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Sociodemographic Characteristics of Heart Failure Associated Hospital Readmissions in Michigan Medicare Patients

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Michigan Medicare Patients

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Dedication

To my parents William and Linda, and my sister Kailey. Thank you for your continual support, words of encouragement, hours of editing, and weeks of insight to my research. Thank you for being my sounding-board and for all of the advice you gave on the relevance and importance of this research. I am forever grateful for all of your support and help throughout this process. And thank you to my little sister for not letting me forget that the world continues to exist outside of my research and for always being able to put a smile on my face.

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Abstract

Repeated hospital admissions constitute a large proportion of healthcare expenses, but are incurred by a small minority of chronically ill patients. Rising healthcare expenditures and the link between readmissions and quality of care make readmission rates a high priority for clinicians as well as insurance payers. Though hospital readmissions have many components, one of the relationships which is still inconclusive is that between socioeconomic status and hospital readmission rates.

Investigating the conditions which have a substantial impact on the rate of hospital readmissions, heart failure stands out as it is the leading cause of death in the United States. This condition disproportionately affects older patients due to the progressive nature of the disease. Assessing differences in sociodemographic characteristics between two groups of heart failure patients, readmitted versus non-readmitted, to determine the factors which are most influential in predicting a readmission was the aim of this study.

A case control study design was used to examine the relationship between indicators of socioeconomic status and the likelihood of a hospital readmission in Medicare patients with heart failure. Hospital administrative data from Michigan hospital inpatient databases was linked to data from the U.S. Census Bureau's American Community Survey.

Two different statistical models were utilized: a binomial model and a multivariate linear regression model. Each of these models presented different variables and allowed for comparison between the models to evaluate fit and relevance to study population. Binomial model was chosen as the best fit, due to violation of normality assumptions in the multivariate linear model.

By linking indicators of socioeconomic status to rates of heart failure readmissions, this study was able to determine which socioeconomic factors most strongly correlated with the

outcome of interest. Assessing the variables included in the final models, it can suggest the target areas in order to most effectively reduce heart failure related hospital readmissions. The final models which were created are listed below:

Linear - Heart Failure Readmissions = 1.245 + (Wh_Cancer.age.45.64. x -3.85e-3) + (Age_65_84 x -3.78e-3) + (Average.Life.Expectancy x -1.12e-2) + (Asian x 1.93e-2) + (Prim_Care_Phys_Rate x -3.43e-4) + (Uninsured x 1.63e-6) + (Pneumo_Vax x -5.38e-4) + (HepA_Rpt x -1.72e-3).

Binomial - Heart Failure Readmissions = 2.09 + (Average.Life.Expectancy x -4.46e-2) + (Asian x 5.90e-2) + (Prim_Care_Phys_Rate x -7.31e-4) + (Disabled_Medicare x 2.98e-6) + (Hispanic x -1.03e-2).

There were three variables which were seen in both final models - Asian ethnicity, average life expectancy, and rate of visits to a primary care provider. Some of the factors which point to increased likelihood of readmission are factors which the patient cannot control, however there are some that are controllable, which will be the target for focused interventions as a result of the study.

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I. Introduction

Introduction

A hospital readmission, as defined by the Centers for Medicare and Medicaid Services (CMS), is an admission to a hospital within 30 days of discharge to any facility, for any reason (Fontanarosa & McNutt, 2013). Hospital admissions are responsible for more than half of the annual healthcare expenditure in the United States, with a small number of patients who contribute greatly through continued hospital admissions (Benbassat & Taragin, 2000). Though the number of chronically ill patients who are frequently readmitted is small, this is an area of concern for healthcare providers, as cost of care has quadrupled since 1990, and 2014 alone saw a 5.6% increase over 2013 (Sisko et al., 2014; Young, 2014). Especially problematic is the Medicare population, as one-tenth to one quarter of Medicare expenses are a result of repeated hospital admissions (Arbaje et al., 2008; Ashton, Kuykendall, Johnson, Wray, & Wu, 1995). In addition to the cost associated with readmissions, CMS has linked hospital reimbursement to readmission rates, indicating that within 30 days post-discharge, patients should not be readmitted if quality of medical care was appropriate (Center for Healthcare Quality & Payment Reform, n.d.).

Readmission rates are being used as a proxy measure of hospital quality and may be able to address concerns regarding the possibility of substandard care. The concern that inpatients are being discharged "quicker and sicker" has been investigated due to the direct relationship between patient admissions and hospital income. Hospitals are reimbursed for the care they provide to patients through DRG codes, Diagnostic Related Groups, which are given to every aspect of patient care (Office of Inspector General, 2001). With each subsequent DRG code for each admission, hospitals are able to bill insurance companies and collect additional funds for each readmission (Qian, Russell, Valiyeva, & Miller, 2011).

Discharging patients too soon without completion of necessary treatment regimens, may lead these patients to return for additional care, in which case hospitals are able to bill again. As this is not an appropriate standard for patient care, the Affordable Care Act began withholding payment for excess readmissions within the designated 30-day window for certain conditions such as pneumonia, heart attack, and heart failure. Readmission rates are being used to quantify quality of care through a link which is not well established (Holloway & Thomas, 1989). Research has found that readmission rates are a poor measure of hospital quality (Benbassat & Taragin, 2000), but this measure is being used by CMS to measure quality of care because it is easily quantifiable.

