ABSTRACT

Socio-ecological Risk Factors of Hospital Readmission in an Underserved Population

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Hospital readmissions are costly, preventable, and currently a significant focus of healthcare reform. The Hospital Readmissions Reduction Program, an Affordable Care Act initiative, financially penalizes hospitals for excessive readmissions based on the premise that it will incentivize hospitals and physicians to provide higher quality patient care. The purpose of this study was to compare socio-ecological risk factors of hospital readmission among 30, 60, and 90 day readmission groups in an underserved population. A retrospective secondary data analysis was conducted using electronic patient medical records from twelve central Texas acute care facilities that serve patients living below 200% of the federal poverty guideline. Eight factors were analyzed as correlates of hospital readmission among 30, 60, and 90 day readmissions groups. A longer time period in days between the initial hospital encounter and the follow-up visit as well as being of the female sex were associated with 60 or 90 day readmission compared to 30 day readmission. In the dawn of policy reform targeted at reducing hospital readmissions, factors that determine readmission risk must be examined. Clarification of

the relationships between risk factors and readmission groups can help inform future policy and practice.

Socio-ecological Risk Factors of Hospital Readmission in an Underserved Population

by

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A Thesis

Approved by the Department of Health, Human Performance, and Recreation

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Administrative variables: are demographic and patient information, primarily collected upon admission to the hospital or assessed at discharge. These include age, sex, race/ethnicity, length of hospital stay, care after discharge, mobility status, stage of illness, prior hospitalization, comorbidities, and the third-party payer.

Blood urea nitrogen (BUN): is nitrogen in the bloodstream that comes from the waste product urea; an indicator of kidney function.

Clinical variables: are physiological measures commonly collected in clinical practice. These include blood pressure, BMI, BUN, creatinine, BUN/creatinine ratio, heart rate, hemoglobin, and temperature.

Creatinine: is a byproduct of muscle metabolism that is excreted by the kidneys; an indicator of kidney function.

Early readmission: is an admission to a Medicare subsection hospital within 14 days of discharge from the same or another subsection hospital (as defined by Medicare).

Preventable readmission: is an unintended and undesired subsequent hospitalization, where the probability is subject to the influence of multiple factors.

Readmission: is an admission to a Medicare subsection hospital within 30 days of discharge from the same or another subsection hospital (as defined by Medicare).

Socio-ecological risk factors: are risk factors of hospital readmission, including administrative and clinical variables, that interact across multiple spheres of influence including intrapersonal, interpersonal, community/organizational and public policy/societal levels.

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To my family

Who support, encourage, and fund my education

CHAPTER ONE

Introduction

The Current State of Health Care

Various study authors, physicians, and politicians suggest the United States is currently in the midst of a health care crisis characterized by extremes in quality and accessibility of health care, unpredictable and hidden health care costs, and the existence of multiple and varying modes of providing and financing health care. The health care system in the U.S. has been described as a "nonsystem", fragmented, chaotic, and inefficient by those in support of healthcare insurance reform (Singer, 2008). Health care insurance seems to be synonymous with heath care as people lacking health insurance receive significantly less health care services and suffer worse health than people who are insured (Kaiser Family Foundation [KFF], 2010). In 2011, 48.6 million Americans were uninsured (U.S. Department of Health and Human Services [HHS], 2012). Furthermore, health care insurance does not guarantee access to affordable and adequate care. There are limitations and gaps in coverage that leave individuals in financial devastation and the economy in crisis. This growing burden has led to a call for health care reform in the U.S. (Cummins, 2011). In response, the U.S. has become focused on identifying areas of healthcare that are associated with excessive cost, have a large potential for saving resources, and are largely preventable (Cloonan, Wood, & Riley, 2013). Excessive hospital readmission has been identified as possible means of controlling costs and saving resources (Centers for Medicare and Medicaid Services [CMS], 2013).

The Affordable Care Act

As of March 2010, The Patient Protection and Affordable Care Act (PPACA) along with the Health Care and Education Reconciliation Act (HCERA), together known as the Affordable Care Act (ACA), have been a proposed approach to lowering costs and increasing access to health insurance. It represents a movement towards a more universal health care system, meant to correct many proposed weaknesses of the current system. The overall arching goals of the supporters of the ACA are to expand health insurance coverage to most U.S. citizens and legal residents of the U.S., control the cost of health care, and strengthen the national health care system (KFF, 2013). National opinion of the ACA is disintegrated, with supporters believing the ACA is the solution to the health care crisis, while critics believe that it will only reduce access to health care and increase the national debt (KFF, 2014). Despite national controversy, initiatives of the ACA have been implemented and will continue to be in the coming years. Among these, are proposed cost-containing initiatives directed at improving quality of care and minimizing inappropriate and unnecessary care of hospital patients through a focus on reducing hospital readmissions (Kiefe, Allison, & de Lissovoy, 2013).

The Hospital Readmissions Reduction Program

Reducing hospital readmissions is an important focus of the ACA with several strategies that attempt to meet this difficult challenge. The strategies are based on the idea that costs can be controlled through laws that demand health care providers deliver a higher quality of care (Chiplin & Lilly, 2013). The Hospital Readmissions Reduction Program (HRRP) is arguably the most significant of these initiatives because it has the potential to substantially impact reimbursements to hospitals as well as quality of patient care (Kocher & Adashi, 2011). The HRRP was established in *Title III – Improving the Quality and Efficiency of Health Care, section*

3025 of the ACA, and went into effect October 1, 2012. It is meant to reduce unnecessary hospital readmissions by penalizing hospitals for high readmission rates (Patient Protection and Affordable Care Act [ACA], 2010). Under the HRRP, Medicare payments to acute care hospitals are reduced based on a calculated readmission payment adjustment factor. In 2013, reimbursement payments were decreased based on that calculation or capped at 1%. In 2014, the penalty cap was raised to 2%, and by 2015, the reimbursement penalty will be capped at 3%. Readmission rates are based on three specific diagnoses: myocardial infarction (heart attack), heart failure, and pneumonia and are measured over a three year period (CMS, 2013). In 2013, payment reductions were based on readmission data from July 1, 2008 through June 30, 2011, and over 2,000 hospitals across the U.S. were penalized, together forfeiting $280 million dollars (KFF, 2012). Hospitals must seek to reduce unnecessary readmissions to avoid penalties and to ensure that patients are receiving the most appropriate, highest quality of care possible (Kocher & Adashi, 2011).

Purpose and Significance of Study

Hospital readmissions are prevalent and costly and now a major focus of ACA initiatives. They are responsible for $15 billion dollars a year in excess cost to Medicare. Twenty percent of Medicare patients experience a subsequent hospital readmission within 30 days of discharge (Jencks, Williams, & Coleman 2009). The Medicare Payment Advisory Commission reports that 75% of these hospital readmissions are preventable (Medicare Payment Advisory Commission [MedPAC], 2007). However, others report that hospital readmissions are frequently unavoidable especially among patients with chronic diseases such as heart failure, myocardial infarction, and pneumonia, the diagnoses on which payment reductions are based (Kociol et al., 2013; Sexton, 2013). Under the HRRP, a hospital is judged less favorably and penalized when the number of hospital readmissions is high. However, physicians suggest that readmission is not always a legitimate indicator of poor quality of health care especially among chronic disease patients (Allred et al., 2013). Furthermore, the diagnoses targeted by the HRRP will be expanded by 2015, affecting a larger number of hospitals (Cloonan et al., 2013). However, the diagnoses to be included are not yet known.

Special populations such as the elderly, children, and ethnic and racial minorities are more likely to be readmitted to the hospital, especially among chronic disease patients (Allred et al., 2012; McHugh, Brooks Carthon, & Kang, 2010; Robinson, Howie-Esquivel, & Vlahov, 2012). Hospitals that treat low-income and ethnic minority patients will likely suffer the most as penalties are increased (KKF, 2012). Despite many programs having focused their efforts on reducing hospital readmissions, rates have not declined significantly especially those for chronic conditions such as congestive heart failure, acute myocardial infarction, and pneumonia. In the dawn of ACA initiatives targeted at reducing readmissions related specifically to these chronic conditions, hospitals must focus on designing and implementing tools to identify those at heightened risk for readmission (Cloonan et al., 2013).

Significance for Public Health

Study implications are significant to the public health profession in light of the importance placed on reducing hospital readmissions through policy initiatives that focus on prevention. The Socio-ecological Model is a public health framework for prevention that considers the influence of numerous factors within multiple spheres of influence – intrapersonal, interpersonal, organizational/community, and public policy/societal (Sallis, Owen & Fisher, 2008). A patient's readmission risk is influenced by numerous factors that interact across all areas of a patient's life. Socio-ecological approaches to understanding factors related with hospital readmission are useful because they highlight the importance of multiple domains of influence. Figure 1.1 is a depiction of the Socio-ecological Model as a framework for identifying and assessing risk factors of hospital readmission.

