations in scale, the eastern half of U.S. showed substantial overlap in hospitals, making it difficult to detect more detailed cluster patterns. Advanced analysis tools such as Moran's Index were needed to evaluate patterns. Simply looking visually for RSRR by hospital state is probably not the most efficient method for assessing the geographic pattern of RSRR. Tighe et al. (2014) experienced similar scale challenge when studying the hospital clustering of pain management scores. Global Moran's Index was a commonly used statistic in addition to the visual estimate of the cluster pattern.

Global Cluster Pattern

Intuitively, it could be assumed that nearby hospitals should have similar RSRR patterns because they shared similar geographic environments or patient populations with similar socioeconomic backgrounds. One can also argue that the dispersed pattern could be more realistic due to the fact that population of patients was fixed. The Global Moran's Index result from this study) showed a significant cluster (Moran's Index = 0.23, $p < .0001$) pattern, rather than dispersion, across the nation. The global cluster pattern was consistent at a wide range of hospital neighbor settings. The peak was at 2,250 km which is about half distance from the east coast to the west coast of U.S. This is consistent with the visual pattern on the map of hospital-wide RSRR (see Figure 3). The geographic disparity was reported in previous healthcare related measure for Medicare patients. Holt, Zhang, Presley-Cantrell, and Croft (2011) found a significant cluster pattern in chronic obstructive pulmonary disease hospitalization for Medicare patients. Used Global Moran's Index, Tighe et al. (2014) found Medicare patient pain management scores were also geographically clustered. The existence of geographic patterns regarding hospital readmission rates could partially support previous arguments on the lack of adjustment of current risk standardized readmission rates (Gu et al., 2014; Herrin et al., 2015).

Local Cluster Pattern

On the bird's eye view, the local cluster pattern identified using a local indicator of spatial association (LISA) was consistent with what was observed using Jenks Natural Breaks algorithm (see Figure 3). The local patterns were different between the eastern and western halves of the continental U.S. On the eastern half of U.S., more hot spots (meaning high RSRR hospitals surrounding by high RSRR neighbors) were grouped in the Mid Atlantic or East South Central Census divisions along the Mississippi river and Eastern or Central Florida (see Figure 7). On the western half of U.S., most hospitals were either not significantly different compared to their neighbor hospitals as marked in a light-colored circle on the map, or were cold spots (meaning low RSRR surrounding by low RSRR neighbors). It supported the different RSRR patterns between east and west of U.S hospitals. Traditionally high health care utilization areas such as New York City, Orlando, and Miami metro area had large number of hospitals marked as hot spots (Anthony et al., 2009; Fuchs, 2003; IOM, 2013).

On the local pattern map (see Figure 7), outliers (meaning high RSRR hospitals surrounding by low RSRR hospitals or low RSRR hospitals surrounding by high RSRR hospitals) were scattered with the hot spots or cold spots. This result indicated that hospital readmission performances could be altered within the similar geographic region. Further consider the differences between outliers and their neighbor hospitals such as the regional population distribution, or health care environment, according to Andersen's Behavioral Model of Health Service Use (Andersen, 1995), might help to find the reason of excess readmission and improve the quality of hospital care.

Cluster Groups

As mentioned previously, hospital risk adjusted readmission rates were visually different between the eastern and western halves of the continental US. Hospital distribution density and readmission rates were different between these two sections. This pattern was also verified using the Minimum Spanning tree with edge removed method; however, after further comparing the different sets of cluster groups at a different number of neighbor hospitals settings, the optimal number of the cluster was determined as 15 with the minimal number of neighbor hospitals of seven.

The Minimum Spanning Tree with edge removal method used in this hospital location and readmission rate based geospatial cluster pattern was different from previous patient zip code based cluster identification method (Cui et al., 2015). There was no pre-defined geopolitical boundary or fixed size of the cluster. This Moran's index based method was previously used by Tighe et al. (2014) in a study on geospatial pattern of hospital pain management scores. They reported four similar sized clusters located in Southeast, Northeast, Midwest, and Pacific coast of U.S and considered that matched with traditional regions of the United States. For hospital-wide readmission rate, we found 15 various sized cluster groups which support the both general readmission pattern and unique population or practice pattern in some focused areas.

The 15 optimal cluster groups not only represented the macro RSRR difference between eastern and western halves through large cluster groups with Group 5, 9, and 12 represented the West vs. Group 6, 15 and 11 represented the East; it also caught the small cluster groups with extremely low or high average RSRRs. The two little Florida cluster groups, Group 7 in Miami and Group 10 in Orlando hospital referral region were marked with extremely high RSRRs. It was consistent with previously reported high healthcare resource utilization regions (Anthony et al., 2009, Fuchs, 2003). The high RSRR cluster located in New York City (Group 14) was already previously reported as the highest-spending HRR in the nation (Institute of Medicine, 2013). The 15 optimal clusters reflected the large area differences and caught the small special regions.

Compare Cluster Group RSRR

Overall hospital-wide RSRR and other disease and surgical type patients RSRR were tested using the Kruskal-Wallis test. The results showed statistically significant differences among all eight RSRR, including hospital-wide, HF, AMI, PN, stroke, COPD, hip/knee arthroplasty, and CABG. Differences among these RSRRs further support the general finding from this study, that hospital RSRRs were geographically cluster distributed.

The cluster pair wise RSRR difference was tested using the DSCF multiple comparison methods. For hospital-wide RSRRs, a majority of pairs were different, especially for those associated with geographically connected clusters. Other diseases or surgical types were not significantly different pair wise. It is probably due to small sample size, due to few patients falling into these categories.

Both overall and pairwise difference tests validated the risk adjusted readmission rates difference among the geographically adjacent cluster groups. It suggested there were unknown factors associated with the risk adjusted readmission rate differences (Cui et al., 2015; Kistemann et al., 2002). Those factors could relate to previously reported community factors (Guerreo et al., 2013;), population social demographics (Tighe et al., 2014), or disease and treatment pattern (Clarke et al., 2007; Chong et al., 2013).

Theoretical Context

The theoretical foundation of this geospatial analysis on hospital readmission rate was Andersen's behavioral model of health service use, which pointed out influential factors associated with the use of health service (Andersen, 1995). Predisposing characteristics, needs, and enabling resources were connected to the physical geographic location of a hospital, where population socio economic status, quality of the social relationship, and health related community facilities contributed to the local health ecology (Andersen, 1995). Following Andersen's theory, the present study conducted geospatial analyses on hospital geographic location and hospital-wide readmission rate. The study found that hospital-wide RSRRs were geographically clustered, which indicated that hospital locations as an external environment were associated with readmission rates even though a majority hospital risk standardized readmission rates were close to the national average.

Of the 15 optimal cluster groups, there are six large clusters with over 100 hospitals. The West and West Central cluster (Group 5), northern states cluster (Group 12), and southern states cluster (Group 9) had much lower RSRR than the New England and East Central cluster (Group 6), Mid-Atlantic cluster (Group 15) and Florida cluster (Group 11). This type of East-West gradient pattern was consistent with previously reported in geographic disparities in COPD hospitalization (Holt et al., 2011) and heart disease mortality in the U.S (Capser et al., 2016). Both diseases had high readmission rates. These health services needs derived the spatial inequality in hospital-wide readmission rate. The consistent East-West gradient pattern among hospital readmission rates, COPD hospitalization, and heart disease mortality were consistent with predictions from the Andersen's health service model.

The cluster pattern in Florida was also consistent with predictions from Andersen's behavioral model of health service use. The state of Florida had a total of 179 hospitals with hospital-wide RSRR data. They were separated into four optimal cluster groups. The majority of the Florida hospitals were clustered as Group 11. The Northwest Florida hospitals were part of the large southern states cluster (Group 9). There were two small clusters located in Miami (Group 7) and Orlando (Group 10) with extremely high average RSRR (17.7% and 18.0% respectively). These two extreme clusters were consistent with previous studies regarding the high health utility in Miami and Orlando, Florida. (Anthony et al., 2009; Fuchs, 2003).

Applying the Andersen's model, two predisposing factors may explain the high readmission rates in Florida, especially in Miami and Orlando regions. First, a large proportion of Florida residents were retirement or seasonal migration of elderly adults. The temporary residency was ranged from 0.5% in summer to 12% in winter. (Smith & House, 2006). These seasonal migrants had relatively high education level, high incomes, and with better health and had greater health awareness. Their health behavior could influence their friends and neighbors, which triggered higher health utilization in those regions. These health beliefs, health education, and social network possibly triggered the higher hospital visit and readmission rate. Their lower risk health profile kept the risk adjusted readmission rates even higher. Also, when migrants turned to older and sicker, they tended to move out of Florida to be close to their children. The lower mortality rate in Florida (Casper et al., 2016; Fuchs, 2003) was another reason contributing to the higher readmission rates.