Two populations who are at highest risk of readmissions are the elderly and severely disabled, both of whom are primarily insured through Medicare (Corrigan & Martin, 1992). The link between advanced age, advanced disease status, Medicare insurance, and the likelihood of readmissions have been studied, indicating that those with Medicare insurance are more likely to be readmitted compared to patients with private health insurance (Corrigan & Martin, 1992). For Medicare beneficiaries with a principal diagnosis of heart failure, between 29% and 47% are readmitted between 3 and 6 months post discharge (Rich et al., 1995).

Heart failure is not a problem exclusive to the Medicare population, but the majority of patients suffering from this disease are in the later decades of their life, due to the progressive nature of the disease. Heart failure is one component of a larger, overarching disease called heart disease, which also includes other conditions such as heart valve problems, arrhythmias, and coronary artery disease (Centers for Disease Control and Prevention [CDC], 2014). Heart disease is the leading cause of death in the United States and is a result of high blood pressure, high blood sugar, and/or inflammation of blood vessels (National Institute of Health [NIH], 2014).

Coronary artery disease, the most common form of heart disease, is a result of plaque buildup within the arteries and eventually results in complete occlusion of blood flow to the heart (NIH, 2014). As plaque slowly and progressively builds up in the arteries over many decades, heart failure is the most common cause of hospital readmission for patients over the age of 65, with almost one quarter being readmitted within a month post-discharge (Fontanarosa & McNutt, 2013; Schwarz & Elman, 2003). Heart failure is responsible for more than 600,000 hospitalizations each year, costing over $10 billion, and accounting for 21% of all hospital readmissions (Hoefer & Hayward, 1995; Schwarz & Elman, 2003).

Assessing the reasons why patients are readmitted to the hospital within 30 days of discharge can identify what factors are influencing readmission and what preventive actions can be taken. In addition to age and insurance status, factors associated socioeconomic status may be another group of descriptors which may impact readmission rates. This group of indicators includes income level, education level, employment status, and age, in addition to many others. As hospital readmissions are complex to predict and understand, it is believed that there is a relationship between socioeconomic status and hospital readmission rates, though research is still inconclusive (Corrigan & Martin, 1992). Multiple studies have found that direct measures of socioeconomic status are able to predict the probability of readmission to a significant degree of accuracy, however determining if this is consistent when applied to a small subgroup, Medicare heart failure patients, will be the aim of this research (Economou & Theodossiou, 2011; Weissman, Stern, & Epstein 1994).

Though there have been studies which have linked socioeconomic status and hospital readmission rates, the algorithm used by CMS to calculate what they would expect hospital readmission rates to be, does not account for socioeconomic variables. Comparing readmission rates across hospitals is a difficult task due to heterogeneity in the underlying patient population. Including socioeconomic status factors in a readmission model may be appropriate once further research is done to investigate the link between the two. Thus, assessing Michigan Medicare beneficiaries with heart failure, those who were readmitted compared to those who were not, to determine differences in socioeconomic variables may be a useful step in indicating which socioeconomic variables are truly relevant to predicting hospital readmissions within this vulnerable population.

Purpose

The purpose of this study was to determine which socioeconomic status factors are associated with hospital readmissions for heart failure Medicare patients.

Scope

This study linked sociodemographic characteristics to patient level healthcare data to determine which sociodemographic factors impact hospital readmission rates in Medicare beneficiaries with heart failure. The patient population for this study were Medicare beneficiaries living in Michigan, who have a primary diagnosis of heart failure.

Assumptions

This study assumes there is an association between socioeconomic characteristics and the related hospital readmission rates in patients with primary heart failure.

Hypothesis

Null hypothesis (Ho): socioeconomic factors are not associated with hospital readmission in Medicare beneficiaries with heart failure.

Alternative hypothesis (Ha:) socioeconomic factors are associated with hospital readmission in Medicare patients with heart failure.

Significance

Due to the link between quality of care and payments to hospitals based on their readmission rates for specified conditions, such as heart failure, it is essential to identify patients who are most at risk to experience a readmission. This will allow targeted interventions to be developed with the aim of reducing readmissions and improving quality of care.

II. Literature Review

Readmissions

The Centers for Medicare and Medicaid Services (CMS) define a hospital readmission as an admission to a hospital occurring within 30 days of discharge from the same or different hospital, for any condition (Fontanarosa & McNutt, 2013). Risk standardized readmission rates do not differentiate between related or unrelated readmissions; any cause of readmission within 30 days of discharge is considered a readmission (National Quality Forum, n.d.). Readmissions constitute a large part of American health care expenditures, and hospitalizations as a whole account for over half these (Benbassat & Taragin, 2000). Furthermore, a small number of patients account for a large hospital bill, as 13% use over half of all hospital resources through repeated readmissions (Benbassat & Taragin, 2000). This is especially problematic within the Medicare population, as 10% to 25% of Medicare expenditures are a result of repeated hospital admissions (Arbaje et al., 2008; Ashton et al., 1995). However, over half of hospital readmissions are avoidable (Williams & Fitton, 2014). Determining the underlying causes of readmissions will be helpful to assess the areas which can be improved. Hospital readmissions are problematic due to the increasing number of preventable readmissions which are occurring as well as the rising healthcare expenditures with which they are associated.

With health care spending quadrupling since 1990 and health care expenses continually increasing, reducing the health care expenditure has been a top priority for government officials in recent years (Young, 2014). In 2014, the final American health care bill totaled $3.06 trillion, which was a 5.6% increase from 2013 (Sisko et al., 2014). Determining ways to effectively contain costs while ultimately reducing healthcare spending will be an essential part of keeping patients healthy while still providing the necessary care. Reducing readmissions will be a fundamental part in reducing healthcare expenditures as a large amount of resources are being spent on providing medical care to the small number of people who experience readmissions.