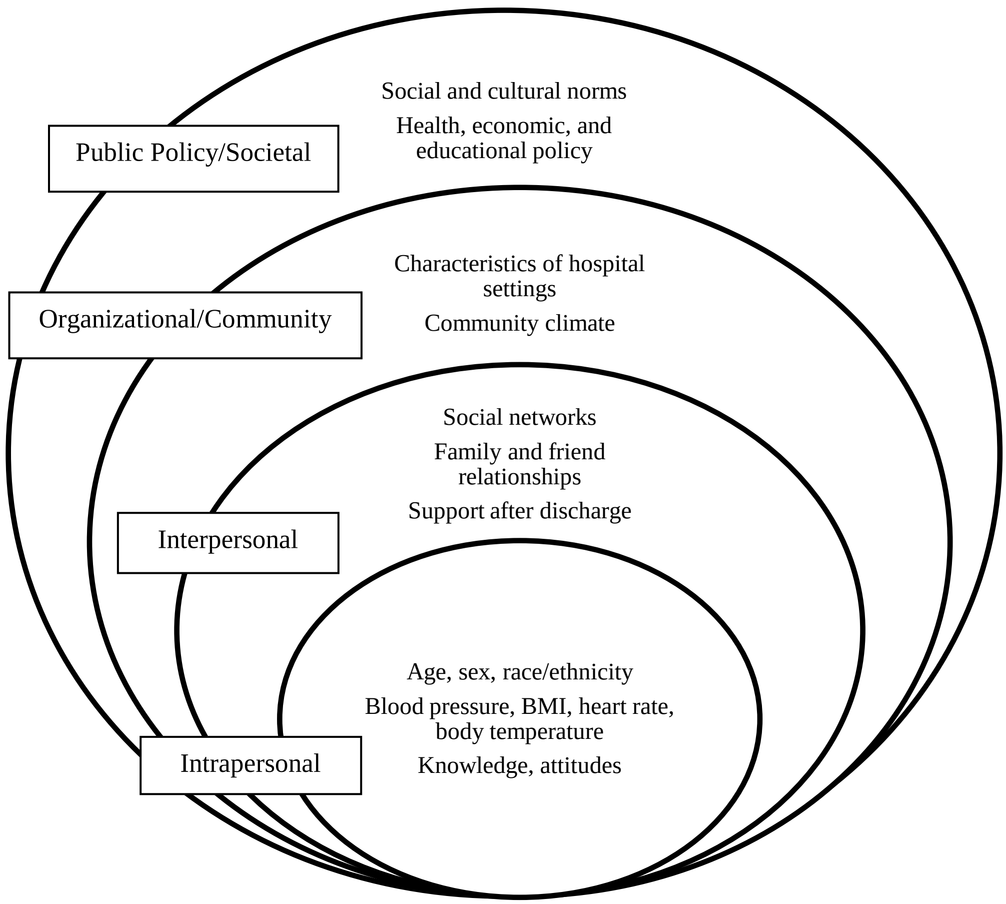

Figure 1.1 The Socio-Ecological Model as a framework for understanding risk factors of hospital readmission.

Essential Services of Public Health

Public health professionals are responsible for promoting and protecting the health of individuals and communities as well contributing to the wellness of the nation. They do this by practicing the 10 Essential Public Health Services as outlined by the National Public Health Performance Standards (Centers for Disease Control and Prevention [CDC], 2013). Public Health professionals are responsible for performing research and creating innovative solutions to public health issues. Excessive hospital readmission is a significant health issue that affects many individuals and communities and has gained national attention due the heavy economic cost associated with it. It is also the role of public health professionals to influence and create policies that ensure the health and safety of people. Socio-ecological approaches to understanding relationships among readmission risk factors allow for multiple levels of influence to be considered and thus can help better inform future policy and practice. Additionally, public health professionals can use research findings to design more comprehensive preventative measures such as tools for risk assessment and patient education programs. Using hospital readmissions research to design and implement measures to avoid unnecessary hospital readmissions is one way for public health professionals to practice and promote public health in the community.

Socio-ecological Risk Factors

Socio-ecological factors related with readmissions risk among patients should be systematically examined. Identification of these risk factors has a great potential to inform practical and sustainable solutions. The examination of factors at multiple levels of influence may in the future lead to the development of a universal scale to more formally assess readmissions risk and thus help medical professionals make decisions concerning discharge planning and the coordination of follow-up care (Sexton, 2013). Socio-ecological risk factors of hospital readmission exist within and across intrapersonal, interpersonal, organizational/community, and public policy/societal realms of a patient's life Intrapersonal factors are biological and psychological including age, sex, and race/ethnicity. Interpersonal factors are social and cultural and include the influences of the patient's close relationships. The organizational and community level emphasizes the importance of characteristics of patient care settings and the community climate. The level of support a patient has after discharge may be an interpersonal factor or an organizational factor. Public policy and societal factors are social and cultural norms, health, economic, and educational policies, as well as inequalities between groups in society. The most commonly studied socio-ecological variables which have been reported to be associated with hospital readmission are administrative variables including age, gender, ethnicity, and length of hospital stay (McHugh et al., 2010; Navarro, Enguídanos, & Wilber, 2012; Kociol et al., 2013). Administrative variables include demographic and other patient information that is commonly collected upon admission to the hospital. Administrative variables are found at the intrapersonal and organizational/community level, where the organization or community usually refers to the hospital or patient care setting. Study authors have also reported an association between clinical variables and hospital readmission, but these have not been studied extensively (Vest, Gamm, Oxford, Gonzalez, & Slawson, 2010). Clinical variables are physiological measures such as blood pressure, heart rate, and hemoglobin which are found at the intrapersonal level. There is a need for more analysis of these variables especially for those that are commonly collected in clinical practice (Navarro et al., 2012). The purpose of this study was to compare socio-ecological risk factors of hospital readmission between 30 and 60 and 30 and 90 day readmission groups in an underserved population.

Study Overview

A retrospective secondary data analysis was conducted with data from the Family Health Center's (FHC) patient electronic health records. The FHC is one of a number of acute care facilities located in central Texas that serve patients living below 200% of the federally identified poverty guidelines. In 2013, the federal poverty guideline was $11,490 for a one person household and $23,550 for a four person household (HHS, 2013). Thus, the FHC serves patients with incomes less than $22,980 for a one person household and $47,100 for a four person household. Approximately two-thirds of the populations served are racial and ethnic minorities. In 2013, 179 hospitals in Texas were financially penalized for excessive readmissions. A full list of these hospitals and their penalties can be found in Appendix A. The sample for analysis included patients who had experienced a hospital encounter within the last seven years and who had been readmitted to the hospital for any cause within 30, 60, or 90 days of the initial encounter. Differences among 30, 60, and 90 day readmission groups were assessed. Factors analyzed as correlates of hospital readmission were chosen based on previous literature and clinical judgment and included:

- Age
- Sex
- Race/ethnicity
- Systolic blood pressure
- Body mass index (BMI)
- Pulse rate
- Body temperature
- Days between hospital encounter and follow-up visit

Assumptions

The assumption is made that hospital records are accurate and readmission of patients occurred at a Central Texas medical facility.

Limitations

There are a few limitations to this study.

1. The nature of a secondary data analysis does not lend control of the data, thus the quality of data collection methods and data is not known.
2. Certain measures reported to be associated with hospital readmission in other studies are not available in the dataset. These include health literacy, mobility status, level of care

after discharge, principal diagnosis, comorbidities, and some clinical variables: creatinine, blood urea nitrogen (BUN), creatinine/BUN ratio, and hemoglobin.

3. Generalizability may be limited due to the specialized population served by the FHC.

CHAPTER TWO

Literature Review

Introduction

Excessive and preventable hospital readmissions are a significant focus of healthcare policy and research as they are common and costly. Recently the ACA has linked hospital readmission rates to Medicare reimbursement through the HRRP with hospitals in the U.S. now facing financial penalties for excessive hospital readmissions. Reducing hospital readmissions has the potential to produce nationwide improvements in quality of care and cost savings (Vest et al., 2010), though the true proportion of preventable hospital readmissions remains unclear (van Walraven et al., 2011). Aligning hospital and physician care management and practices with quality improvement, the end goal of the HRRP, requires that risk factors for readmission be identified and addressed in quality improvement practices (Cloonan et al., 2013; Navarro et al. 2012). Research has been conducted to identify a plethora of risk factors that significantly increase a patient's risk for hospital readmission. The significance of these predictive factors is still emerging. Excessive hospital readmissions have long been identified as an area of healthcare that is excessively costly (Kiefe et al., 2013). Early hospital readmissions research was driven by the depletion of health care resources and a need to reduce the cost of health care to both hospitals and patients (Vest et al., 2010). The most current research has been driven by the HRRP's focus on incentivizing hospitals and physicians to reduce readmission rates through financial penalties (Cloonan et al. 2013). A review of the literature on hospital readmissions reveals strongly supported trends among some risk factors for readmission as well inconsistent findings among other risk factors.

Significance of Hospital Readmissions Research

Those in opposition to the ACA contend that its initiatives, such as the HRRP, are not efficient or direct strategies for improving quality of care and reducing preventable, excessive readmissions. For the HRRP to be effective, the assumption must be made that if hospitals are penalized for excessive readmissions, administrative staff, physicians, and other medical personnel will be forced to deliver a higher quality of care to patients. The end result is intended to be a significant reduction in the heavy burden of medical costs and improved quality of care for patients. Although this desired reduction may occur to some extent, it has not been the end result in many acute care hospitals targeted by the HRRP (Kocher & Adashi, 2011). Hospitals and physicians may be redistributing patients to a subsection facility who would otherwise be readmitted to the hospital (Naylor et al. 2012). Additionally, this proposed solution may be leading to an avoidance of admitting patients from a special population who may be more vulnerable to readmission. For example, older adults are more likely than any other age group to have comorbidities and thus are at a higher risk of being readmitted. Kocher & Adashi (2011) suggest that hospitals may respond to this by limiting access to the elderly.