Second, clustering of readmission rates in Florida could be tight due to lack of health insurance. Florida ranked 48th in the nation and had one-fifth of Floridians without health insurance coverage (Zevallos, Wilcox, Jean & Acuna, 2016). In a health care survey in the Miami area, one-third of Florida residents fell below U.S. poverty thresholds. They relied on emergency room visits to receive the medical treatment. The excessive emergency room visits caused tight availability of health resources in Florida. A study found that high volume of hospital admissions were associated with high readmission rates (Horwitz et al., 2015). Therefore, the higher uninsured rate could indirectly contribute to the high readmission rates in Miami. The special population characteristics, their health behavior, and the environment in Orlando and Miami area generated the two extremely high readmission clusters.

Limitations of the Study

Cluster regions were identified based on hospital RSRR without considering other RSRRs related to 7 categories of diseases or surgery. Although the hospital-wide RSRR is the most inclusive readmission, it did not consider the RSRR variation among different diseases or surgical types. The minimum spanning tree method provided in ArcMap can evaluate multiple factors simultaneously. However, due to a small number of patients, some RSRRs such as CABG only had about 1000 non-missing hospitals. If all 8 RSRR had been included, it would not have been possible to analyze data from over 3,000 hospitals. Even if only one additional RSRR had been included, for example, pneumonia RSRR, over 300 (8%) hospitals would have been lost to analysis. Since this study focused on the broader patterns, only hospital-wide RSRR was used to detect the cluster regions.

Although the study showed that readmission rates were different across the cluster groups and that most geographically connected cluster regions had statistically different RSRRs, it was impossible to conclude that the regional differences caused different RSRRs. The geographic variation in readmission rates observed in this study might be confounded by other factors, such as socioeconomic factors (AHA, 2015; Jencks & Brock, 2013), race/ethnicity (Letimer, 2011), or urban and rural status (Chen, Carlson, Popoola & Suzuki, 2016; Horwitz et al., 2017). Further investigation could simultaneously evaluate patient socioeconomic factors, hospital characteristics, hospital geographical location, health care facility within the region with in one regression model. A Geographically Weighted Regression (Wu et al., 2016) might be an approach that could yield more information.

Lastly, hospitals were not evenly distributed by geographic locations. The difference between eastern and western halves of the continental U.S. was significant. To use the same neighbor distance criteria to find the cluster is not an ideal solution.

Recommendations

First, it is worthwhile to test the cluster within a smaller region. As noted multiple times in this study, the most significant cluster groups were the western half of the U.S and eastern half of the U.S. Hospitals in the eastern half of the U.S. were more densely distributed and with higher readmission rates. Within the same designated radius of distance, there were more hospitals in the eastern half than in the western half. Using the same distance to define neighbors made the range too wide for the hospitals in the east of U.S and too narrow for hospitals in the west of U.S. Similarly, requiring the same number of neighbor hospitals in the minimum spanning tree method set the cluster region to be too small in the eastern half and too large in the western half of the U.S. Although the density of hospital distribution was the result of healthcare needs, the actual geographic distance also limited the hospital choice list. For example, in the eastern half of the U.S., patient could simultaneously choose 7 to 10 hospitals for a disease, but in the western half of the U.S. or rural regions, the candidate hospitals numbered only 2 to 3. It is highly recommended for the future to study clusters within each region separately.

Second, researchers should compare hospital characteristics, such as teaching status, urban or rural, disproportionate status, or hospital quality measure other than hospital readmission rates, for each of the 15 clusters, broken down by patient disease type and patient socio demographics. Descriptive statistics should be used to evaluate the potential common factors for the small cluster regions. Following the univariate analysis, multiple independent variables should be combined together with the cluster category to conduct a multiple regression (Banta et al., 2015; Sharma 2014) or Geographically Weighted Regression which adds distance as an independent variable to the regression method (Comber, Brundon, & Radburn, 2011) In addition, future researchers could consider including health care system as a factor, where a number of hospitals could be grouped under similar healthcare protocols.

Implications

This study showed hospital-wide readmission rate were geographically clustered across the continental U.S. The readmission rates for HF, PN, AMI, COPD, stroke, hip/knee arthroplasty, or CABG were also significantly different across the 15 cluster groups. According to Tighe et al. (2014), there is no evidence that geographic differences could be standalone from the regional community factors. Although the study did not further investigate any patient social demographic or community factors associated with geographic difference, the findings on geographic cluster provide initial evidence on the association between risk standardized readmission and non-hospital healthcare related variables. Comparing the social economic factors, patient demographics, as well as the community health related facilities within these cluster regions may reveal additional drivers for a difference in the readmission rates.

Among the 15 cluster groups, the most significant cluster groups were located in relatively small regions. Policymakers could focus on these small cluster groups with extremely high or low average readmission rates to conduct a case study and to collect detailed data. The specific lessons could guide other regions to reduce readmission rates and lower healthcare costs. On the other hand, the local governments could use the local pattern of the cluster to adjust the distribution of health facilities, increase patient education programs, and improve health care quality to prevent the hospital readmissions.

This study found might also help the individual hospital to improve the efficiency of reduction readmission effort. Hospitals capture patient address data, and they may use the geospatial pattern identified in this study to help to forecast the readmission risk and actively performed the preventive steps to reduce the readmission. On average, hospitals spent over $1,300 on post discharge intervention for each heart failure patient (Bayati et al., 2014), targeting specific geographic regions may reduce the intervention cost efficiently.

This study is the first geospatial analysis on hospital readmission based on hospital geographic locations. This research method was adapted from Tighe et al. (2014) who conducted a hospital geospatial analysis on pain management score. Unlike prior readmission studies which used existing cluster settings such as postal area (Cui et al., 2015), or county location (Herrin et al., 2015), this readmission study applied the minimal spanning tree with edge removal and identified 15 optimal clusters based on hospital geographic locations and their hospital-wide readmission rates. The size of each cluster varies from 5 hospitals to over one thousand hospitals. The data-driven clusters efficiently pointed the areas which had significantly different readmission pattern compare to their neighbors. The facility based geospatial analysis method could be applied to other country wide healthcare data analyses.

Conclusions

Hospital-wide readmission rates were geographically clustered across the continental U.S. These results showed a significant global pattern, local pattern, and significant differences in readmission rates across the identified 15 cluster groups. The finding of a regional or location effect associated with hospital readmission rate was consistent with the finding of a large variance among hospital readmission rates associated with hospital county location (Herrin et al., 2015) and a patient-level readmission study in Canada (Cui et al., 2015). Although it is not clear whether the cluster group distribution was consistent with hospital care quality, it is difficult to conclude that current risk adjusted readmission rates were entirely related to hospital quality (Krumholz et al., 2011).

The study found the hospital RSRRs were geographically bounded. Hospital clusters were distributed across the country, within a regional area, or at the local level. Overall, the readmission rates were clustered as the eastern half, and the western half of the continent with higher RSRR observed in the eastern half, lower in the western half of the U.S. Using graph analytic approaches, the study further identified 15 optimal cluster group of various sizes. The average hospital-wide RSRRs were comparable among the large cluster groups despite the East-West gradient. The small-sized cluster groups had extremely high or low readmission rates compared to their neighbor cluster groups. These clusters could be specific targets for the policymakers or healthcare vendors to focus on and make adjustments in current HRRP program and facilities settings. Geospatial analyses will improve the efficiency of reducing hospital readmission rates effort and has an immediate positive impact on social change.

This study investigated the relationship between geographic location and the hospital readmission rates. Population socio-demographic factors, local health care resources, transportations, other healthcare policies were not included in the scope of this analysis. Further study will be necessary to understand the causation of the geographical difference in hospital RSRR.