Through the implementation of the Affordable Care Act, the Centers for Medicare and Medicaid Services (CMS) have reduced payments to hospitals with excess 30 day readmissions rates as it pertains to specific conditions including pneumonia, heart attack, and heart failure (Centers for Medicare & Medicaid Services [CMS], 2014b). Through this Hospital Readmissions Reduction Program, hospital penalties for readmission rates translate to savings of more than $300 million for CMS (Fontanarosa & McNutt, 2013). Hospitals are not being reimbursed by CMS for any readmission within 30 days of discharge, which is how CMS is able to save money. These savings, though modest, represent an area where CMS has focused in order to reduce expenses while simultaneously improving quality of care.

When looking at readmission rates, they are not randomly distributed across time, but follow an exponential decay curve with the majority of readmissions clustered shortly after discharge, and subsequently declining over time. It is estimated that one third of readmissions happen within the first month, half within three months, and 80% within one year; inclusive of the previous readmissions (Benbassat & Taragin, 2000). In looking at the first 30 days and noticing that one third of patients are readmitted during this time frame compared to an additional 47% in the next 11 months, points to an area of concern and a place where targeted interventions could be most useful.

For some patient populations though, such as Medicare patients, the likelihood that they will be readmitted to the hospital is extremely high; regardless of whether or not it falls within the 30-days post discharge period. Not all of the subsequent admissions for Medicare patients are preventable due to complexity of care for the majority of chronically ill elderly patients, however

CMS has set an arbitrary 30-day window in which they believe readmissions are preventable (Center for Healthcare Quality & Payment Reform, n.d.). If patients are receiving proper medical care and are not discharged until they are stable, there is no reason their health status should decline so rapidly over the next month leading to a readmission.

Through better management of severe chronic conditions for severely ill Medicare patients, the majority of these readmissions can be avoided. Though it may not eliminate all readmissions, it will certainly decrease the frequency with which the patients return. By increasing the time between hospital admissions for patients with severe heart failure, it is expected that their care will be better managed and they will have a higher quality of life (America's Health Insurance Plan [AHIP], 2010).

Some of the factors which influence an individuals' likelihood of being readmitted may include uncontrollable factors such as age, gender, occupation, and quality of medical care (Williams & Fitton, 2014). These factors, as well as many others, are a critical component for identifying patients who are at a greater likelihood for readmission (Librero, Peiro, & Ordinana, 1999). Prediction of hospital readmission rates through use of socioeconomic indicators is the primary focus of this study. The importance of being able to identify patients who are more likely to experience repeated readmissions can aid in identifying appropriate and cost effective prevention efforts targeted toward individuals who need them most, to ensure that patients are kept healthy and out of the hospital, while still controlling expenses. Modifiable risk factors will be the most effective target to decrease a patient's risk for readmission. Sometimes however, due to the complexity of readmissions, presence of comorbidities, as well as a combination of other patient factors, preventing hospital readmissions can prove to be a difficult task (Fontanarosa & McNutt, 2013).

Readmissions and Quality

A component of the Affordable Care Act (ACA), part of the payment to hospitals through government insurance, i.e. Medicare and Medicaid, has been linked to readmissions (CMS, 2014b). As previously mentioned, hospitals are not being paid by the government for readmissions linked to specific medical conditions: heart failure, pneumonia, and heart attacks. CMS believes that by incentivizing physicians and hospitals to modify the care they provide in ways which limit reimbursement, the quality of care will increase and the cost will decrease. As clinicians are forced to work smarter, not harder, with the care they are providing to their patients, patients are able to receive the best care while the clinicians are being cost-conscious.

Readmission shortly after discharge is commonly thought to be connected to the quality of care being delivered, however that link has yet to be firmly established (Holloway & Thomas, 1989). The reason that early readmission is a widely used indicator of hospital quality is because it is easily quantified. So although the link has not been well established, it is an easy way for CMS to compare hospitals on an otherwise indescribable or unquantifiable variable (Ashton et al., 1995; Hoefer & Hayward, 1995). In order to compare readmission rates from hospitals in different areas of the state as well as the country, the different nature of the patient populations must be addressed first, in order to make the rates comparable. Differences in readmission rates between hospitals are not currently comparable due to the heterogeneity of populations at different hospitals.

The research base for readmissions and its link to quality is still growing. There have only been 10 studies which have examined the readmission rates of elderly patients with substandard care compared to those who received normative care (Ashton et al., 1995). These ten studies have differing results, some which found that changes to medication regimens are predictive of readmissions, while others found no difference. In addition, patient perception of care did not differ between patients who were readmitted and those who were not (Ashton et al., 1995). Other studies however have found that 1 in 5 readmissions for patients with heart failure, for example, could be attributed to substandard care (Ashton et al., 1995; Benbassat & Taragin, 2000).

Patients with heart failure are being readmitted more frequently than people with other less threatening chronic conditions simply because they are sicker. However, with equal application of sound medical care, the variability in readmission rates should be reduced, assuming that all patients are getting the same care. Wide variability in readmissions rates speaks to other variables such as quality measures, physician attention to detail, or socioeconomic status indicators which will be investigated here.