The HRRP is also meant to provide an incentive to hospitals and medical staff to better coordinate post-charge care of patients. Improving care transitions, patient education, and self-management support has been reported to be effective in reducing excessive readmissions (Sexton, 2013). However, there are many other factors that influence readmission since often readmission is unavoidable. The HRRP does not address additional factors, and thus, those in opposition to it, suggest that is not a sufficient solution. In the dawn of ACA initiatives targeted at reducing readmissions related specifically to chronic conditions, hospitals and physicians are becoming more interested in designing and implementing tools to identify those at risk for readmission (Cloonan et al., 2013). The factors that influence risk for readmission are numerous and complex. The development and use of predictive models of hospital readmission have the potential to create a more efficient, more accurate method for identifying patients at risk for preventable readmission to the hospital. Previous researchers have reported that patients with a high risk for readmission can be identified early in their hospital stay by examining multiple risk factors for readmission (Silverstein, Huanying, Mercer, Fong, & Haydar, 2008). Some of these factors include age, race/ethnicity, gender, comorbidities, commonly collected clinical variables, physical address (a proxy for quantifying SES), insurance status, and income level. These measures are known early in a patient's hospital stay, and thus risk can be assessed soon after admission. Other variables reported to be associated with readmission may be more appropriately assessed at discharge planning. These include length of hospital stay, and level of outside support or follow-up care.

The utility of predictive models such as scales that assess risk of readmission has been demonstrated by some researchers. Silverstein et al. (2008) developed and validated predictive models of hospital readmission in patients at seven acute care hospitals within the Baylor Health Care System in Dallas and Fort Worth. Patients (n=29,292; age >65) were identified through an electronic medical record database within a two year period. Readily available clinical and demographic data was used to assess risk of readmission. Validity was measured through a second patient cohort. Predictive models of 30-day readmission based on these variables were shown to be valid predictors of readmission. This type of study is useful in two ways. First, the likelihood of readmission can be determined early during the patient's hospital stay. This may help hospital staff to identify patients who will likely benefit the most from care management plans or other additional services. Second, if readmission risk is known, hospital administrators may more efficiently prioritize resources and personnel based on patient needs regarding discharge planning. This approach to reducing excessive hospital readmissions is more direct because it seeks to identify preventable readmissions by providing hospitals and physicians with a systematic way to measure patient readmission risk. Hospital personnel have a more appropriate and accurate method for providing better quality of care to patients. They know which patients need more support upon discharge, and they are able to better quantify the difference between unavoidable and preventable readmissions. Models that identify readmission risk factors have been moderately used in general patient populations in acute care hospitals and even less used in specialty populations. Eventually scales for more specific populations may be developed for patients with diagnoses targeted by the HRRP. Since predictive models are based on data commonly collected in most hospitals, the integration of such methods into clinical practice would be relatively smooth. Hospital readmissions research to identify socio-ecological risk factors of hospital readmission is essential to future development of these tools as well as to avoiding the financial penalties that are currently in place.

Major Trends in Hospital Readmissions Research

The majority of hospital readmission studies are analyses of risk factors thought to be associated with hospital readmission using medical record data collected at acute care facilities. Administrative variables (intrapersonal and organization/community level factors) have been included in the majority of analyses, while clinical variable (biological, intrapersonal level factors) are largely underrepresented. Age, gender, race/ethnicity and length of hospital stay are the most commonly examined variables. The majority of study authors report statistically significant relationships between these proposed risk factors and readmission risk. Hospital readmissions are common in all populations especially among Medicare patients (Vest et al. 2010). Early studies were performed in more general patient populations while the most current studies typically employ very specific patient populations such as patients with chronic disease. McPhee et al. (2013) assessed risk factors for 30 day readmission in patients who had infrainguinal bypass surgery for critical limb ischemia. Liotta et al. (2013) performed a similar analysis in patients who had been diagnosed with an intracerebral hemorrhage. More common are studies in patients with heart failure, acute myocardial infarction, or pneumonia, the diagnoses targeted by the HRRP (Eapen et al., 2013; Krumholz et al., 2000). Many of these studies include assessments of the same risk factors as those performed in a more general population. A large majority of studies assess risk factors for readmission within 30 days of discharge. Few studies perform analyses within 60 and 90 days of discharge. Many studies assess prior hospitalizations, usually defined as readmission within one year of discharge, as a proposed risk factor. One third of hospital readmissions occur within 30 days of discharge, one half of them occur within 90 days, and 80% occur within one year of discharge (Benbassat & Taragin, 2000). Although, there are currently no financial penalties tied to 60 and 90 day readmission, there is no consensus on the definition of readmission and readmission beyond 30 days may become a potential target of policy reform. Thus, it is important to begin examining risk factors of 60 and 90 day readmission as well as 30 day readmission.

Administrative and Demographic Risk Factors

Administrative and demographic variables are well represented in hospital readmissions studies. Risk factors consistently evaluated for associations with risk for readmission include age, gender, race/ethnicity, length of hospital stay, care after discharge, mobility status, and stage of illness (Vest et al., 2010). Moderately studied risk factors include prior hospitalization, comorbidities, and the third-party payer (usually Medicare).

An early study (Corrigan & Martin 1991) assessed the relationship between patient characteristics (age, disease stage, length of stay, prior hospitalization, and third-party payer) and likelihood of readmission at a community teaching hospital in Michigan. For analysis the sample was divided into two groups, those who survived (n=3,823) and those who died (n=396). A regression model was fit to the subsample of patients who survived using the patient's diagnostic category as a stratification variable. Increasing length of stay and increasing disease stage were found to be directly associated with increased likelihood of readmission. Prior hospitalization was the most significant predictor of subsequent hospital readmissions. Both increasing age and being a Medicare patient were directly associated with increased likelihood of readmission. However, the majority of patients, age 65 and older, were Medicare patients, and thus it was difficult to determine the true effect of age and payer. To control for this, a second model, excluding the payer variable, was analyzed. There was a direct association between increased age and likelihood of readmission.

A second early study (Reed, Pearlman, & Buchner, 1991) employed a matched case-control design with patients admitted to the Seattle Veterans Affairs Medical Center. Early readmissions, those occurring within 14 days of discharge, were known to be common at the facility. The case group consisted of patients (male; age >65) who were readmitted to the hospital within 14 days of discharge (n=155). The control group consisted of patients who were not readmitted (n=155). Cases and controls were matched by the week they were discharged. A total of 31 risk factors were analyzed as correlates of readmission, and three were found to be significantly associated with risk for readmission. Prior hospitalization (having two or more hospital readmissions within one year) was found to be a significant risk factor for readmission (OR=3.06). Any change in medication dosage within 48 hours prior to discharge was also found to be significant (OR=2.34), as was obtaining a referral for follow-up care (OR=2.78). The study authors concluded that these three risk factors are useful in identifying populations most at risk for readmission. Study authors suggest that, of the most commonly researched risk factors for hospital readmission, follow-up care after discharge is the most malleable variable.

A more recent study (McHugh et al. 2010) was a secondary data analysis from the Medicare Provider Analysis and Review (MEDPAR) file. Patients were selected if they had experienced a 30 day all-cause hospital readmission, were classified as a Medicare fee-for-service patient, and were discharged from an acute care hospital in 2008 with a principal diagnosis of heart failure (n=239,953), acute myocardial infarction (n=193,421), or pneumonia (n=350,740). Patient race was identified from MEDPAR categorical data which identifies patients as White, Black, Hispanic, Asian, North American native, other, or unknown. Data from the 2008 American Hospital Association's Annual Survey was used to link hospital characteristics to MEDPAR data. Generalized estimating equation models were used to estimate the odds of 30 day all-cause readmission based on patient race classification. Hospital characteristics and patient comorbidities were controlled for. Overall, patient readmission rates for Black and Hispanic minorities were significantly higher than that for White majority groups ($p<.01$). Table 2.1 shows the results from the generalized estimating equation models. Black patients were 9% (heart failure), 13% (AMI), and 21% (pneumonia) more likely than White patients to experience a 30 day hospital readmission. Hispanic patients with an AMI diagnosis were 20% more likely to experience a 30 day hospital readmission than White patients. Hispanic patients with a diagnosis of heart failure or pneumonia were not significantly more likely be readmitted to the hospital.

Table 2.1 Odds Ratios for Readmission based on Race

Race by condition	Odds ratio	95% Confidence interval
Heart Failure		
Black	1.09	[1.12, 1.05]
Hispanic	1.04	[0.96, 1.11]
Acute myocardial infarction		
Black	1.13	[1.18, 1.08]
Hispanic	1.20	[1.32, 1.10]
Pneumonia		
Black	1.21	[1.25, 1.17]
Hispanic	1.01	[0.94, 1.08]

Adapted from McHugh et al., 2010.