References

Agency for Healthcare Research and Quality [AHRQ]. (2016a). National quality measures NQF-endorsed measure: Total hip arthroplasty (THS) and /or total knee arthroplasty (TKA) hospital-level 30-day, all-cause, risk-standardized readmission rate (RSRR) following elective primary THA and TKA. Retrieved from https://www.qualitymeasures.ahrq.gov/summaries/summary/49200/total-hip-arthroplasty-tha-andor-total-knee-arthroplasty-tka-hospitallevel-30day-allcause-riskstandardized-readmission-rate-rsrr-following-elective-primary-tha-andor-tka

AHRQ. (2016b). HCUP Home. Retrieved December 4, 2016 from www.hcup-us.ahrq.gov

Altfeld, S. J., Shier, G. E., Rooney, M., Johnson, T. J., Golden, R. L., Karavolos, K., ... Perry, A. J. (2013). Effects of an enhanced discharge planning intervention for hospitalized older adults: A randomized trial. *The Gerontologist*, *53*(3), 430-440. doi:10.1093/geront/gns109

American Hospital Association. (2015). Rethinking the hospital readmissions reduction program. *TrendWatch*. Retrieved from http://www.aha.org

Andersen, R. M. (1968). *Behavioral model of families' use of health services: A behavioral model of predisposing, enabling, and need components* (Doctoral dissertation). Available from ProQuest Dissertations and Theses database. (UMI No. 6902884)

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, *36*(1), 1–10. Retrieved from http://www.jstor.org/stable/2137284

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, *27*, 93–115. doi:10.1111/j.1538-4632.1995.tb00338.x

Anthony, D. L., Herndon, M. B., Gallagher, P. M., Barnato, A. E., Bynum, J. P., Gottlieb, D. J., ... Skinner, J. S. (2009). How much do patients' preferences contribute to resource use? *Health Affairs*, *28*(3), 864-873. doi:10.1377/hlthaff.28.3.864

Ash, A. S., Fienberg, S. E., Louis, T. A., Normand, SL., Stukel, T. A., Utts, J. (2012). Statistical issues on assessing hospital performance. Retrieved from http://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Downloads/Statistical-Issues-in-Assessing-Hospital-Performance.pdf

Assunção, R. M., Neves, M. C., Câmara, G., & da Costa Freitas, C. (2006). Efficient regionalization techniques for socio-economic geographical units using minimum spanning trees. *International Journal of Geographical Information Science*, *20*(7), 797-811. doi:10.1080/13658810600665111

Atkinson, J. G. (2012). Flaws in the Medicare readmission penalty. *New England Journal of Medicine*, *367*(21), 2056-7. doi:10.1056/nejmc1212281

Averill, R. F., Goldfield, N., & Hughes, J. S. (2013). Medicare payment penalties for unrelated readmissions require second look. *Healthcare Financial Management*, *67*(10), 96-98. Retrieved from https://www.hfma.org/hfm/

Banta, J. E., Addison, A., & Beeson, W. L. (2015). Spatial patterns of epilepsy-related emergency department visits in California. *Journal of Public Health Research*, *4*(1), 50-57. doi:10.4081/jphr.2015.441

Barrett M, Raetzman S, & Andrews R. (2012) Overview of key readmission measures and methods. 2012. *HCUP Methods Series Report #2012-04*. Retrieved from n https://www.hcup-us.ahrq.gov/reports/methods/2012_04.pdf.

Barton, P. L. (2010). *Understanding the U.S. health services system* (4th ed.). Chicago: Health Administration Press.

Bayati, M., Braverman, M., Gillam, M., Mack, K. M., Ruiz, G., Smith, M. S., & Horvitz, E. (2014). Data-driven decisions for reducing readmissions for heart failure: general methodology and case study. *Plos ONE*, *9*(10), 1-9. doi:10.1371/journal.pone.0109264

Berenson, R. A., Paulus, R. A., & Kalman, N. S. (2012). Medicare's readmissions-reduction program—a positive alternative. *New England Journal of Medicine*, *366*(15), 1364-1366. doi:10.1056/nejmp1201268

Bikdeli, B., Wayda, B., Bao, H., Ross, J. S., Xu, X., Chaudhry, S. I., ... Krumholz, H. M. (2014). Place of residence and outcomes of patients with heart failure analysis from the telemonitoring to improve heart failure outcomes Trial. *Circulation: Cardiovascular Quality and Outcomes*, *7*(5), 749-756. doi:10.1161/CIRCOUTCOMES.113.000911

Boccuti, C., & Casillas, G. (2016). Aiming for fewer hospital U-turns: the Medicare hospital readmission reduction program. *The Henry J. Kaiser Family Foundation*, 1-10. Retrieved from http://kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/

Brown, J. R., Sox, H. C., & Goodman, D. C. (2014). Financial incentives to improve quality: skating to the puck or avoiding the penalty box? *Journal of The American Medical Association*, *311*(10), 1009-1010. doi:10.1001/jama.2014.421

Cartabia, M., Campi, R., Clavenna, A., Bortolotti, A., Fortino, I., Merlino, L., & Bonati, M. (2012). Geographical epidemiology of antibacterials in the preschool age. *International Journal of Health Geographics*, 11, 52. doi:10.1186/1476-072X-11-52

Casper, M., Kramer, M. R., Quick, H., Schieb, L. J., Vaughan, A. S., & Greer, S. (2016). Changes in the geographic patterns of heart disease mortality in the United States. *Circulation*, *133*(12), 1171-1180. doi:10.1161/CIRCULATIONAHA.115.018663

CDC. (2016). National Syndromic Surveillance Program (NSSP): Bio Sense 2.0. Retrieved from http://www.cdc.gov/nssp/biosense/biosense20.html

Chan M. F., & Wong, F. Y. (2014). The risk factors for hospital re-admission in medical patients in Singapore. *Health & Social Care in The Community*, *22*(5), 488-496. doi:10.1111/hsc.12108

Chaney, R. A., & Rojas-Guyler, L. (2015). Spatial patterns of adolescent drug use. *Applied Geography*, 56, 71-82. doi:10.1016/j.apgeog.2014.11.002

Chen, D., Cunningham, J., Moore, K., & Tian, J. (2011). Spatial and temporal aberration detection methods for disease outbreaks in syndromic surveillance systems. *Annals of GIS*, *17*(4), 211-220.

Chen, H., Carlson, E., Popoola, T., & Suzuki, S. (2016). The impact of rurality on 30-day preventable readmission, illness severity, and risk of mortality for heart failure

Medicare home health beneficiaries. *Journal of Rural Health*, *32*(2), 176-187. doi:10.1111/jrh.12142

Chong, S., Nelson, M., Byun, R., Harris, L., Eastwood, J., & Jalaludin, B. (2013). Geospatial analyses to identify clusters of adverse antenatal factors for targeted interventions. *International Journal of Health Geographics*, *12*(1), 1-20. doi:10.1186/1476-072X-12-46

Clarke, K. C., McLafferty, S. L., & Tempalski, B. J. (1996). On epidemiology and geographic information systems: a review and discussion of future directions. *Emerging Infectious Diseases*, *2*(2), 85-92. doi:10.3201/eid0202.960202

Clark, R., Driscoll, A., Nottage, J., McLennan, S., Coombe, D., Bamford, E., ... Stewart, S. (2007). Inequitable provision of optimal services for patients with chronic heart failure: a national geo-mapping study. *Medical journal of Australia*, *186*(4), 169-173. Retrieved from https://www.mja.com.au/

CMS. (2014). *HCAHPS: Patients' Perspectives of Care Survey*. Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-instruments/HospitalQualityInits/HospitalHCAHPS.html

CMS. (2016a). *Readmissions reduction program (HRRP)*. Retrieved from https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html

CMS. (2016b). *Acute inpatient PPS*. Retrieved from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/index.html

CMS. (2016c). *Glossary*. Retrieved from https://www.cms.gov/apps/glossary/default.asp?Letter=P&Language=English

CMS. (2016d). *Hospital Compare datasets* [Data file]. Retrieved November 29, 2016 from https://data.medicare.gov/views/bg9k-emty/files/a24d7358-cadb-4d3e-bebc-ecf41e8a74b9?content_type=application%2Fzip%3B%20charset%3Dbinary&filename=Hospital_Revised_FlatFiles.zip

CMS. (2016e). *National health expenditure data: historical*. Retrieved from https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nationalhealthaccountshistorical.html

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

Cornett, B. S., & Latimer, T. M. (2011). Managing hospital readmissions: an overview of the issues. *Journal of Health Care Compliance*, *13*(6), 5-14. Retrieved from https://lrus.wolterskluwer.com/store/product/journal-of-health-care-compliance/

Cui, Y., Torabi, M., Forget, E. L., Metge, C., Ye, X., Moffatt, M., & Oppenheimer, L. (2015). Geographical variation analysis of all-cause hospital readmission cases in Winnipeg, Canada. *BMC Health Services Research*, *15*(1), 129-135. doi:10.1186/s12913-015-0807-2