Hospital Payment for Readmissions

Readmission rates are currently being used to measure hospital quality and concerns regarding the notion that patients are being discharged from the hospital "quicker and sicker" (Qian et al., 2011). This is backed by the thought that patients are purposely being discharged too early with the understanding that they will be back, and upon that readmission, hospitals are able to assign another DRG code to that patient, ultimately leading to increased revenue for the hospital. DRGs, or Diagnostic Related Groups, are how CMS reimburses hospitals for the care they are providing to patients who are insured under Medicare or Medicaid. DRGs are numbers that are assigned to all aspects of acute care during a hospitalization, whether it is a condition, procedure, or the amount of resources estimated to be used by that patient during their stay (Office of Inspector General, 2001). Based on the conditions that patients present with, they are given a DRG each time they are admitted to the hospital (American Health Information

Management Association, 2010), with more costly conditions having higher DRG weights, resulting in higher reimbursement rates for the hospital (Office of Inspector General, 2001). When patients are admitted to the hospital with more than one medical condition, they are often assigned the highest weighted DRG, allowing hospitals to capitalize on the payments they are receiving from CMS (American Health Information Management Association, 2010).

"Premature discharge increases provider profitability in two ways. DRG payment represents an average cost, so by sending the patient home early, the hospital saves on the funds which were not used on that patient. Second, premature discharge creates the opportunity for a second DRG payment upon readmission of a patient who was discharged inappropriately" (Office of Inspector General, 1988).

The Office of Inspector General regards readmissions as necessary in some situations, but voiced concerns regarding "whether financial incentives were influencing readmissions decisions, rather than the beneficiaries' medical conditions" (Office of Inspector General, 2014). As this was becoming a problem, CMS developed an 'interrupted stay' policy so that for each DRG, the hospital only gets paid once per patient, rather than treating a readmission as a separate event and allowing the hospital to charge for two DRGs (Office of Inspector General, 2014). Though this would be an improvement, in 2010 and 2011, over $4 million was paid to hospitals for what Medicare deemed as 'inappropriate readmissions' for interrupted stays (Office of Inspector General, 2014).

The concern that patients are being discharged quicker and sicker led Hoefer and Hayward (1995) to conduct a study to determine whether or not readmissions are truly a good way to measure quality. They hypothesized that hospitals with higher readmission rates would be those who were delivering poorer quality of care. Thus their patients needed to come back again for follow up care which otherwise would not have been necessary (Hoefer & Hayward, 1995). In the study, 21% of all readmitted patients had a primary diagnosis of heart failure, and those patients who were non-compliant were more likely to be readmitted compared to those who were compliant (Hoefer & Hayward, 1995).

The readmission rate found in Hoefer and Hayward's 1995 study, was not based on quality of care, but instead looked at the impact of patient factors on their likelihood of being readmitted. As DRGs seem to be a driving factor of how long patients stay in the hospital, it is worth noting that this could be tied to readmission rates as well. This study did not mention if the DRG system has contributed to higher readmission rates, based on the financial interests of the hospital, however it is of interest for further investigation.

The interrupted stay policy will eliminate readmission payments through the DRG system, ensuring that patients are being discharged only when they are ready, as there will not be the potential for additional payments upon their readmission. Thus, early readmission rates are a poor measure on which to evaluate hospital quality as it relates to premature discharge. This can be attributed to the fact that most hospital systems do not have large and consistent differences in premature discharges to have the necessary level of accuracy to draw useful conclusions (Hoefer & Hayward, 2005). This is the same conclusion Benbassat and Taragin (2000) found, stating that readmission rates are a poor measure of hospital quality. These authors concluded that although improved hospital care is associated with fewer readmissions, readmissions in and of themselves, are not a true indicator of the level of care provided (Benbassat & Taragin, 2000). With incomplete or inconsistent follow up, patients being discharged without the right medications, premature discharge, and the overall non-compliance of many patients, readmissions are more complicated than simply whether or not the patient is readmitted within 30 days, based on the care they received while hospitalized.

The studies above which failed to show a link between hospital quality and readmissions, are comparable to others which also have not been able to determine a concrete relationship between quality of care received by hospitalized patients and their likelihood of readmissions (Benbassat & Taragin, 2000; Hoefer & Hayward, 1995).

Medicare and the Elderly

Medicare is the primary insurer of the elderly and severely disabled populations, two populations who are at higher risk of readmissions due to comorbidities and complexity of care (Corrigan & Martin, 1992). One study cites that "the highest readmission rates have been observed in high-risk, severely ill geriatric patients" (Benbassat & Taragin, 2000, p.1075). Corrigan and Martin (1992) similarly concluded that the likelihood of readmission was closely linked to increased age, advanced disease stage, as well as Medicare insurance. The link seen in both of these studies is that age, which is the determining factor in qualifying for Medicare insurance, is a significant predictor of readmission status. Therefore, patients with Medicare insurance are more likely to be readmitted than those with private health insurance, as this population is of a much different age and sociodemographic status, on which readmissions and overall health status seem to correlate.

Additional risks to the Medicare population also include the number of healthcare providers they see and the intricacy of their medication regimen (Arbaje et al., 2008). As elderly individuals have more health problems, in general, then younger individuals, they are often on complicated medication regimens and medical treatments in addition to having more frequent doctor visits. The medication burden is disproportionately placed on the sick and elderly, which many times they may not be able to afford, making compliance an issue.