Navarro et al. (2012) performed retrospective analyses (binary logistic regression analyses and bivariate comparisons) of electronic medical records at a single hospital in California using logistic models of factors hypothesized to be associated with 30 day hospital readmission. Patients (n=6,232; µ age=78.7) with 8,298 total readmissions among them were included in the analysis. Odds ratios were reported for hierarchical models of readmission including models of sociodemographics (age, sex, race/ethnicity), clinical factors of primary diagnoses and comorbidities, and care processes. Frequencies for the selected independent variables were reported for bivariate comparisons. Age was found to be a weak risk factor of hospital readmission (OR = 0.99, 95% CI [0.98, 1.00]). Being male was significantly related with hospital readmission among patients age 65-85 (43.4%, p=.02) as was being African American (15.8%, p=.001). In patients who were readmitted to the hospital, the average number of comorbidities was slightly higher than that of patients who were not readmitted, (1.7 ±1.4, t=9.08, p<.001) and (1.3 ± 1.3) respectively. Care processes including a longer average hospital stay (µ=6.7, an average of 1.5 days longer) and a discharge of home self-care (56.7% compared to 39.1%, p<.001), home health service (28.1% compared to 19.7%, p<.001) or skilled nursing service (32.8% compared to 23.6%, p<.001) were more frequent among patients who experienced readmission.

Kaboli et al. (2012) hypothesized an inverse relationship between 30 day readmission rates and length of hospital stay in patients (n= 4,124 ,907) over a 14 year period admitted to 129 VA hospitals in the U.S. Unadjusted trends in length of stay among all patients were observed. Multivariable regression analyses were used to adjust for administrative and demographic characteristics. Study authors were not able to demonstrate that a reduction in length of stay increased risk of readmission as other studies have shown. The authors suggest that the VA health care system may have had inefficiencies in care that resulted in longer stays and thus a reduction in stay would not lead to readmission.

Fuller, Atkinson, McCullough, & Hughes (2013) identified all-cause 30 day readmissions that occurred in 164 acute care Florida hospitals. Data was drawn from all-payer claims (n=3,616,169) from the Florida Agency for Health Care Administration. Claims from 2007 (n=1,807,617) and 2008 (n=1,808,552) were used. The potentially preventable readmissions (PPRs) method, used widely by state and federal agencies, was used to identify preventable readmissions. The PPR uses administrative data to identify preventable hospital readmissions that occur due to poor quality of care. Regression analysis was used to quantify the effect of age, payer, and mental health on hospital readmissions. Medicaid payment and age were associated with a higher risk for readmission. The likelihood for readmission was found to decrease with age (0-65 years) but increase after age 65.

Clinical Risk Factors

Few study authors report on relationships among clinical variables commonly collected in clinical practice and risk for hospital readmission. Risk factors that have been evaluated include measures of blood pressure, blood urea nitrogen (BUN), creatinine, BUN/creatinine ratio, heart rate, and hemoglobin. Studies that examine physiological variables also include administrative and demographic variables (Vest et al., 2010).

Krumholz et al. (2000) identified a number of demographic and clinical risk factors for hospital readmission among heart failure patients (n=2,176; μ age = 78.9 years; 59% female; 89% White) at nine acute care hospitals in Connecticut. Two cohorts were formed, a derivation set (n=2,176) and a validation set (n=1,047). Data was obtained from medical records and entered into a computerized database. Thirty-two variables were evaluated and categorized under six groupings: demographics, medical history, admission clinical characteristics, hospital course, discharge laboratory tests, and discharge mobility. Bivariate analyses were performed to identify associations among risk factors and all-cause readmission in the derivation cohort. Cox proportional hazard models were used for the final selection of predictive risk factors. The Cochran-Armitage test for trend was used to identify associations among risk factors and all-cause readmission in the validation cohort. There was no significant difference between the derivation and validations cohorts. In the derivation cohort, 50% of patients were readmitted for heart failure. Pneumonia and myocardial infarction were also common reasons for readmission. Table 2.2 is a summarization of a selection of the numerous variables that were analyzed through the initial bivariate analyses. The strongest bivariate associations with increased risk for all-cause readmission within six months of discharge were prior medical history (heart failure, renal failure, diabetes, and prior readmission with the past year) and discharge labs (creatinine and

BUN levels). Length of stay (>4 days) and discharge mobility status were not found to be significant. Demographic variables (age, sex, and race) were not found to be statistically significant.

Table 2.2 Patient Characteristics and Risk of Readmission Among Derivation Cohort (n=1129)

Characteristics	No readmission n[%]	Readmission n[%]	P value
Demographics			
Age			
65-74	183(47)	209(53)	.03
75-84	233(48)	249(52)	
≥85	143(56)	112(44)	
Sex			
Male	219(47)	248(53)	.14
Female	340(51)	322(49)	
Race			
White	510(49)	527(51)	.45
Other	49(53)	43(47)	
Medical history			
Heart failure	311(46)	371(54)	.001
Renal failure	84(39)	131(61)	.001
Diabetes	180(44)	232(56)	.003
Readmission within 1y	244(44)	312(56)	.001
Discharge labs			
BUN >40 mg/dL	150(42)	204(58)	.001
Creatinine >2.5 mg/dL	33(29)	82(71)	.001
BUN/creatinine >20	311(48)	335(52)	.35
Discharge mobility			
Independent	324(49)	334(51)	.94
Assisted	235(50)	236(50)	

Adapted from Krumholz et al., 2000.

Tsuchihashi et al. (2001) sought to assess the significance of demographic, medical, and socio-environmental risk factors for hospital readmission. The medical records of five hospital cardiology units were queried for patients (n=230) with a primary diagnosis of congestive heart failure (CHF) from January through December of 1997. Univariate analysis was performed to compare patient characteristics between two groups, those who experienced a readmission within one year and those who did not. Variables shown to be significant through Univariate analysis (p<.05) were fit to a multiple logistic regression model. Five variables were significantly associated with hospital readmission among CHF patients: poor follow-up visits (OR= 4.9, 95% CI [2.0, 11.8]), a previous CHF hospital admission (OR= 3.3, 95% CI [1.8, 6.1]), no occupation (OR= 2.6, 95% CI [1.2, 5.5]), a longer length of stay (OR= 3.2, 95% CI [1.2, 8.5]), and hypertension (OR=2.0 95% CI [1.1, 3.7]).

Eapen et al. (2012) examined variations in length of hospital stay among heart failure patients (n=6848) at 389 sites in North America, Latin America, Europe, and Asia. There was an inverse correlation between mean length of stay (4.9-14.6 days) and 30 day hospital readmission rates (2.5%-25.0%) across all countries (P<0.01). Multivariate adjustment was used to explore the independent relationship between mean length of stay across countries and risk of all-cause readmission. It was reported that each additional day of hospital stay was associated with lower risk of heart failure readmission as well as all-cause readmission. Similar results were found across U.S. sites with mean length of stay, 6.1 days, and all-cause readmission rate, 17.8%. Although the focus of the study was on the significance of length of hospital stay, data on additional patient characteristics including measures of blood pressure, BUN, creatinine, heart rate, and hemoglobin was collected. Patients readmitted within 30 days were more likely to have lower blood pressure and hemoglobin levels and higher BUN and creatinine levels. Higher risk for readmission was also associated with prior hospitalization for heart failure within the previous year and the presence of comorbidities such as hypertension and diabetes. The authors suggest that these findings may be significant in developing quality measures of risk for readmission.

Conclusion

The majority of risk factors that have been analyzed are variables obtained from administrative data such as demographic variables that lack a clinical characteristic. Although the significance of these variables has been assessed by many study authors, evidence of the relationships between demographic variables and risk for readmission is still needed. Reed et al. (1991) reported that patients age 65 and older had the highest risk for readmission. Corrigan & Martin (1991) reported that patients between age 46 and 65 had the highest risk for readmission. Meiring et al. (1992) reported that patients older than 80 years of age were most at risk for readmission. Older patients are also more likely to be Medicare patients making it difficult determine the true effect of either. More recently, several researchers have reported race/ethnicity as a significant determinant of readmission in patients with chronic conditions (McHugh et al., 2010; Navarro et al., 2012). Others have not found race/ethnicity to be a significant determinant (Deswal, Petersen, Souchek, Ashton, & Wray, 2004). Additionally, the examination of clinical variables as correlates of readmission is underrepresented in the literature. Numerous clinical measures are collected routinely that may be significant indicators of risk for readmission such as heart rate, temperature, and blood glucose. These physiological measures have immense potential value in hospital readmissions research, but currently lack emphasis in the literature.

CHAPTER THREE

Methodology

Participants

Medical records from adult patients of the Family Health Center (FHC), a number of acute care facilities in Central Texas, were collected. All patient records were electronically stored in the Epic Systems database management system (Epic, Verona, Wisconsin), which is a commonly used system by many hospitals and clinics. The analysis included 2,191 patients (μ age=44 years; 72.5% female; 10.1% African American, 26.2% Hispanic, 63.7% White) who experienced a hospital encounter between 2006 and October 1, 2013 and who had been readmitted to the hospital for any cause within 30, 60, or 90 days of the initial encounter.