Dartmouth. (2017a). *The Dartmouth atlas of health care*. Retrieved from http://www.dartmouthatlas.org/tools/faq/researchmethods.aspx

Dartmouth. (2017b). *The Dartmouth atlas of health care: terms and conditions*. Retrieved from http://www.dartmouthatlas.org/pages/terms_and_conditions

Dharmarajan, K., Hsieh, A. F., Lin, Z., Bueno, H., Ross, J. S., Horwitz, L. I., ... Drye, E. E. (2013). Diagnoses and timing of 30-day readmissions after hospitalization for heart failure, acute myocardial infarction, or pneumonia. *JAMA*, *309*(4), 355-363. doi:10.1001/jama.2012.216476

Diniz-Filho, J. A. F., Bini, L. M., & Hawkins, B. A. (2003). Spatial autocorrelation and red herrings in geographical ecology. *Global ecology and Biogeography*, *12*(1), 53-64. doi:10.1046/j.1466-822x.2003.00322.x

Duque, J. C., Ramos, R., & Suriñach, J. (2007). Supervised regionalization methods: a survey. *International Regional Science Review*, *30*(3), 195-220. doi:10.1177/0160017607301605

ESRI. (2017). How grouping analysis works. Retrieved from http://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/how-grouping-analysis-works.htm

Field, T. S., Ogarek, J., Garber, L., Reed, G., & Gurwitz, J. H. (2015). Association of early post-discharge follow-up by a primary care physician and 30-day rehospitalization among older adults. *Journal of general internal medicine*, *30*(5), 565-571. doi:10.1007/s11606-014-3106-4

Fiscella, K., Burstin, H. R., & Nerenz, D. R. (2014). Quality measures and sociodemographic risk factors: to adjust or not to adjust. *JAMA*, *312*(24), 2615-2616. doi:10.1001/jama.2014.15372

Fradelos, E. C., Papathanasiou, I. V., Mitsi, D., Tsaras, K., Kleisiaris, C. F., &

Kourkouta, L. (2014). Health based geographic information systems (GIS) and their applications. *Acta Informatica Medica*, *22*(6), 402. doi:10.5455/aim.2014.22.402-405

Fuchs, V. R. (2003). Floridian exceptionalism. *Health affairs*, W3. doi:10.1377/hlthaff.W3.357

Gardner, R., Li, Q., Baier, R. R., Butterfield, K., Coleman, E. A., & Gravenstein, S. (2014). Is implementation of the care transitions intervention associated with cost avoidance after hospital discharge? *Journal of General Internal Medicine*, *29*(6), 878-884. doi:10.1007/s11606-014-2814-0

Gerhardt, G., Yemane, A., Apostle, K., Oelschlaeger, A., Rollins, E., & Brennan, N. (2014). Evaluating whether changes in utilization of hospital outpatient services contributed to lower Medicare readmission rate. *Medicare & Medicaid research review*, *4*(1). doi:10.5600/mmrr.004.01.b03

Gesler, W. (1986). The uses of spatial analysis in medical geography: a review. *Social science & medicine*, *23*(10), 963-973. doi:10.1016/0277-9536(86)90253-4

Green, B. K., Leal, S., Sheehan, V. C., & Sobolik, R. (2015). Hospital readmissions reduction program: implications for pharmacy. *American journal of health-system pharmacy*, *72*(3), 237-244. doi:10.2146/ajhp140177

Gu, Q., Koenig, L., Faerberg, J., Steinberg, C. R., Vaz, C., & Wheatley, M. P. (2014). The Medicare hospital readmissions reduction program: potential unintended consequences for hospitals serving vulnerable populations. *Health Services Research*, *49*(3), 818-837. doi:10.1111/1475-6773.12150

Guerrero, E. G., Kao, D., & Perron, B. E. (2013). Travel distance to outpatient substance use disorder treatment facilities for Spanish-speaking clients. *International Journal of Drug Policy*, *24*(1), 38-45. doi:10.1016/j.drugpo.2012.04.004

Hansen, L., Young, R., Hinami, K., Leung, A., & Williams, M. (2011). Interventions to reduce 30-day rehospitalization: a systematic review. *Annals of Internal Medicine*, *155*(8), 520-528. doi:10.7326/0003-4819-155-8-201110180-00008

Hawkins, N. M., Jhund, P. S., McMurray, J. J., & Capewell, S. (2012). Heart failure and socioeconomic status: accumulating evidence of inequality. *European journal of heart failure*, *14*(2), 138-146. doi:10.1093/eurjhf/hfr168

Heidenreich, P. A., Trogdon, J. G., Khavjou, O. A., Butler, J., Dracup, K., Ezekowitz, M. D., ... Lloyd-Jones, D. M. (2011). Forecasting the future of cardiovascular disease in the United States a policy statement from the American heart association. *Circulation*, *123*(8), 933-944. doi:10.1161/CIR.0b013e31820a55f5

Hempel, S. (2013). John Snow. *The Lancet, 381*(9874), 1269-1270. doi:10.1016/s0140-6736(13)60830-2

Herrin, J., St Andre, J., Kenward, K., Joshi, M. S., Audet, A. M. J., & Hines, S. C. (2015). Community factors and hospital readmission rates. *Health Services Research*, *50*(1), 20-39. doi:10.1111/1475-6773.12177

Holt, J. B., Zhang, X., Presley-Cantrell, L., & Croft, J. B. (2011). Geographic disparities in chronic obstructive pulmonary disease (COPD) hospitalization among Medicare beneficiaries in the United States. *International journal of chronic obstructive pulmonary disease*, 6, 321. doi:10.2147/COPD.S19945

Horwitz, L. I., Bernheim, S. M., Ross, J. S., Herrin, J., Grady, J. N., Krumholz, H. M., ... Lin, Z. (2017). Hospital characteristics associated with risk-standardized readmission rates. *Medical Care*, *55*(5), 528-534. doi:10.1097/MLR.0000000000000713

Horwitz, L. I., Partovian, C., Lin, Z., Grady, J. N., Herrin, J., Conover, M., ... Drye, E. E. (2014). Development and use of an administrative claims measure for profiling hospital-wide performance on 30-day unplanned readmission. *Annals of Internal Medicine*, *161*(10_Supplement), S66-S75. doi:10.7326/M13-3000

Howie-Esquivel, J., & Spicer, J. G. (2012). Association of partner status and disposition with rehospitalization in heart failure patients. *American Journal of Critical Care*, *21*(3), e65-e73. doi:10.4037/ajcc2012382

Hu, J., Gonsahn, M. D., & Nerenz, D. R. (2014). Socioeconomic status and readmissions: evidence from an urban teaching hospital. *Health Affairs*, *33*(5), 778-85. doi:10.1377/hlthaff.2013.0816

Institute of Medicine. (2013). *Variation in health care spending: Target decision making, not geography*. Washington, DC: The National Academies Press. doi:10.17226/18393

Jencks, S. F., & Brock, J. E. (2013). Hospital accountability and population health: lessons from measuring readmission rates. *Annals of Internal Medicine*, *159*(9), 629-631. doi:10.7326/0003-4819-159-9-201311050-00010

Jencks, S. F., Williams, M. V., & Coleman, E. A. (2009). Rehospitalizations among patients in the Medicare fee-for-service program. *New England Journal of*

Medicine, 360(14), 1418-1428. doi:10.1056/NEJMsa0803563

Joynt, K. E., & Jha, A. K. (2012). Thirty-day readmissions—truth and consequences. *New England Journal of Medicine*, *366*(15), 1366-1369. doi:10.1056/NEJMp1201268

Joynt, K. E., & Jha, A. K. (2013). Characteristics of hospitals receiving penalties under the hospital readmissions reduction Program. *JAMA*, *309*(4), 342-343. doi:10.1001/jama.2012.94856

Joynt, K. E., Orav, E. J., & Jha, A. K. (2011). Thirty-day readmission rates for Medicare beneficiaries by race and site of care. *JAMA*, *305*(7), 675-681. doi:10.1001/jama.2011.123

Jung, I. (2009). A generalized linear models approach to spatial scan statistics for covariate adjustment. *Statistics in Medicine*, *28*(7), 1131-1143. doi:10.1002/sim.3535

Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. (2011). Risk prediction models for hospital readmission: a systematic review. *JAMA*, *306*(15), 1688-1698. doi:10.1001/jama.2011.1515