For adults in the Medicare population, with a principle diagnosis of heart failure between 29% and 47% of these patients are being readmitted between 3 and 6 months (Rich et al., 1995). It is hypothesized that many of these readmissions are preventable through better management of heart failure in an outpatient setting, but this needs to be investigated in greater detail (Agency for Healthcare Research and Quality, [AHRQ], 2013).

Impact of Heart Disease on Hospital Readmissions

Due to the impact of heart disease on Medicare beneficiaries as a whole, it is the aim of this study to determine how this underlying condition impacts a patient's likelihood of readmission. Heart failure is responsible for over 600,000 hospitalizations in the United States each year, costing the patient and healthcare system more than $10 billion annually (Schwarz & Elman, 2003). Additionally, 21% of all hospital readmissions have been attributed to heart failure (Hoefer & Hayward, 1995). Thus, the emphasis of heart disease in regards to its impact on hospital readmissions and patient care is justified, especially as it concerns the Medicare population.

Heart disease is the leading cause of death in America, and can be attributed to high cholesterol, high blood pressure, high blood sugar, inflammation of blood vessels, and/or smoking (NIH, 2014). The term ‘heart disease’ encompasses several different heart conditions, including heart valve problems, arrhythmias, heart attack, stroke, and most commonly, coronary artery disease (CDC, 2014). Coronary artery disease is a result of plaque buildup causing the constriction of the coronary arteries, which are the main blood supply to the heart (CDC, 2014). The plaque in these arteries builds up over time, through a process known as atherosclerosis, causing the arteries to narrow; ultimately resulting in complete obstruction of blood flow to the heart (CDC, 2014). Through the continued buildup of plaque in the arteries accompanied by restricted blood flow to the heart, heart disease weakens the heart muscle, ultimately leading to heart failure (NIH, 2014). Heart failure is a progressive condition, which causes the heart muscle to become increasingly weak, resulting in the loss of the ability to pump blood throughout the rest of the body (American Heart Association, n.d.). Through the process of atherosclerosis, there is the potential that the plaques occlude the entire artery if they become large enough, preventing the heart from receiving any oxygenated blood; this is when a heart attack occurs (NIH, 2014).

The body has innate response mechanisms which begin working when the heart is no longer able to keep up with the demands of the body, in order to help compensate for the overwhelming workload (American Heart Association, n.d.). These response mechanisms include an enlargement of the heart chambers, increase in heart rate, and development of a larger heart muscle, which enables the heart to pump more strongly (American Heart Association, n.d.). Initially these adjustments work well, however with the gradual worsening of the condition, eventually these mechanisms begin to fail and more severe symptoms being to surface (American Heart Association, n.d.). Some of the more severe symptoms of heart failure include fatigue, shortness of breath, and fluid buildup in legs, ankles, and feet (NIH, 2014).

As this condition is progressive in nature, it is no coincidence that the majority of individuals who are affected by severe heart disease and heart failure are in the later decades of their lives. As such, heart failure was found to be the most common cause of hospital readmission for individuals over 65 years of age (Schwarz & Elman, 2003), with almost a quarter of these patients being readmitted within 30 days of discharge (Fontanarosa & McNutt, 2013). Another study found that 25% of readmissions due to heart failure occurred within 6 months, as compared to one month (Philbin, Dec, Jenkins, & DiSalvo, 2001). Though not exact replications, it is clear that readmissions of elderly patients who are suffering from heart failure present a large burden on both the healthcare system as well as their government insurer - Medicare. A third study found that 44% of patients were readmitted within 90 days of discharge, and with the exception of comorbidities, there were no significant differences between the patients who were readmitted and those who were not (Schwarz & Elman, 2003). The difference in number of comorbidities between the two groups was statistically significant, being more prevalent in individuals who were readmitted compared to those who were not (Schwarz & Elman, 2003). Greater severity of cardiac illness ($p < .01$) and greater functional impairment ($p < .001$) predicted higher hospital readmissions in this study (Schwarz & Elman, 2003). These studies indicate that individuals who have more chronic conditions, are more likely to be severely ill, and thus will require serious medical interventions - i.e. hospitalization.

As comorbidities have been identified as an influential factor in hospital readmissions (Librero et al., 1999), some of the conditions commonly seen alongside heart failure include diabetes, hypertension, heart attacks, atherosclerotic heart disease, and chronic obstructive pulmonary disease (COPD) (Schwarz & Elman, 2003). Chronic comorbidities are not only important for short term outcomes such as readmissions, but also seem to be a predictor for long term outcomes, including mortality and readmissions after one year (Librero et al., 1999).

Socioeconomic status and Readmissions

Assessing readmissions through filters such as age, insurance status, and county of residence, there is evidence to suggest that each of these factors impact the likelihood of a patient being readmitted to the hospital. These characteristics are all part of a larger concept, commonly referred to as socioeconomic status (SES). In addition to age, insurance status, and comorbid conditions, income level, education level, and employment status have been thought to impact readmissions as well.

As hospital readmissions are a thoroughly complex issue in healthcare, it is believed that there is a relationship between socioeconomic status and the corresponding hospital readmission rate, however the results are inconclusive (Corrigan & Martin, 1992). “The importance of demographic and socioeconomic factors in predicting readmission to hospitals has not been consistently supported by earlier work on this topic” (Weissman et al., 1994, p.170).