Research Design

This study was a retrospective secondary data analysis of the FHC's electronic patient records. Data collected were chosen based on previous research and the clinical judgment of the research team. They include age, sex, race/ethnicity, systolic blood pressure, body mass index (BMI), pulse rate, body temperature, and number of days between hospital encounter and follow-up visit. The purpose of this study was to compare socio-ecological risk factors associated with 60 and 90 day hospital readmission compared to 30 day readmission.

Procedures

FHC staff physicians queried the database to include patient data by first selecting patients who had experienced a hospital encounter between 2006 and October 1, 2013. Secondly the sample was narrowed to patients who were readmitted to the hospital within 0-30 days, 31-60, or 61-90 days after the patient's initial hospital encounter. For data collection, staff physicians merged the Epic Systems Corporation "Clarity" relational database management system and the business intelligence application, Crystal Reports. The merging of these two software data packages made it possible to filter and sort the data of interest. Once the final query was completed, all data was downloaded into an Excel file without patient names or any other identifying information for analysis. The data from the Excel file was transferred into the SPSS software package version 21.0 for statistical analyses (IBM, Armonk, New York). There were no risks to the patients whose data was used, and all patient information was provided to the researchers in a blinded dataset. IRB approval by Baylor University was obtained for the use of the Epic Systems database management system data (approved October 14, 2013 #523332-1).

Statistical Analysis

Relationships among the eight variables of interest (age, sex, race/ethnicity, systolic blood pressure, BMI, pulse rate, body temperature, and number of days between hospital encounter and follow-up visit) and readmission were assessed. A descriptive and graphical analysis was generated reporting frequency distributions, medians, means, and standard deviations. A multinomial analysis was conducted to allow for comparisons between 30 and 60 and 30 and 90 day readmission groups. The 30 day readmission group served as the reference category to which both the 60 and 90 day readmission groups were compared. Results of multinomial regression models were presented as odds ratios. Statistical analyses were performed using SPSS software version 21.0 (IBM, Armonk, New York).

CHAPTER FOUR

Manuscript

Risk Factors of Hospital Readmission in an Underserved Low SES Population

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Abstract

Importance Excessive hospital readmissions are costly, preventable and of increased importance based on recent changes in healthcare. The Hospital Readmissions Reduction Program, an Affordable Care Act initiative, financially penalizes hospitals for excessive readmissions in an effort to incentivize hospitals and physicians to provide higher quality patient care. Risk factors of hospital readmission have been identified, but only within a 30 day readmission window. Low income patients have a greater readmission risk, yet few studies have examined risk factors within underserved populations.

Objective To compare risk factors of hospital readmission between 30 and 60 and 30 and 90 day readmission groups in an underserved low SES population.

Design A retrospective secondary data analysis of medical records for 2,191 patients.

Setting A central Texas acute health and primary care facility.

Participants Low income patients (μ age=44 years; 72.5% female; 10.1% African American, 26.2% Hispanic, 63.7% White) who experienced a 30, 60, or 90 day readmission to the hospital.

Main Outcomes and Measures Descriptive statistics by readmission group for age, race/ethnicity, and sex. Odds ratios and confidence intervals for multinomial regression analysis of a 30-60 day comparison and of a 30-90 day comparison.

Results Days between hospital encounter and follow-up visit was associated with readmission risk in both the 30-60 day comparison (OR=1.051) and the 30-90 day comparison (OR=1.081). The female sex was associated with readmission risk in the 30-90 day comparison (OR=1.535).

Conclusion and Relevance Readmission risk did not differ considerably between 30 and 60 day readmission groups or 30 and 90 day readmission groups. Future research should identify differences between readmitted patients and non-readmitted patients.

The U.S. has become focused on identifying areas of healthcare that are associated with excessive cost, have a large potential for saving resources, and are largely preventable[1]. Excessive hospital readmission has been identified as a possible means of controlling costs and saving resources[2]. Improving quality of patient care and minimizing inappropriate and unnecessary care of hospital patients is an important focus of the Patient Protection and Affordable Care Act with several initiatives that attempt to meet this difficult challenge through a focus on reducing hospital readmissions[3]. This strategy is based on the premise that costs can be controlled through laws that demand health care providers deliver a higher quality of care[4]. Initiatives such as the Hospital Readmissions Reduction Program (HRRP) have the potential to substantially impact reimbursements to hospitals as well as quality of patient care [5]. Under the HRRP, Medicare payments to acute care hospitals are reduced based on a calculated readmission payment adjustment factor. In 2013, reimbursement payments were decreased based on that calculation or capped at 1%. In 2014, the penalty cap was raised to 2%, and by 2015, the reimbursement penalty will be capped at 3%. Readmission rates are based on three specific diagnoses: myocardial infarction, heart failure, and pneumonia and are measured over a three year period[2]. In 2013, payment reductions were based on readmission data from July 1, 2008 through June 30, 2011, and over 2,000 hospitals across the U.S. were penalized, together forfeiting $280 million dollars[6]. Hospitals must seek to reduce unnecessary readmissions to avoid penalties and to ensure that patients are receiving the most appropriate, highest quality of care possible[5].

Under the HRRP, a hospital is judged less favorably and penalized when the number of hospital readmissions is higher than the national average[2]. However, physicians suggest that readmission is not always an accurate indicator of poor quality of care especially among chronic disease patients as readmission is frequently unaviodable[7]. The true proportion of preventable hospital readmissions remains unclear [8]. Aligning hospital and physician care management and practices with quality improvement, the end goal of the HRRP, requires that risk factors for readmission be identified and addressed in quality improvement practices[1,9].

Numerous risk factors have been reported to be significantly associated with a patient's readmission risk with the significance of these factors still emerging. Demographic variables such as age, sex, and race/ethnicity are among the most commonly examined variables[10]. McHugh et al. (2010) reported race as a significant correlate of readmission among heart failure, acute myocardial infarction (AMI), and pneumonia patients. Black patients were 9% (heart failure), 13% (AMI), and 21% (pneumonia) more likely than White patients to experience a 30 day hospital readmission. Hispanic patients with an AMI diagnosis were 20% more likely to experience a 30 day hospital readmission than White patients. Navarro et al. (2012) found age to be a weak risk factor of hospital readmission (OR = 0.99, 95% CI [0.98, 1.00]). Being male was significantly related with hospital readmission among patients age 65-85 (43.4%, p=.02) as was being African American (15.8%, p=.001). Other study authors have found evidence to refute associations between demographic variables and readmission risk[10].

Clinical variables lack emphasis in current literature, but should be included in future research as they are commonly collected in clinical practice and have been reported to be significantly associated with readmission risk. Eapen et al. (2012) reported that patients readmitted within 30 days were more likely to have lower blood pressure and hemoglobin levels and higher blood urea nitrogen (BUN) and creatinine levels. Pulse rate was examined but not found to be significant. Further evidence of the relationships between these key proposed risk factors and readmission risk is needed.

Research has largely focused on 30 day hospital readmissions[1,12,13]. Few studies examine 60 and 90 day readmissions. Currently, there are no financial penalties tied to 60 and 90 day readmission rates; however, there is no consensus as to how readmission should be defined. Two thirds of hospital readmissions occur outside the 30 day readmissions window[14]. Thus, 60 and 90 day readmissions may become potential targets of policy reform. Additionally, low socioeconomic patients are at a greater risk for readmission[6], yet few studies have been conducted in an underserved population. The purpose of this study was to compare risk factors of hospital readmission between 30 and 60 and 30 and 90 day readmission groups in an underserved low-socioeconomic population.

Methods

Data Collection

Data was obtained from patient medical records electronically stored in the Epic Systems database management system, a commonly used system by many hospitals and clinics. Medical data was acquired for patients (≥13 years of age) who were admitted to the hospital between 2006 and October 1, 2013 and who had been readmitted to the hospital for any cause within 30, 60, or 90 days of their initial hospital encounter. All patient information was deidentified and encrypted. This study was approved by the appropriate University Institutional Review Board.

Participants

Data was from patients from twelve acute and primary care facilities (PCF) in the Central Texas area that had been readmitted to a hospital in the Central Texas area and had been readmitted for any cause in 30, 60, and 90 days post discharge. The PCF are federally qualified clinics serving patients living below 200% of the federally identified poverty guideline. In 2013, the federal poverty guideline was $11,490 for a one person household and $23,550 for a four person household[15]. The final sample for analysis included 2,191 patients (μ age=44 years; 72.5% female; 10.1% African American, 26.2% Hispanic, 63.7% White).

Proposed risk factors of hospital readmission were chosen based on previous literature and clinical judgment[10,13]. Patient demographic variables collected included sex, race/ethnicity, and age at the time of the initial hospital encounter. Race and ethnicity were self-reported upon admission to the hospital with preselected options based on federal government classification standards[16]. Clinical variables collected included body mass index (BMI), systolic blood pressure, pulse rate, body temperature, and number of days between patient's initial hospital encounter and a follow-up visit to the PCF. The most recent clinical measures were pulled from either the initial hospital encounter or a follow-up visit.