Keddem, S., Barg, F. K., Glanz, K., Jackson, T., Green, S., & George, M. (2015). Mapping the urban asthma experience: using qualitative GIS to understand contextual factors affecting asthma control. *Social Science & Medicine*, 140, 9-17. doi:10.1016/j.socscimed.2015.06.039

Keenan, P. S., Normand, S. L. T., Lin, Z., Drye, E. E., Bhat, K. R., Ross, J. S., ... Krumholz, H. M. (2008). An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. *Circulation: Cardiovascular Quality and Outcomes*, *1*(1), 29-37. doi:0.1161/CIRCOUTCOMES.108.802686

Kind, A. H., Jencks, S., Brock, J., Yu, M., Bartels, C., Ehlenbach, W., ... Smith, M. (2014). Neighborhood socioeconomic disadvantage and 30-day rehospitalization: a retrospective cohort study. *Annals of Internal Medicine*, *161*(11), 765-774. doi:10.7326/M13-2946

Kistemann, T., Dangendorf, F., & Schweikart, J. (2002). New perspectives on the use of geographical information systems (GIS) in environmental health sciences. *International journal of hygiene and environmental health*, *205*(3), 169-181. doi:10.1078/1438-4639-00145

Konetzka, R. T., Polsky, D., & Werner, R. M. (2013). Shipping out instead of shaping up: Rehospitalization from nursing homes as an unintended effect of public reporting. *Journal of Health Economics*, *32*(2), 341-352. doi:10.1016/j.jhealeco.2012.11.008

Krumholz, H. M., & Bernheim, S. M. (2014). Considering the Role of Socioeconomic Status in Hospital Outcomes Measures. *Annals of Internal Medicine*, *161*(11), 833-834. doi:10.7326/M14-2308.

Krumholz, H. M., Lin, Z., Drye, E. E., Desai, M. M., Han, L. F., Rapp, M. T., ... Normand, S. L. T. (2011). An administrative claims measure suitable for profiling hospital performance based on 30-day all-cause readmission rates among patients with acute myocardial infarction. *Circulation: Cardiovascular Quality and Outcomes*, *4*(2), 243-252. doi:10.1161/CIRCOUTCOMES.110.957498

Kuhn, D., & Brown, C. (2015). Exploration of factors associated with hospital readmissions in patients with chronic heart failure: a pilot study. *Professional case management*, *20*(2), 106-109. Doi:10.1097/NCM.0000000000000086

Kulldorff, M. (1997). A spatial scan statistic. *Communications in Statistics-Theory and methods*, *26*(6), 1481-1496. doi:10.1080/03610929708831995

Kulldorff, M., & Nagarwalla, N. (1995). Spatial disease clusters: detection and inference. *Statistics in medicine*, *14*(8), 799-810. doi:10.1002/sim.4780140809

Lagoe, R. J., Nanno, D., & Luziani, M. (2013). Clinical identification of patients readmitted to hospitals: why patients return. *BMC Research Notes*, *6*(1), 1-12. doi:10.1186/1756-0500-6-419

Lave, J. R. (1989). The effect of the Medicare prospective payment system, *Annual Review of Public Health*, 10, 141-61. doi:10.1146/annurev.publhealth.10.1.141

Lavenberg, J. G., Leas, B., Umscheid, C. A., Williams, K., Goldmann, D. R., & Kripalani, S. (2014). Assessing preventability in the quest to reduce hospital readmissions. *Journal of Hospital Medicine*, *9*(9), 598-603. doi:10.1002/jhm.2226

Leatherman, S., Berwick, D., Iles, D., Lewin, L. S., Davidoff, F., Nolan, T., & Bisognano, M. (2003). The business case for quality: case studies and an analysis. *Health affairs*, *22*(2), 17-30. doi:10.1377/hlthaff.22.2.17

Lee, P., Andrade, D., Mastey, A., Sun, J., & Hicks, L. (2014). Institution specific risk factors for 30 day readmission at a community hospital: a retrospective observational study. *BMC Health Services Research*, *14*(1), 1-12. doi:10.1186/1472-6963-14-40

Leibovici, D. G., Anand, S., Jackson, M., Bastin, L., & Hobona, G. (2011). Spatially clustered associations in health related geospatial data. *Transactions in GIS*, *15*(3), 347-364. doi:10.1111/j.1467-9671.2011.01252.x

Linden, A., & Butterworth, S. W. (2014). A comprehensive hospital-based intervention to reduce readmissions for chronically ill patients: a randomized controlled trial. *American Journal of Managed Care*, *20*(10), 783-792. Retrieved from http://www.ajmc.com/

Lindenauer, P. K., Normand, S. L. T., Drye, E. E., Lin, Z., Goodrich, K., Desai, M. M., ... Krumholz, H. M. (2011). Development, validation, and results of a measure of 30-day readmission following hospitalization for pneumonia. *Journal of Hospital Medicine*, *6*(3), 142-150. doi:10.1002/jhm.890

Lipstein, S. H., & Dunagan, W. C. (2014). The risks of not adjusting performance measures for sociodemographic factors. *Annals of Internal Medicine*, *161*(8), 594-596. doi:10.7326/M14-1601

Marshall, R. J. (1991). A review of methods for the statistical analysis of spatial patterns of disease. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 421-441. doi:10.2307/2983152

McLafferty, S. L. (2003). GIS and health care. *Annual Review of Public Health*, *24*(1), 25-42. doi:10.1146/annurev.publhealth.24.012902.141012

MedPAC. (2007). Report to the congress promoting greater efficiency in Medicare. Retrieved from http://www.medpac.gov

Miller, M. E. (2015). Hospital Policy issues. MedPAC testimony. Retrieved from http://www.medpac.gov

Moran, P. A. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society. Series B (Methodological)*, *10*(2), 243-251.

Nagasako, E. M., Reidhead, M., Waterman, B., & Dunagan, W. C. (2014). Adding socioeconomic data to hospital readmissions calculations may produce more useful results. *Health Affairs*, *33*(5), 786-91. doi:10.1377/hlthaff.2013.1148

National Quality Forum. (2014). *Risk adjustment for socioeconomic status or other sociodemographic factors*. Retrieved from http://www.qualityforum.org

National Quality Forum. (2015) *All-Cause Admissions and Readmissions Measures - Final Report*. Retrieved from http://www.qualityforum.org

Neupane, I., Arora, R. C., & Rudolph, J. L. (2017). Cardiac surgery as a stressor and the response of the vulnerable older adult. *Experimental gerontology*, 87, 168-174. doi:10.1016/j.exger.2016.04.019

Newgard, C. D., Schmicker, R. H., Sopko, G., Andrusiek, D., Bialkowski, W., Minei, J. P., ... the Resuscitation Outcomes Consortium Investigators. (2011). Trauma in the neighborhood: a geospatial analysis and assessment of social determinants of major injury in north America. *American Journal of Public Health*, *101*(4), 669-677. doi:10.2105/AJPH.2010.300063

Nuckols, T. K. (2015). County-level variation in readmission rates: implications for the hospital readmission reduction program's potential to succeed. *Health Services Research*. *50*(1), 12-19. doi:10.1111/1475-6773.12268

Nykiforuk, C. I. J., & Flaman, L. M. (2011). Geographic information systems (GIS) for health promotion and public health: A review. *Health Promotion Practice*, 12, 63-73. doi:10.1177/1524839909334624

Oddone, E. Z., & Weinberger, M. (2012). Hospital readmission rates: are we measuring the right thing? *Annals of Internal Medicine*, 910-911. doi:10.7326/0003-4819-157-12-201212180-00013

Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: distributional issues and an application. *Geographical analysis*, *27*(4), 286-306. doi:10.1111/j.1538-4632.1995.tb00912.x

Panning, R. (2014). Healthcare reform 101. *Clinical Laboratory Science*, *27*(2), 107-111. Retrieved from http://members.ascls.org/journal

Passalent, L., Borsy, E., Landry, M. D., & Cott, C. (2013). Geographic information systems (GIS): an emerging method to assess demand and provision for rehabilitation services. *Disability & Rehabilitation*, 35(20), 1740-1749. doi:10.3109/09638288.2012.750690

Patient Protection and Affordable Care Act, 42 U.S.C. §3025 (2010)

Penney, T. L., Rainham, D. G. C., Dummer, T. J. B., & Kirk, S. F. L. (2014). A spatial analysis of community level overweight and obesity. *Journal of Human Nutrition and Dietetics*, *27*(s2), 65-74. doi:10.1111/jhn.12055