A study conducted by Weissman et al. (1994) found that direct measures of socioeconomic status, such as low income, less education, self pay/free care patients, or Medicare insurance, were significantly related to the probability of readmission ($p< .01$). Economou and Theodossiou (2011) stated that “higher socioeconomic status, which is approximated by employment status, education level, and income, seem to be correlated with better physical health” (p.396). Though these are not the only measures of socioeconomic status, these are some of the ways that this indicator is measured, as they are concrete numbers which are easy to obtain and subsequently link to the process of readmissions.

Due to the limited number of studies which have linked hospital readmissions to different socioeconomic status indicators, it is hard to definitively say whether or not socioeconomic status as a whole, all factors combined, have an impact on the likelihood of readmission. Some research even argues that because of the consistency in variables used to measure socioeconomic status, such as education level or employment prestige, these non-transient measures are not a useful indicator of a fluid measure such as hospital readmissions (Fethke, Smith, & Johnson, 1986). Corrigan and Martin (1992) concluded that more research is needed to understand this complex relationship between socioeconomic status and corresponding readmission rates.

Education

Research suggests that socioeconomic status impacts the likelihood of hospital readmission. Independently looking at some of the individual factors that comprise socioeconomic status may reveal one which is significantly associated with readmission rates. Education seems to be a good starting point, as education level is impacted at an early age by the environment a child grows up in, the emphasis their parents and family place on education, and the type of school they attend; which ultimately determines their job status and income level later in life.

Being a high school graduate was not a statistically significant measure of readmission status as a result of heart failure (Schwarz & Elman, 2003). Likewise, Fethke et al. (1986) found that education level was not a significant predictor of readmission in any of the three regression models they created. Another study found that no singular socioeconomic indicator, such as education level, was predictive of readmissions, thus being of relative unimportance when trying to predict hospital readmissions (Holloway, Thomas, & Shapiro, 1988). Ashton et al. (1995) concluded that no independent sociodemographic variables, such as education, showed a statistically significant association to readmissions. Though this evidence seems firm that there is a non-existent relationship between readmissions and education, other studies have concluded otherwise.

Other research on the topic shows different results, as some studies have found a relationship between educational attainment and the likelihood of a patient being readmitted. A study conducted by Arbaje et al. (2008), found a ‘lack of education’, which was not clearly defined, in addition to low SES, to be associated with early hospital readmission. These results were supported by Fethke et al. (1986) who found that the individuals in their study who were readmitted, had a lower average education level than those who were not readmitted, however this difference was not statistically significant ($p < 0.05$). The education level in this study was measured by how many years of school each individual completed, and was then used to calculate an average for both the readmitted group and non-readmitted group. Though Fethke et al. (1986) concluded that there was a difference, even though it was insignificant, we do not know what direction it occurs in; does education influence readmission rate, or did individuals who were readmitted simply have a lower level of education? The results of these studies are not easy to tease apart, especially with regards to the conclusions, which simply leave the main questions still unanswered - leaving room for additional research.

Additionally, research seems to indicate that education has a positive effect on health (Economou & Theodossiou, 2011), and that the relationship between education level and mortality rate is somewhat linear (Backlund, Sorlie, & Johnson, 1996). This conclusion would indicate a stronger relationship between the two, however is this truly the case?

Income

Income levels are closely tied to education and in the majority of cases these two have a positive linear association. Literature seems much more conclusive with regards to this factor in the sense that the majority of the studies which were reviewed showed the same connection between income and readmissions rate; lower income is associated with an increase likelihood of readmission (Corrigan & Martin, 1992; Gornick et al., 1996; Philbin et al., 2001; Weissman et al., 1994), and it seems to be the greatest singular factor relating to ill health (Economou & Theodossiou, 2011).

There has been a strong positive relationship observed between household income and overall health, suggesting that those who are at the lowest income levels are also the sickest

(Economou & Theodossiou, 2011). Weissman et al. (1994) concluded that those who were ‘very poor’ were between 20% and 27% more likely to experience a readmission within 60 days of discharge. Another study came to the same conclusion; patients in the lowest quartile of income had the highest number of comorbid conditions as well as the highest mean risk for readmission, $p<0.0001$ (Philbin et al., 2001).

Increased socioeconomic status, being measured by median household income for the area where the patient lived, was found to be inversely associated with the likelihood of readmission (Corrigan & Martin, 1992). This conclusion was confirmed through a study done by Gornick et al. (1996), which linked census data on median incomes to Medicare data, and found that the least affluent white patients were hospitalized 28% more often than the most affluent patients of the same race. There could be a number of different explanations for this statistic, one being that because wealthy patients are capable of paying, thus they are more likely to be receiving routine care, which in turn can prevent more serious and costly hospitalizations. For those individuals who are not able to pay for their health care, waiting until they are in a crisis to visit an emergency room will be the only way they receive care. Many times this will lead to a hospitalization, as they may have additional underlying medical problems which require prompt medical care. Since emergency rooms are required by law to see every patient that comes through their door, this is how many low income patients receive routine care, as they have little alternative.

Assessing the extent to which income level influences the probability of readmission, it is notable that in the six weeks following an initial discharge, those from high income groups had the highest probability of readmission, but after a years’ time, the probability of readmission was highest for patients from low income groups (Schwarz & Elman, 2003). This may suggest that patients in higher income groups, who have the capacity to pay for their care, are more apt to return to the hospital following a hospitalization if they felt as though something was not adequately addressed during their stay. For those individuals who cannot afford to do so, they will wait until something is more seriously wrong before seeking treatment, at which point they may require more invasive care. Additionally, it seems that income and comorbidities are closely related, with those who are poorer also being sicker, with corresponding, higher readmissions rates (Philbin et al., 2001). This study also showed a stepwise decrease in the number of readmissions from lowest income quartile to the highest; as income increased, readmission rates declined significantly (Philbin et al., 2001).