Data Analysis

Relationships among the variables of interest between 30 and 60 and 30 and 90 days were assessed (N=2,191). Descriptive and graphical analyses by readmission group were generated reporting frequency distributions for sex and race/ethnicity and mean, median, and standard deviation for age, days to follow-up, BMI, systolic blood pressure, body temperature, and pulse rate. Bivariate correlations among age, days to follow-up, BMI, systolic blood pressure, body temperature, and pulse rate were calculated. Cross tabulation was performed for sex and race/ethnicity. A multinomial regression analysis was conducted to allow for comparisons of both demographic and clinical variables among the 30, 60, and 90 day readmission groups. The 30 day readmission group served as the reference category to which both the 60 and 90 day readmission groups were compared. Odds ratios and confidence intervals were calculated. Statistical analyses were performed in SPSS software version 21.0 (IBM, Armonk, New York).

Results

The majority of patients were female (72.5%) and White, non-Hispanic (63.7%) while 26.2% were Hispanic and 10.1% were African American. The frequencies of sex and race/ethnicity by readmission group are shown in Table 4.1. The mean age of patients was 44.45 years (SD, 19.058) for all groups combined. Table 4.2 reports the mean, median, and standard deviation of age, days to follow-up, BMI, systolic blood pressure, body temperature, and pulse rate by readmission group. Results of bivariate correlations and cross tabulation are shown in Appendix B

There were a total of 2,191 readmissions (60.2% 30 day; 24.7% 60 day; 15.1% 90 day). Results of the multinomial regression analysis are shown in Table 4.4. For the 30- 60 day comparison: The 95% confidence interval for the odds ratio for age was .997 to 1.011. For a one year increase in age, the odds of readmission increases by 1.004. The 95% confidence interval for the odds ratio of days to follow-up was 1.040 to 1.062. For each additional day between the initial hospital encounter and a follow-up visit, the odds in readmission increases by 1.051. The 95% confidence interval for the odds ratio of BMI was .995 to 1.004. For a one unit increase in BMI, the odds in readmission remains the same (OR=1.000). The 95% confidence interval for the odds ratio of systolic blood pressure was .993 to 1.005. For a one unit increase in systolic blood pressure, the odds in readmission increases by .999. The 95% confidence interval for body temperature was .828 to 1.159. For a one unit increase in body temperature, the odds in readmission increased by .980. The 95% confidence interval for the odds ratio of pulse rate was .998 to 1.013. For a one unit increase in pulse, the odds in readmission increases by 1.005. The 95% confidence interval for the odds ratio of female sex was .797 to 1.383. For a one unit change in sex, the odds in readmission increases by 1.050. The 95% confidence interval for the odds ratio of African American was .492 to 1.156. For a one unit change in race (from White to African American), the odds in readmission increases by .754. The 95% confidence interval for the odds ratio of Hispanic was .592 to 1.024. For a one unit change in race (from White to Hispanic), the odds in readmission increases by .799.

Table 4.1 Frequencies of Categorical Variables by Readmission Group

Readmission Group		Frequency	Percent
	Race/ethnicity		
	African American	136	10.3
	Hispanic	373	28.3
	White	809	61.4
30 day readmit	Total	1318	100
N=1318	Sex		
	Female	954	72.4
	Male	364	27.6
	Total	1318	100
	Race/ethnicity		
	African American	49	9.0
	Hispanic	131	24.2
	White	362	66.8
60 day readmit	Total	542	100
N=542	Sex		
	Female	387	71.4
	Male	155	28.6
	Total	542	100
	Race/ethnicity		
	African American	37	11.2
	Hispanic	69	20.8
	White	255	68.0
90 day readmit	Total	331	100
N=331	Sex		
	Female	248	74.9
	Male	83	25.1
	Total	331	100
	Race/ethnicity		
	African American	222	10.1
	Hispanic	573	26.2
Total readmit	White	1396	63.7
N=2191	Total	2191	100.0
	Sex		
	Female	1586	72.5
	Male	602	27.5
	Total	2191	100.0

Table 4.2 Descriptive Statistics for Clinical Variables by Readmission Group

Readmission group		Mean	Median	Standard deviation
30 day readmit N=1318	Age	44.07	41.00	19.285
	Days to follow-up	2.97	3.00	11.931
	BMI	33.00	29.69	58.482
	Systolic BP	127.71	126.00	20.529
	Temperature	97.98	97.90	.717
	Pulse	85.37	84.00	15.274
60 day readmit N=524	Age	45.19	44.50	19.161
	Days to follow-up	10.31	9.00	12.678
	BMI	31.63	29.82	9.534
	Systolic BP	127.05	126.00	19.125
	Temperature	98.00	98.00	.681
	Pulse	86.32	85.00	16.476
90 day readmit N=331	Age	44.75	44.00	17.963
	Days to follow-up	15.98	11.00	17.228
	BMI	31.89	30.52	9.166
	Systolic BP	128.93	126.00	20.825
	Temperature	97.96	97.90.	.693
	Pulse	86.09	85.00	15.827
Total readmit N=2191	Age	44.45	43.00	19.058
	Days to follow-up	6.93	6.00	14.044
	BMI	32.48	29.86	45.218
	Systolic BP	127.75	126.00	20.237
	Temperature	97.98	97.90	.704
	Pulse	85.72	84.00	15.664

For the 30-90 day comparison: The 95% confidence interval for the odds ratio for age was .994 to 1.011. For a one year increase in age, the odds in readmission increases by 1.003. The 95% confidence interval for the odds ratio of days to follow-up was 1.069 to 1.094. For each additional day between the initial hospital encounter and a follow-up visit, the odds in readmission increases by 1.081. The 95% confidence interval for the odds ratio of BMI was .996 to 1.005. For a one unit increase in BMI, the odds in readmission remains the same (OR=1.000). The 95% confidence interval for the odds ratio of systolic blood pressure was .998 to 1.012. For a one unit increase in systolic blood pressure, the odds in readmission increases by1.005. The 95% confidence interval for body temperature was .728 to 1.095. For a one unit increase in body temperature, the odds in readmission increased by .839. The 95% confidence interval for the odds ratio of pulse rate was .995 to 1.013. For a one unit increase in pulse, the odds in readmission increases by 1.004. The 95% confidence interval for the odds ratio of female sex was 1.088 to 2.167. For a one unit change in sex, the odds in readmission increases by .754. The 95% confidence interval for the odds ratio of African American was .602 to 1.552. For a one unit change in race (from White to African American), the odds in readmission increases by .966. The 95% confidence interval for the odds ratio of Hispanic was .471 to .933. For a one unit change in race (from White to Hispanic), the odds in readmission increases by .633.

Table 4.3 Results of Multinomial Regression

Readmission group[a]		B	Std. Error	Sig	Odds Ratio	95% Confidence Interval for odds ratio Lower Bound	Upper Bound
60 day readmit	Age	.004	.003	.265	1.004	.997	1.011
	Days to follow-up	.050	.005	.000	1.051	1.040	1.062
	BMI	.000	.002	.856	1.000	.995	1.004
	Systolic BP	-.001	.003	.655	.999	.993	1.005
	Temperature	-.020	.086	.812	.980	.828	1.159
	Pulse	.005	.004	.178	1.005	.998	1.013
	<u>Sex</u>						
	Female	.049	.141	.727	1.050	.797	1.383
	Male	0[b]	.	.	.	.	.
	<u>Race/ethnicity</u>						
	African American	-.282	.218	.195	.754	.492	1.156
	Hispanic	-.250	.140	.074	.799	.592	1.024
	White	0[b]	.	.	.	.	.
90 day readmit	Age	.003	.004	.519	1.003	.994	1.011
	Days to follow-up	.078	.006	.000	1.081	1.069	1.094
	BMI	.000	.002	.937	1.000	.996	1.005
	Systolic BP	.005	.004	.155	1.005	.998	1.012
	Temperature	-.114	.104	.277	.893	.728	1.095
	Pulse	.004	.005	.412	1.004	.995	1.013
	<u>Sex</u>						
	Female	.429	.176	.015	1.535	1.088	2.167
	Male	0[b]	.	.	.	.	.
	<u>Race/ethnicity</u>						
	African American	-.034	.242	.887	.966	.602	1.552
	Hispanic	-.411	.174	.019	.663	.471	.933
	White	0[b]	.	.	.	.	.

[a]The reference category is 30 day readmissions.
[b]This parameter is set to zero because it is redundant.

Discussion

Excessive hospital readmission is a significant public health issue responsible for $15 billion dollars a year in excess cost to Medicare. The Medicare Payment Advisory Commission reports that 75% of these hospital readmissions are preventable[17]. Thus, controlling costs and improving the quality of patient care by financially penalizing hospitals for excessive hospital readmissions is a significant focus of the Affordable Care Act[2]. Many hospitals have become involved in efforts to identify and reduce preventable hospital readmissions, yet readmission rates have not declined significantly[1]. Numerous demographic and clinical factors have been examined for associations to the odds in readmission with few studies tracking risk factors beyond 30 days. Therefore, the purpose of this study was to compare risk factors of hospital readmission between 30 and 60 and 30 and 90 day readmission groups in an underserved low SES population.