QualityNet. (2016). *Scoring methodology, Hospital readmissions reduction program*. Retrieved November 29, 2016 from https://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier3&cid=1228775713046

Rohit, G. (2013). Readmissions – a quality metric with financial penalties? *Journal Of Community Hospital Internal Medicine Perspectives*, (1), 1. doi:10.3401/jchimp.v3i1.20219

Rossen, L. M., Khan, D., & Warner, M. (2014). Hot spots in mortality from drug poisoning in the United States, 2007–2009. *Health & place*, 26, 14-20. doi:10.1016/j.healthplace.2013.11.005

Sales, V. L., Ashraf, M. S., Lella, L. K., Huang, J., Bhumireddy, G., Lefkowitz, L., ... Norenberg, J. (2013). Utilization of trained volunteers decreases 30-day readmissions for heart failure. *Journal of Cardiac Failure*, *19*(12), 842-850. doi:10.1016/j.cardfail.2013.10.008

SAS. (2013). *SAS/STAT 13.1 User's guide: The NPAR1WAY procedure*. Retrieved from https://support.sas.com/documentation/onlinedoc/stat/131/npar1way.pdf

Semple, H. M., Cudnik, M. T., Sayre, M., Keseg, D., Warden, C. R., Sasson, C., & Columbus Study Group. (2013). Identification of high-risk communities for unattended out-of-hospital cardiac arrests using GIS. *Journal of community health*, *38*(2), 277-284. doi:10.1007/s10900-012-9611-7

Shimizu, E., Glaspy, K., Witt, M. D., Poon, K., Black, S., Schwartz, S., ... Spellberg, B. (2014). Readmissions at a public safety net hospital. *Plos ONE*, *9*(3), 1-7. doi:10.1371/journal.pone.0091244

Smith, S. K., & House, M. (2006). Snowbirds, sunbirds, and stayers: seasonal migration of elderly adults in Florida. *Journal of Gerontology*, *61*(5), S232-S239. doi:10.1093/geronb/61.5.S232

Sopan, A., Noh, A. S. I., Karol, S., Rosenfeld, P., Lee, G., & Shneiderman, B. (2012). Community health map: a geospatial and multivariate data visualization tool for public health datasets. *Government Information Quarterly*, *29*(2), 223-234. doi:10.1016/j.giq.2011.10.002

Spiro, T., Lee, E. O., & Emanuel, E. J. (2012). Price and utilization: why we must target both to curb health care costs. *Annals of Internal Medicine*, *157*(8), 586-590. doi:10.7326/0003-4819-157-8-201210160-00014

Squires, D., & Anderson, C. (2015). US health care from a global perspective: spending, use of services, prices, and health in 13 countries. *Issue brief (Commonwealth Fund)*, 15, 1-15. doi:10.15868/socialsector.25051

Steiniger, S., & Hunter, A. J. (2013). The 2012 free and open source GIS software map– A guide to facilitate research, development, and adoption. *Computers, Environment and Urban Systems*, 39, 136-150. doi:10.1016/j.compenvurbsys.2012.10.003

Tian, W. (2016). An all-payer view of hospital discharge to postacute care, 2013. *Statistical brief* #205. Retrieved from http://www.hcup-us.ahrq.gov/reports/statbriefs/sb205-Hospital-Discharge-Postacute-Care.pdf

Tighe, P. J., Fillingim, R. B., & Hurley, R. W. (2014). Geospatial analysis of hospital consumer assessment of healthcare providers and systems pain management experience scores in US hospitals. *PAIN®*, *155*(5), 1016-1026. doi:10.1016/j.pain.2014.02.003

Tilson, S., & Hoffman, G. J. (2012). Addressing Medicare hospital readmissions.

Congressional Research Service.

Traynor, K. (2015). Inpatient payment rule for 2016 continues volume-to-value shift. *American Journal of Health-System Pharmacy*, *72*(19), 1600-1603. doi:10.2146/news150067

Trooskin, S. B., Hadler, J., Louis, T. S., & Navarro, V. J. (2005). Geospatial analysis of hepatitis C in Connecticut: a novel application of a public health tool. *Public health*, *119*(11), 1042-1047. doi:10.1016/j.puhe.2005.03.016

Walden University. (2016). *IRB Guide for Archival Researchers. Research ethics & compliance: guides and FAQs*. Retrieved from http://academicguides.waldenu.edu/researchcenter/orec/guides

Walder, L. A., & Gotway, C. A. (2004). *Spatial statistics for public health data*. John Wiley and Sons. New York.

Wartenberg, D. (1985). Multivariate spatial correlation: a method for exploratory geographical analysis. *Geographical Analysis*, *17*(4), 263-283. doi:10.1111/j.1538-4632.1985.tb00849.x

White, M., Garbez, R., Carroll, M., Brinker, E., & Howie-Esquivel, J. (2013). Is “teach-back” associated with knowledge retention and hospital readmission in hospitalized heart failure patients? *Journal of Cardiovascular Nursing*, *28*(2), 137-146. doi:10.1097/JCN.0b013e31824987bd

Wong, F., Chan, M., Chow, S., Chang, K., Chung, L., Lee, W., & Lee, R. (2010). What accounts for hospital readmission? *Journal of Clinical Nursing*, *19*(23/24), 3334-3346. doi:10.1111/j.1365-2702.2010.03366.x

Wu, L., Deng, F., Xie, Z., Hu, S., Shen, S., Shi, J., & Liu, D. (2016). Spatial analysis of severe fever with thrombocytopenia syndrome virus in China using a geographically weighted logistic regression model. *International Journal of Environmental Research And Public Health*, *13*(11). doi:10.3390/ijerph13111125

Zevallos, J. C., Wilcox, M. L., Jean, N., & Acuña, J. M. (2016). Profile of the older population living in Miami-Dade county, Florida: an observational study. *Medicine*, *95*(20). doi:10.1097/MD.0000000000003630

Appendix A: Supporting Tables

Table A1

Summary of Hospital-wide RSRR by Hospital State

State	Statistics	HW	AMI	HF	PN	COPD	Hip/ knee	CABG	Stroke
All	Mean (SD)	15.2 (0.8)	17.0 (1.1)	22.0 (1.6)	17.0 (1.1)	20.3 (1.3)	4.9 (0.6)	15.0 (1.3)	12.8 (1.1)
	n	4360	2188	3697	4022	3658	2735	1044	2678
Alabama	Mean (SD)	15.2 (0.7)	17.4 (1.1)	22.1 (1.4)	16.9 (1.0)	20.1 (1.1)	5.2 (0.7)	15.6 (1.4)	13.0 (0.9)
	n	86	35	77	83	80	44	22	63
Arkansas	Mean (SD)	15.5 (0.9)	17.5 (1.4)	22.6 (1.3)	17.2 (1.0)	20.7 (1.2)	5.2 (0.7)	15.6 (1.6)	12.9 (0.9)
	n	72	25	66	68	64	28	17	45
Arizona	Mean (SD)	15.0 (0.8)	16.7 (0.9)	21.4 (1.5)	17.0 (0.9)	20.2 (1.0)	4.8 (0.6)	14.8 (1.2)	12.3 (0.8)
	n	72	44	55	65	56	47	27	43
California	Mean (SD)	15.2 (0.8)	17.0 (1.2)	22.0 (1.6)	16.8 (1.1)	20.2 (1.1)	4.7 (0.6)	14.8 (1.1)	12.8 (1.1)
	n	316	191	267	271	256	205	100	231
Colorado	Mean (SD)	14.6 (0.7)	16.5 (0.6)	20.9 (1.5)	16.4 (0.8)	19.4 (0.9)	4.8 (0.6)	14.4 (1.1)	11.8 (0.9)
	n	73	32	51	62	48	50	14	36
Connecticut	Mean (SD)	15.4 (0.7)	17.4 (1.2)	21.8 (1.7)	17.3 (1.1)	21.1 (1.3)	4.9 (0.7)	14.4 (1.5)	12.7 (1.1)
	n	29	25	28	29	28	26	10	27
D.C	Mean (SD)	16.0 (0.7)	17.2 (1.0)	23.3 (1.3)	17.6 (1.1)	21.4 (1.6)	5.8 (1.6)	12.1 (0.1)	14.8 (1.4)
	n	7	7	7	7	7	5	2	7
Delaware	Mean (SD)	15.5 (0.8)	16.8 (0.7)	21.2 (1.2)	16.9 (0.9)	20.2 (0.9)	4.8 (0.6)	15.0 (1.3)	12.3 (1.5)
	n	6	6	6	6	6	5	3	6
Florida	Mean (SD)	15.8 (1.0)	17.3 (1.2)	22.6 (1.6)	17.1 (1.2)	20.4 (1.3)	4.9 (0.7)	15.4 (1.4)	13.1 (1.3)
	n	179	144	174	176	173	148	74	153