Previous research on the link between income and overall health status has been consistent, indicating that those with higher income levels are also those with better health statuses. This study may be able to confirm the link between socioeconomic status, with regards to income, and the impact on heart failure related hospital readmissions.

Location

Through the accumulation of research done on the topic and the available evidence, it seems there is an interconnectedness between readmission rates, socioeconomic factors, race, insurance status, and geographic location. Hospital location, whether urban or rural, and the population which it serves, seems to be indicative of the readmission rate of that hospital; regardless of quality of care. Not only have readmission rates been associated with the treatment of low-income patients, but those suffering from congestive heart failure as well (Williams, Javed, Hamid, & Williams, 2014).

Philbin et al. (2001) compared socioeconomic status to geographic-based risk of hospital readmissions due to heart failure. This study was conducted in New York State and used administrative discharge data complete with International Classification of Disease (ICD) classification codes, linking them to median household income by zip code, to compare readmission rates among diverse groups of patients (Philbin et al., 2001). Philbin et al. (2001) concluded that among patients who were hospitalized for heart failure, they were more often minority women with comorbid illnesses, and were more frequently admitted to rural hospitals. Patients in the lowest quartile of income were much more likely to be admitted to a rural hospital, which may not have the programs needed for effective treatment and management of heart failure in severely ill geriatric patients (Philbin et al., 2001). Additionally, there were notable differences in readmission rates between urban and rural hospitals across all income quartiles ($p<0.05$) (Philbin et al., 2001).

Deciphering the differences between readmission rates in urban and rural hospitals can give more insight as to how readmission rates vary depending on the location of the hospital. County level measures may be able to account for variations in hospital readmission at a county level, when considering the impact that access to care has on readmission rates (Herrin et al., 2014). One study showed that only 42% of variation in readmission rates can be attributed to individual hospital performance, suggesting that a larger portion of readmissions can be attributed to other factors, including socioeconomic characteristics (Herrin et al., 2014).

Broken into size, all of the areas along the rural/urban continuum were statistically significant ($p<0.05$) with regards to risk standardized readmission rates (Herrin et al., 2014). Additionally, the number of Medicare beneficiaries per 100,000 population in the 3rd, 4th and 5th (highest) quintiles were significant predictors of readmission rates as well (Herrin et al., 2014). A limitation of this study however could be the unmeasured, indirect ecological effects such as living in a lower income community which is not identifiable without patient level data (Herrin et al., 2014). These could include factors such as air pollution, access to grocery stores, or even access to healthcare.

One study suggests that in theory, it is reasonable to expect health to be influenced both by individuals as well as the communities within which they reside. Measuring these micro level variables can be done through proxy area based socioeconomic measures (ABSMs) which combines census data and health information (Geronimus, 2006).

Socioeconomic status does not directly measure location, however the impact of the lived environment on the health of the patient prior to being hospitalized and post-discharge have much to do with rates of readmissions for elderly and non-elderly alike (Hood, 2005). Due to the impact of various socioeconomic factors on the individuals in the surrounding community, readmission rates serve as a reflection of the level of wealth and prosperity for that location.

Michigan

When looking at readmission rates of Michigan hospitals, there are hospitals on the eastern side of the state with readmission rates that far surpass the national average of 16.1% (Goodman, 2011). Data from a 2013 CMS report showed hospital wide readmission rates across each state as part of mandated reporting for the Hospital Inpatient Quality program (CMS, 2013). This report indicated seven areas in Michigan that were significantly different than the national average; Dearborn (18%), Detroit (17.9%) and Royal Oak (18.8%) performed worse, whereas Grand Rapids (15.7%), Kalamazoo (15.3%), Muskegon (14.3%) and Petoskey (15.7%) performed better (CMS, 2013; Goodman, 2011).

Hospitals in Detroit had the highest mean readmission penalties among the largest metropolitan areas in the five states of the East North Central Region ($p<0.05$); Michigan, Illinois, Ohio, Wisconsin and Indiana (Williams et al., 2014). Detroit also had the highest income disparities, highest poverty rate, and highest unemployment level of the five cities evaluated, which also included Chicago, Columbus, Milwaukee, and Indianapolis (Williams et al., 2014). All of these hospitals had higher readmission rates compared to the rest of their state, however the differences in Detroit were significant (Williams et al., 2014). All 5 of the Detroit hospitals and all of the 12 hospitals in the metro-Detroit area had readmissions penalties, compared to only 37 of the other 75 hospitals across the state (100% vs. 49%; $p<0.001$) (Williams et al., 2014).

Due to the impact of community factors on the general health of individuals who live there, a yearlong collaborative was conducted which targeted heart failure readmissions in metro-Detroit, and was successfully able to reduce readmissions by 9.5%, as compared to a 4.9% reduction in other Michigan hospitals who were not participating ("Michigan Hospitals", 2014). Through improving the quality of care delivered by these hospitals, this project titled "See You in 7" was able to effectively reduce readmissions related to heart failure. Being aware of a problem within the hospital was the first step to correcting it, and through a gap analysis conducted in this study, it allowed hospitals to identify areas of need and improve on them, ultimately improving patient care and reducing the number of readmissions ("Michigan Hospitals", 2014).