Differences in risk factors did not increase considerably between the 30 and 60 day readmission group or between the 30 and 90 day readmission group. However, two risk factors, days to follow-up and sex, emerged when conducting odds ratio calculations and were found to be associated with 60 or 90 day readmission compared to 30 day readmission. A longer period of time between the initial hospital encounter and a follow-up visit was associated with both 60 and 90 day readmission when compared to 30 day readmission. Our study suggests if a patient is not readmitted after 30 days, their 60 and 90 day odds in readmission will slightly increase (OR=1.051 and 1.081 respectively) with each additional day between the initial hospital encounter and a follow-up visit. This may be significant when the time frame for which the odds ratio was calculated is considered. If the odds in readmission increases slightly with each additional day between the initial hospital encounter and a follow-up visit then the odds in readmission increases considerably with a ten day difference in days to follow-up. Additionally, this variable is likely one of the most malleable variables. A follow-up visit can be considered a form of support following discharge which other studies have found to be significantly associated with preventing readmission[18]. There are numerous strategies that physicians and hospitals can use to increase the level of support a patient has upon discharge such as making follow-up phone calls, providing patient education, and improving patient care transitions from the hospital to another setting. Furthermore, patients who have experienced a prior readmission are more likely to incur subsequent readmissions that may occur within 60 or 90 days or even within one year. Thus, it is important to examine factors associated with readmission periods beyond 30 days.

An interesting finding occurred regarding sex. Females were less likely to be readmitted within 30 days and more likely to be readmitted with 90 days (OR=1.535) suggesting an important consideration of 30 day discharge is sex and specifically higher risk for males. Our study findings partially agree with the literature as study authors have reported equivocal findings between sex and readmission risk[10].

There were some limitations to this study. The nature of a secondary data analysis did not lend control of the data, thus the quality of data collection methods is not known. Previously examined risk factors of hospital readmission that were reported as significant including principle diagnosis and existing comorbidities were not available in this dataset. Generalizability may be limited due to the specialized population served by a federally qualified health facility. Future research should incorporate variables that are commonly recorded for all patients. Differences not only across 30, 60, and 90 day readmission groups but also between readmission groups and groups that were not readmitted or readmitted after 90 days should be identified. Our study suggests that risk factors identified at 30 days are similar to those at 60 and 90 days, with the exception of days to follow-up and sex, and tracking readmission between 31-90 days may not be of much value. This study has implications for clinical practice as it revealed that the odds in readmission increases as the number of days between the initial hospital encounter and a follow-up visit increases. Previous studies have shown that hospitals with higher timely follow-up rates have lower 30 day readmission rates[18]. Our study suggests that scheduling a follow-up visit soon after the initial hospital stay is an effective strategy in preventing readmission. Our study also suggests that males are at a greater risk for 30 day readmission than females. However, the underlying causes of this finding should be further investigated. Having a better understanding of the relationships that exist between demographic and clinical patient characteristics and the odds in readmission can help inform future policy and practice.

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APPENDIX

Appendix A

2013 Medicare Readmission Penalties for Texas Hospitals

**Hospitals penalized in the Waco, TX region*

Hospital Name	City in Texas	Hospital Referral Region	Readmission Penalty
Abilene Regional Medical Center	Abilene	Abilene, TX	0.32%
Anson General Hospital	Anson	Abilene, TX	0.23%
Baylor Medical Center at Carrollton	Carrollton	Dallas, TX	0.13%
Baylor Medical Center at Irving	Irving	Dallas, TX	0.31%
Baylor Regional Medical Center at Grapevine	Grapevine	Dallas, TX	0.32%
Bayshore Medical Center	Pasadena	Houston, TX	0.01%
Bellville General Hospital	Bellville	Houston, TX	0.54%
Bowie Memorial Hospital	Bowie	Wichita Falls, TX	0.65%
Brownsville Surgical Hospital	Brownsville	Harlingen, TX	0.14%
Cedar Park Regional Medical Center	Cedar Park	Austin, TX	0.88%
Centennial Medical Center	Frisco	Dallas, TX	0.38%
Childress Regional Medical Center	Childress	Amarillo, TX	0.30%
Christus Hospital	Beaumont	Beaumont, TX	0.08%
Christus Spohn Hospital Alice	Alice	Corpus Christi, TX	0.58%
Christus Spohn Hospital Corpus Christi	Corpus Christi	Corpus Christi, TX	0.01%
Christus Spohn Hospital Kleberg	Kingsville	Corpus Christi, TX	0.36%
Christus St. Catherine Hospital	Katy	Houston, TX	0.57%
Christus St. John Hospital	Nassau Bay	Houston, TX	0.36%
Christus St. Michael Health System	Texarkana	Texarkana, AR	0.21%
Clear Lake Regional Medical Center	Webster	Houston, TX	0.18%
Cleveland Regional Medical Center	Cleveland	Houston, TX	0.85%
Cogdell Memorial Hospital	Snyder	Lubbock, TX	0.02%
Colorado Fayette Medical Center	Weimar	Houston, TX	0.76%
Columbus Community Hospital	Columbus	Houston, TX	0.38%
Comanche County Medical Center	Comanche	Abilene, TX	1.00%
Community General Hospital	Dilley	San Antonio, TX	0.01%
Connally Memorial Medical Center	Floresville	San Antonio, TX	0.09%
Conroe Regional Medical Center	Conroe	Houston, TX	0.75%

Corpus Christi Medical Center, The	Corpus Christi	Corpus Christi, TX	0.58%
Covenant Hospital Levelland	Levelland	Lubbock, TX	0.30%
Covenant Hospital Plainview	Plainview	Lubbock, TX	0.76%
Cozby Germany Hospital	Grand Saline	Tyler, TX	0.47%
Cuero Community Hospital	Cuero	Victoria, TX	0.84%
Cypress Fairbanks Medical Center	Houston	Houston, TX	0.05%
Dallas Medical Center	Dallas	Dallas, TX	0.34%
Dallas Regional Medical Center	Mesquite	Dallas, TX	1.00%
Denton Regional Medical Center	Denton	Dallas, TX	0.11%
Detar Hospital Navarro	Victoria	Victoria, TX	0.07%
Dimmit County Memorial Hospital	Carrizo Springs	San Antonio, TX	1.00%
Doctors Hospital	Bridgeport	Dallas, TX	0.30%
Doctors Hospital	Dallas	Dallas, TX	0.02%
Doctors Hospital at Renaissance	Edinburg	McAllen, TX	0.02%
Doctors Hospital of Laredo	Laredo	San Antonio, TX	1.00%
Doctors Hospital Tidwell	Houston	Houston, TX	0.04%
East El Paso Physicians Medical Center, LLC	El Paso	El Paso, TX	0.31%
East Texas Medical Center	Tyler	Tyler, TX	0.14%
**East Texas Medical Center Fairfield*	*Fairfield*	*Waco, TX*	*0.83%*
East Texas Medical Center Athens	Athens	Dallas, TX	0.30%
East Texas Medical Center Crockett	Crockett	Tyler, TX	0.73%
East Texas Medical Center Jacksonville	Jacksonville	Tyler, TX	0.95%
East Texas Medical Center Mount Vernon	Mount Vernon	Tyler, TX	0.25%
East Texas Medical Center Trinity	Trinity	Houston, TX	0.55%
Eastland Memorial Hospital	Eastland	Abilene, TX	0.21%
El Campo Memorial Hospital	El Campo	Houston, TX	0.65%
Ennis Regional Medical Center	Ennis	Dallas, TX	0.85%
ETMC Carthage	Carthage	Shreveport, LA	0.22%
ETMC Clarksville	Clarksville	Dallas, TX	1.00%
ETMC Henderson	Henderson	Tyler, TX	1.00%
Faith Community Hospital	Jacksboro	Wichita Falls, TX	0.07%
**Falls Community Hospital and Clinic*	*Marlin*	*Waco, TX*	*1.00%*
Good Shepard Medical Center	Longview	Longview, TX	0.48%
Good Shepard Medical Center Marshall	Marshall	Shreveport, LA	1.00%
**Good Witcher Hospital*	*Clifton*	*Waco, TX*	*0.27%*
Graham Regional Medical Center	Graham	Fort Worth, TX	0.24%
Guadalupe Regional Medical Center	Seguin	San Antonito, TX	0.01%
Gulf Coast Medical Center	Wharton	Houston, TX	0.07%