(*table continues*)

State	Statistics	HW	AMI	HF	PN	COPD	Hip/ knee	CABG	Stroke
Georgia	Mean (SD)	15.1 (0.7)	17.0 (1.2)	21.8 (1.4)	16.9 (0.9)	20.1 (1.1)	5.0 (0.7)	15.3 (1.5)	12.8 (0.9)
	n	128	60	113	120	111	74	18	71
Iowa	Mean (SD)	15.0 (0.5)	16.3 (1.0)	21.5 (1.1)	16.5 (0.9)	20.1 (0.9)	4.7 (0.5)	14.6 (1.0)	12.1 (0.7)
	n	109	27	87	106	81	51	11	46
Idaho	Mean (SD)	14.8 (0.6)	15.6 (0.8)	21.0 (1.3)	16.5 (0.7)	19.6 (1.1)	4.6 (0.5)	13.6 (1.0)	12.1 (0.8)
	n	38	9	21	31	23	24	5	12
Illinois	Mean (SD)	15.5 (0.9)	17.2 (1.0)	22.2 (1.6)	17.3 (1.2)	20.4 (1.4)	5.0 (0.6)	15.1 (1.2)	13.1 (1.1)
	n	175	105	171	172	171	115	55	117
Indiana	Mean (SD)	14.8 (0.8)	16.8 (1.2)	21.5 (1.5)	16.6 (1.1)	20.0 (1.3)	4.8 (0.6)	15.0 (1.6)	12.6 (1.3)
	n	120	58	111	112	111	80	32	77
Kansas	Mean (SD)	15.1 (0.7)	16.5 (1.0)	21.5 (1.1)	16.7 (1.0)	20.1 (1.0)	4.8 (0.6)	14.6 (1.0)	12.6 (0.9)
	n	123	23	75	107	76	44	14	34
Kentucky	Mean (SD)	15.7 (1.0)	17.5 (1.1)	23.0 (1.9)	17.7 (1.4)	21.2 (1.7)	4.8 (0.6)	15.4 (1.1)	12.9 (0.8)
	n	93	40	89	93	93	43	17	49
Louisiana	Mean (SD)	15.4 (0.8)	17.1 (1.0)	22.4 (1.6)	17.0 (1.1)	20.2 (1.2)	4.9 (0.6)	15.1 (1.3)	12.8 (1.1)
	n	103	42	84	87	81	49	27	49
Massachusetts	Mean (SD)	15.5 (1.0)	17.2 (1.0)	22.4 (1.3)	17.1 (1.1)	20.7 (1.4)	4.9 (0.6)	14.5 (1.6)	13.0 (1.1)
	n	60	48	57	58	57	53	14	51
Maryland	Mean (SD)	15.6 (1.0)	17.0 (1.0)	22.6 (1.6)	17.6 (1.3)	20.3 (1.4)	5.2 (0.7)	14.3 (1.0)	13.2 (1.2)
	n	45	39	44	44	44	39	9	43
Maine	Mean (SD)	15.1 (0.7)	16.6 (0.7)	21.1 (1.4)	16.6 (1.0)	19.9 (1.1)	4.8 (0.6)	15.0 (1.8)	12.2 (0.6)
	n	33	22	32	33	32	24	3	24
Michigan	Mean (SD)	15.3 (1.0)	16.9 (1.4)	21.8 (1.7)	16.9 (1.0)	20.0 (1.2)	4.8 (0.6)	14.9 (1.4)	12.7 (1.4)
	n	124	69	112	120	117	96	33	89
Minnesota	Mean (SD)	15.1 (0.5)	16.7 (0.9)	21.6 (1.2)	16.8 (0.7)	20.2 (0.8)	4.8 (0.5)	15.5 (0.9)	12.2 (0.8)
	n	122	25	79	100	61	61	13	38

(*table continues*)

State	Statistics	HW	AMI	HF	PN	COPD	Hip/ knee	CABG	Stroke
Missouri	Mean (SD)	15.4 (0.8)	17.0 (0.9)	22.1 (1.5)	17.1 (1.2)	20.4 (1.3)	5.0 (0.7)	15.2 (1.2)	12.6 (1.1)
	n	103	52	94	102	99	67	31	56
Mississippi	Mean (SD)	15.5 (0.6)	17.5 (1.0)	22.8 (1.3)	17.3 (0.9)	20.7 (1.1)	5.0 (0.6)	15.4 (1.4)	13.2 (1.0)
	n	86	25	77	81	77	28	17	47
Montana	Mean (SD)	15.0 (0.6)	16.0 (1.1)	20.9 (1.5)	16.4 (0.8)	19.7 (1.1)	4.7 (0.6)	14.0 (1.1)	12.0 (0.9)
	n	45	9	26	36	24	20	5	15
North Carolina	Mean (SD)	15.1 (0.9)	16.8 (1.1)	22.0 (1.6)	17.0 (1.1)	20.0 (1.2)	4.9 (0.6)	14.8 (1.2)	12.8 (1.1)
	n	101	61	95	98	96	79	22	85
North Dakota	Mean (SD)	15.1 (0.4)	16.8 (0.6)	20.9 (1.1)	16.6 (0.7)	19.9 (1.0)	4.6 (0.5)	15.5 (1.6)	12.3 (0.6)
	n	39	7	23	38	19	9	6	7
Nebraska	Mean (SD)	14.9 (0.6)	16.6 (0.7)	21.1 (1.2)	16.7 (0.9)	20.1 (0.7)	4.6 (0.6)	14.0 (1.4)	12.2 (0.9)
	n	84	17	45	71	42	38	8	23
New Hampshire	Mean (SD)	15.2 (0.7)	16.4 (1.1)	21.9 (1.3)	16.3 (0.9)	20.1 (1.1)	4.8 (0.4)	14.3 (1.3)	12.1 (0.8)
	n	26	15	25	26	26	23	4	20
New Jersey	Mean (SD)	15.8 (1.2)	17.4 (1.0)	23.0 (2.0)	17.2 (1.3)	20.9 (1.5)	5.1 (0.7)	15.0 (1.5)	13.6 (1.2)
	n	64	61	63	64	63	51	17	62
New Mexico	Mean (SD)	15.3 (0.9)	16.3 (0.7)	21.5 (1.2)	16.6 (0.9)	19.8 (1.1)	4.8 (0.5)	14.0 (0.1)	12.4 (0.9)
	n	39	10	30	37	32	20	4	19
Nevada	Mean (SD)	15.5 (0.6)	17.5 (1.0)	22.5 (1.3)	17.3 (1.4)	20.6 (1.2)	4.8 (0.5)	15.9 (1.2)	12.7 (0.7)
	n	30	17	28	28	26	23	12	17
New York	Mean (SD)	16.1 (1.2)	17.3 (1.0)	23.2 (1.8)	17.7 (1.4)	21.1 (1.4)	4.8 (0.6)	14.8 (1.2)	13.4 (1.3)
	n	162	122	156	159	157	112	34	128
Ohio	Mean (SD)	15.2 (0.7)	17.1 (0.9)	22.1 (1.4)	17.0 (1.1)	20.5 (1.3)	5.0 (0.6)	15.4 (1.5)	12.8 (1.1)
	n	158	90	143	147	146	131	50	106
Oklahoma	Mean (SD)	15.1 (0.8)	17.0 (1.2)	21.9 (1.4)	16.9 (0.9)	20.3 (1.2)	4.9 (0.6)	14.5 (1.2)	12.8 (0.9)
	n	119	31	80	104	90	50	15	44

(*table continues*)