**Hamilton General Hospital*	*Hamilton*	*Waco, TX*	*0.56%*
Harlingen Medical Center	Harlingen	Harlingen, TX	0.19%
Harris County Hospital District	Houston	Houston, TX	0.21%
Heart Hospital of Austin	Austin	Data not available	0.05%
**Hill Regional Hospital*	*Hillsboro*	*Waco, TX*	*0.04%*
**Hillcrest Baptist Medical Center*	*Waco*	*Waco, TX*	*0.04%*
Huguley Health System	Fort Worth	Fort Worth, TX	0.15%
Hunt Regional Medical Center	Greenville	Dallas, TX	0.13%
Huntsville Memorial Hospital	Huntsville	Houston, TX	0.03%
JPS Health Network	Fort Worth	Fort Worth, TX	0.07%
Kingwood Medical Center	Kingwood	Houston, TX	0.22%
Knapp Medical Center	Weslaco	Harlingen, TX	0.07%
Lake Pointe Medical Center	Rowlett	Dallas, TX	0.25%
Laredo Medical Center	Laredo	San Antonio, TX	0.65%
Las Colinas Medical Center	Irving	Dallas, TX	0.15%
Las Palmas Medical Center	El Paso	El Paso, TX	0.12%
Longview Regional Medical Center	Longview	Longview, TX	0.09%
Mainland Medical Center	Texas City	Houston, TX	0.51%
Matagorda Regional Medical Center	Bay City	Houston, TX	0.37%
Medical Center of Arlington	Arlington	Fort Worth, TX	0.66%
Medical Center of Lewisville	Lewisville	Dallas, TX	0.45%
Medical Center of McKinney	McKinney	Dallas, TX	0.36%
Medical Center of Plano	Plano	Dallas, TX	0.21%
Medical City Dallas Hospital	Dallas	Dallas, TX	0.14%
Memorial Health System of East Texas Lufkin	Lufkin	Houston, TX	0.10%
Memorial Herman Baptist Beaumont Hospital	Beaumont	Beaumont, TX	0.16%
Memorial Herman Baptist Orange Hospital	Orange	Beaumont, TX	0.17%
Memorial Hermann Katy Hospital	Katy	Houston, TX	0.11%
Memorial Herman Northeast	Humble	Houston, TX	0.18%
Memorial Herman Sugar Land Hospital	Sugar Land	Houston, TX	0.18%
Memorial Hospital	Nacogdoches	Houston, TX	1.00%
Memorial Medical Center Livingston	Livingston	Houston, TX	0.26%
Methodist Charlton Medical Center	Dallas	Dallas, TX	0.08%
Methodist Dallas Medical Center	Dallas	Dallas, TX	0.22%
Methodist Mansfield Medical Center	Mansfield	Fort Worth, TX	0.11%
Methodist Richardson Medical Center	Richardson	Dallas, TX	0.12%
Methodist Stone Oak Hospital	San Antonio	San Antonio, TX	0.20%
Methodist Sugar Land Hospital	Sugar Land	Houston, TX	0.12%

Metroplex Hospital	Killeen	Temple, TX	0.33%
Mission Regional Medical Center	Mission	McAllen, TX	0.68%
Nacogdoches Medical Center	Nacogdoches	Houston, TX	0.23%
Navarro Regional Hospital	Corsicana	Dallas, TX	0.21%
Nix Health Care System	San Antonio	San Antonio, TX	0.01%
North Austin Medical Center	Austin	Austin, TX	0.02%
North Hills Hospital	North Richland Hills	Fort Worth, TX	0.02%
North Texas Medical Center	Gainesville	Dallas, TX	0.11%
Oakbend Medical Center	Richmond	Houston, TX	0.12%
Odessa Regional Hospital	Odessa	Odessa, TX	0.58%
Palestine Regional Medical Center	Palestine	Tyler, TX	0.10%
Palo Pinto General Hospital	Mineral Wells	Fort Worth, TX	0.14%
Pampa Regional Medical Center	Pampa	Amarillo, TX	0.44%
Paris Regional Medical Center	Paris	Dallas, TX	0.30%
Parkland Health and Hospital System	Dallas	Dallas, TX	0.03%
Parkview Regional Hospital	Mexia	Waco, TX	1.00%
Pecos County Memorial Hospital	Fort Stockton	Odessa, TX	0.21%
Plaza Medical Center of Fort Worth	Fort Worth	Fort Worth, TX	0.30%
**Providence Health Center*	*Waco*	*Waco, TX*	*0.01%*
Providence Memorial Hospital	El Paso	El Paso, TX	0.13%
Renaissance Hospital Terrell	Terrell	Dallas, TX	0.17%
Rio Grande Regional Hospital	McAllen	McAllen, TX	0.30%
Rolling Plains Memorial Hospital	Sweetwater	Abilene, TX	0.13%
San Angelo Community Medical Center	San Angelo	San Angelo, TX	0.38%
Scenic Mountain Medical Center	Big Springs	Lubbock, TX	0.44%
Scott & White Memorial Hospital	Temple	Temple, TX	0.14%
Seton Northwest Hospital	Austin	Austin, TX	0.05%
Seton Medical Center Austin	Austin	Austin, TX	0.36%
Seton Medical Center Hays	Kyle	Austin, TX	0.56%
Seton Medical Center Williamson	Round Rock	Austin, TX	0.07%
Seton Smithville Regional Hospital	Smithville	Austin, TX	0.06%
Seton Southwest Hospital	Austin	Austin, TX	0.04%
Shelby Regional Medical Center	Center	Houston, TX	0.81%
Sierra Medical Center	El Paso	El Paso, TX	0.05%
Sierra Providence East Medical Center	El Paso	El Paso, TX	0.23%
South Texas Health System	Edinburg	McAllen, TX	0.43%
Southwest General Hospital	San Antonio	San Antonio, TX	0.06%
Springs Branch Medical Center	Houston	Houston, TX	0.10%

St. Joseph Medical Center	Houston	Houston, TX	0.26%
St. Joseph Regional Health Center	Bryan	Bryan, TX	0.07%
St. Marks Medical Center	La Grange	Houston, TX	0.60%
Stamford Memorial Hospital	Stamford	Abilene, TX	0.55%
Starr County Memorial Hospital	Rio Grande City	McAllen, TX	1.00%
Texas Health Arlington Memorial Hospital	Arlington	Fort Worth, TX	0.23%
Texas Health Harris Methodist Forth Worth	Fort Worth	Fort Worth, TX	0.62%
Texas Health Harris Methodist Hospital Cleburne	Cleburne	Fort Worth, TX	0.22%
Texas Heath Harris Methodist Hospital Southwest Fort Worth	Fort Worth	Fort Worth, TX	0.01%
Texas Health Presbyterian Hospital Dallas	Dallas	Dallas, TX	0.56%
Texas Health Presbyterian Hospital Allen	Allen	Dallas, TX	0.28%
Texas Health Presbyterian Hospital Denton	Denton	Dallas, TX	0.78%
Texas Health Presbyterian Hospital Flower Mound	Flower Mound	Dallas, TX	0.10%
Texas Health Presbyterian Plano	Plano	Dallas, TX	0.22%
Texas Health Presbyterian Rockwall	Rockwall	Dallas, TX	0.60%
Texas Health Presbyterian WNJ	Sherman	Dallas, TX	0.09%
Texas Regional Medical Center at Sunnyvale	Sunnyvale	Dallas, TX	0.22%
Texoma Medical Center	Denison	Dallas, TX	0.44%
Texsan Heart Hospital	San Antonio	San Antonio, TX	0.31%
Tomball Regional Medical Center	Tomball	Houston, TX	0.11%
Trinity Medical Center	Brenham	Houston, TX	0.09%
Trustpoint Hospital	Lubbock	Lubbock, TX	0.18%
Tyler County Hospital	Woodville	Beaumont, TX	0.49%
United Regional Health Care Center	Wichita Falls	Wichita Falls, TX	0.02%
University Health System	San Antonio	San Antonia, TX	0.04%
University Medical Center	Lubbock	Lubbock, TX	0.39%
University Medical Center at Brackenridge	Austin	Austin, TX	0.12%
University of Texas Health Science Center at Tyler	Tyler	Tyler, TX	0.19%
University of Texas Medical Brach Galveston	Galveston	Houston, TX	0.06%
Uvalde Memorial Hospital	Uvalde	San Antonio, TX	1.00%
Val Verde Regional Medical Center	Del Rio	San Antonio, TX	0.08%
Valley Regional Medical Center	Brownsville	Harlingen, TX	0.83%
VHS Brownsville Hospital Company, LLC	Brownsville	Harlingen, TX	0.75%
VHS Harlingen Hospital Company LLC	Harlingen	Harlingen, TX	0.84%
Wadley Regional Medical Center	Texarkana	Texarkana, AR	0.45%
Wise Regional Health System	Decatur	Dallas, TX	0.19%
Woodland Heights Medical Center	Lufkin	Houston, TX	0.32%

Adapted from Kaiser Health News analysis of data from Centers for Medicare & Medicaid Services

Note: Hospitals with fewer than 25 cases in each of three categories (heart failure, heart attack, pneumonia) were exempt.

Appendix B

Additional Descriptive Statistics

Bivariate Correlations

		Age	Days to follow-up	BMI	Systolic BP	Temperature	Pulse
Age	Pearson	1	.055*	.027	.184**	.032	-.142**
	Significance		0.18	.240	.000	.169	.000
	N	2191	1833	1861	1871	1870	1869
Days to follow-up	Pearson	.055*	1	-.052*	-.021	.018	-.009
	Significance	0.18		0.33	.368	.445	.691
	N	1833	1833	1694	1833	1831	1833
BMI	Pearson	.027	-.052*	1	.093**	-.022	.011
	Significance	.240	.033		.000	.356	.643
	N	1861	1695	1861	1730	1729	1728
Systolic BP	Pearson	.184**	-.021	.093**	1	.006	-.014
	Significance	.000	.368	.000		.791	.532
	N	1871	1833	1730	1871	1869	1869
Temperature	Pearson	.032	.018	-.022	.006	1	.084**
	Significance	.169	.445	.356	.791		.000
	N	1870	1831	1729	1869	1870	1867
Pulse	Pearson	-.142**	-.009	.011	-.014	.084**	1
	Significance	.000	.691	.643	.532	.000	
	N	1869	1833	1728	1869	1867	1869

*Correlation is significant at the .05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Cross Tabulation for Categorical Variables

	Race/ethnicity			
	African American	Hispanic	White	Total
Sex Female	151	416	1022	1589
Male	71	157	374	602
Total	222	573	1396	2191

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