State	Statistics	HW	AMI	HF	PN	COPD	Hip/ knee	CABG	Stroke
Oregon	Mean (SD)	14.7 (0.6)	16.4 (1.1)	21.2 (1.4)	16.4 (0.9)	19.6 (1.0)	4.6 (0.5)	14.1 (1.4)	12.2 (0.8)
	n	58	23	52	55	50	39	12	39
Pennsylvania	Mean (SD)	15.4 (0.8)	17.1 (0.9)	22.1 (1.6)	16.9 (1.2)	20.4 (1.3)	4.9 (0.6)	14.7 (1.0)	12.9 (1.1)
	n	160	113	148	148	146	128	58	121
Rodhe island	Mean (SD)	15.4 (0.8)	17.2 (0.6)	22.3 (2.0)	16.7 (1.0)	20.7 (1.3)	4.7 (0.5)	16.3 (.)	12.5 (0.6)
	n	11	10	10	10	10	9	1	10
South Carolina	Mean (SD)	15.1 (0.9)	17.0 (1.2)	21.7 (1.6)	17.2 (1.0)	20.0 (1.1)	4.9 (0.6)	14.4 (1.5)	12.6 (1.0)
	n	60	33	55	57	55	43	17	46
South Dakota	Mean (SD)	14.9 (0.8)	16.4 (0.7)	20.9 (1.4)	16.4 (1.0)	19.9 (0.9)	4.7 (0.6)	14.9 (1.0)	11.8 (0.9)
	n	47	9	22	38	21	17	3	12
Tennessee	Mean (SD)	15.4 (0.7)	17.0 (1.0)	22.2 (1.5)	17.2 (1.1)	20.6 (1.5)	4.7 (0.6)	15.1 (1.0)	12.9 (1.0)
	n	104	50	98	98	96	55	22	69
Texas	Mean (SD)	15.0 (0.7)	16.8 (0.9)	21.7 (1.3)	16.8 (1.0)	19.9 (1.2)	4.9 (0.6)	15.0 (1.2)	12.7 (1.0)
	n	339	162	270	288	267	205	105	186
Utah	Mean (SD)	14.8 (0.6)	16.4 (0.9)	20.8 (1.7)	16.3 (0.8)	19.2 (0.9)	4.8 (0.5)	14.5 (1.0)	12.0 (0.8)
	n	42	14	27	37	17	30	8	14
Virginia	Mean (SD)	15.4 (0.8)	17.2 (1.1)	22.5 (1.6)	17.5 (1.2)	20.6 (1.3)	5.3 (0.9)	15.3 (1.5)	13.1 (1.3)
	n	78	60	78	76	77	61	20	69
Vermont	Mean (SD)	14.9 (0.7)	16.3 (0.7)	21.2 (1.0)	16.2 (0.9)	20.3 (1.3)	4.4 (0.5)	17.0 (.)	12.3 (0.7)
	n	14	6	13	14	13	12	1	12
Washington	Mean (SD)	14.8 (0.6)	16.8 (1.1)	21.6 (1.4)	16.6 (0.9)	19.8 (1.3)	4.6 (0.5)	14.0 (1.0)	12.0 (0.9)
	n	83	43	64	75	68	55	17	56
Wisconsin	Mean (SD)	14.9 (0.6)	16.6 (1.2)	21.2 (1.2)	16.7 (0.8)	19.8 (0.9)	4.8 (0.7)	15.0 (1.3)	12.0 (0.7)
	n	122	48	112	116	102	83	27	73
West Virginia	Mean (SD)	15.5 (0.6)	17.2 (1.1)	22.7 (1.3)	17.6 (1.1)	21.0 (1.3)	5.1 (0.6)	17.2 (0.7)	13.1 (0.9)
	n	48	21	42	48	47	23	6	25

(*table continues*)

State	Statistics	HW	AMI	HF	PN	COPD	Hip/ knee	CABG	Stroke
Wyoming	Mean (SD)	15.1 (0.5)	16.5 (0.2)	21.7 (1.2)	16.6 (0.7)	20.1 (1.0)	4.9 (0.5)	16.3 (0.4)	12.2 (0.9)
	n	25	3	15	21	16	13	2	6

Note. HW = hospital-wide, AMI = acute myocardial infarction, HF = heart failure, PN = pneumonia, COPD = chronic obstructive pulmonary disease, Hip/Knee = total hip or knee arthroplasty, CABG = coronary artery bypass graft.

Table A2

Summary of Eight CMS Published Hospital RSRRs by Cluster Groups

Cluster Group ID	Statistics	HW	AMI	HF	PN	COPD	Hip/knee	CABG	Stroke
All	Mean (SD)	15.2 (0.8)	17 (1.1)	22 (1.6)	17 (1.1)	20.3 (1.3)	4.9 (0.6)	15 (1.3)	12.8 (1.1)
	n	4360	2188	3697	4022	3658	2735	1044	2678
1	Mean (SD)	15.8 (0.6)	17.2 (1)	22.2 (1.2)	17.3 (1)	21 (1.2)	5.1 (0.6)	14.8 (1.4)	12.7 (1.1)
	n	45	23	43	45	42	31	14	23
2	Mean (SD)	16.7 (0.6)	17.5 (1.3)	23.6 (1.6)	18 (0.9)	21 (1)	5.1 (0.5)	15.3 (1.1)	14.2 (1.4)
	n	24	23	23	24	23	23	12	23
3	Mean (SD)	14.4 (0.2)	16.6 (0.7)	21.8 (2.6)	16.1 (0.8)	19.7 (1.9)	4.8 (0.6)	15.1 (0.6)	12.1 (0.8)
	n	9	9	9	9	9	9	5	9
4	Mean (SD)	15.8 (0.7)	17.3 (1.1)	22.6 (1.4)	17.6 (1.3)	20.7 (1.4)	5 (0.6)	15.5 (1.4)	13.2 (1.1)
	n	61		54	58	56	31	15	33
5	Mean (SD)	15 (0.8)	16.8 (1.1)	21.6 (1.5)	16.7 (1)	20 (1.1)	4.8 (0.6)	14.7 (1.2)	12.5 (1)
	n	1447	622	1114	1289	1073	869	328	779

(*table continues*)

Cluster Group ID	Statistics	HW	AMI	HF	PN	COPD	Hip/knee	CABG	Stroke
6	Mean (SD)	15.4 (0.9)	17.1 (1)	22.3 (1.6)	17.2 (1.2)	20.6 (1.4)	4.9 (0.6)	15 (1.4)	12.9 (1.1)
	n	762	484	718	741	732	545	172	561
7	Mean (SD)	17.7 (0.4)	18 (1)	25 (1.5)	18.5 (0.7)	20.7 (1)	5 (0.8)	14.8 (0)	13.4 (1.3)
	n	7	6	7	7	7	5	1	6
8	Mean (SD)	15.7 (0.9)	17.6 (1.1)	22.9 (1.7)	17.4 (1.1)	20.7 (1.2)	5.2 (0.8)	15.6 (1.8)	12.9 (1)
	n	84	27	73	82	76	28	17	44
9	Mean (SD)	15.1 (0.7)	17 (1)	21.9 (1.3)	16.9 (1)	20.1 (1.2)	4.9 (0.6)	15.1 (1.3)	12.8 (1)
	n	953	402	795	850	792	511	227	533
10	Mean (SD)	18 (0.8)	19.1 (0.1)	24.8 (1.1)	17.9 (1.2)	22.7 (1.6)	4.9 (0.9)	16.7 (0.9)	14.6 (0.4)
	n	5	5	5	5	5	4	3	5
11	Mean (SD)	15.7 (0.9)	17.3 (1.1)	22.5 (1.5)	17.1 (1.1)	20.4 (1.2)	5 (0.7)	15.3 (1.4)	13 (1.2)
	n	189	143	181	185	181	152	73	155
12	Mean (SD)	15 (0.7)	16.7 (1.1)	21.5 (1.4)	16.7 (0.9)	20.1 (1.2)	4.8 (0.5)	15.1 (1.4)	12.4 (0.9)
	n	443	153	360	412	347	260	83	218
13	Mean (SD)	14.6 (0.5)	16.5 (1.6)	20.9 (1.8)	16.6 (1.1)	19.5 (1)	4.7 (0.5)	14.8 (1)	11.7 (1.3)
	n	19	8	15	17	17	12	5	11
14	Mean (SD)	17.5 (0.6)	18 (0.8)	24.9 (1.8)	18.6 (1.3)	22 (1.7)	4.9 (0.6)	15.4 (0.9)	14.1 (1.2)
	n	37	33	37	37	37	19	9	35
15	Mean (SD)	15.5 (0.9)	17.1 (1)	22.4 (1.7)	17.2 (1.3)	20.5 (1.4)	5.1 (0.8)	14.8 (1.3)	13.2 (1.2)
	n	275	225	263	261	261	236	80	243

Note. HW = hospital-wide, AMI = acute myocardial infarction, HF = heart failure, PN = pneumonia, COPD = chronic obstructive pulmonary disease, Hip/Knee = total hip or knee arthroplasty, CABG = coronary artery bypass graft.