Summary

The research base is still insufficient with regards to the association between SES and readmissions in Michigan, although there has been extensive research done on the topic of readmissions in general (Economou & Theodossiou, 2011). When looking at socioeconomic status as a whole, it is apparent that all of the individual components that make up this overarching concept play a role in influencing hospital readmissions. A further investigation into how these socioeconomic status indicators influence readmission rates within the Michigan

Medicare population, especially as it pertains to those with comorbid heart failure, is the purpose of this research.

The influence of individual factors on readmission rates may change when aggregated with other factors. How these socioeconomic factors interact with each other to produce an outcome of hospital readmission will be examined. This study aims to determine whether or not socioeconomic status has an impact on readmission rates of the elderly Medicare population within Michigan, specific to heart failure.

III. Methods

A case control study was used to determine the differences in 30-day hospital readmission rates between Medicare patients with heart failure. The cases were those who were readmitted within 30 days of discharge, while the controls were not readmitted within 30 days; both groups had heart failure. Through linking socioeconomic status indicators to rates of heart failure related readmissions in Michigan Medicare patients, the strongest predictors of hospital readmissions were determined.

Data Sources

Data for this project was obtained from two different sources; one which provided individual, patient level data regarding hospital admissions and health status (Michigan Inpatient Database), and the other which provided publically available indicators of socioeconomic status (United States Census).

Michigan Inpatient Database

State inpatient databases are a longitudinal measure of state-specific hospital measures that were developed as part of the Healthcare Cost and Utilization Project (HCUP) (AHRQ, 2011). The main goal of state inpatient databases is to allow researchers and policy makers the ability to investigate questions specific to one state, with regards to quality of care, access to care, cost, and utilization of services, among others (AHRQ, 2011). State inpatient databases are the largest collection of this type of data in the United States, and each state collects the same basic information regarding patient care. HCUP was the result of the Institute of Medicine (IOM) asking states to create mandated reporting systems to identify medical errors and learn from them to improve patient safety (Rosenthal, 2007).

Readmissions data was taken from the Michigan Inpatient Database (MIDB), which is derived from administrative data, and includes demographic information (zip code, age, gender, residence) as well as clinical information (discharge status, DRG, procedure (CPT) codes, and medical record number) (AHRQ, 2014).

The Michigan Health and Hospital Association (MHA) is the only organization in Michigan that has access to this dataset, functioning as a middleman between the hospitals and AHRQ, as both want metrics of hospital quality. AHRQ realizes that trying to collect this information from each hospital within every state would be a significant task, so they have delegated this to various organizations within every state. State inpatient databases are a collaboration of many different organizations including state organizations, hospital associations, private data organizations, and the Federal government (AHRQ, 2011).

Some states require their hospitals to report to their state inpatient databases, however Michigan is not a mandated reporting state, meaning that Michigan hospitals are not required by law to submit their data. "As of November 2009, 27 states including the District of Columbia had passed legislation or regulation regarding hospital reporting of adverse events to a state agency, however Michigan is not included in that list" (National Academy for State Health Policy, 2009). Though Michigan is not a mandated reporting state, hospitals can voluntarily enter into a data use agreement with MHA who then enforces the collection of this data. Due to the non-mandated reporting nature of the state of Michigan, not all hospitals submit their data to MHA. With the exception of Veteran Affairs (VA) Hospitals, some small Critical Access Hospitals, and in-patient psychiatric facilities, the majority (99%) do voluntarily submit their data for review (D. Barnes, personal communication, March 2015).

Hospitals believe that in order to keep Michigan a 'non-mandated reporting state', it is in their best interest to report their data as accurately and completely as possible (J. Lee, personal communication, March 2015). Thus, though it is not mandatory, the reporting rate is very high as hospitals comply in order to improve the quality of care they provide to their patients. Additionally, with high participation from Michigan hospitals, it allows the hospitals to compare themselves against their peers with regards to selected quality measures. Initially this was a significant reason why hospitals agreed to report their data, as it became useful from a marketing perspective that they would be able to say that they were the best hospital in the area with regards to readmissions, or other factors (J. Lee, personal communication, March 2015).

Hospitals who have agreed to submit their clinical patient encounter data to MHA do so through a variety of different reporting tools, such as Data Koala and Interactive Data (J. Lee, personal communication, March 2015). Each hospital has their own method of submitting the data as well as different timelines for doing so, as some submit monthly, while others may only submit quarterly. Additionally, the information which is being shared with MHA may come from different areas of the hospital system such as the billing department, the electronic health record (EHR), or the discharge transfer system. All of these areas report the same information regarding clinical patient encounters, it is just a matter of how the individual hospital has structured their reporting mechanisms (J. Lee, personal communication, March 2015).

Though not every hospital in Michigan reports to MHA, the vast majority do (99%), which makes the MIDB the most comprehensive source of patient level healthcare data available for research.

United States Census

Commonly used indicators of socioeconomic status such as poverty level, median household income, education level, and number of uninsured, are widely reported and publicly available. These variables are collected through the American Community Survey which is conducted annually by the United States Census Bureau to help state and local governments determine how to spend allocated funds each year (United States Census Bureau, n.d.). These variables comprise a larger group of measures known as Community Health Status Indicators (CHSI), as these variables are believed to measure the health of the community on an overarching level. The relationship of the variables from this survey and the patient level health information was examined to determine if an association exists between socioeconomic status factors and hospital readmissions among Michigan Medicare patients with heart failure. The indicators which were analyzed were those that have the potential to impact readmissions, especially as it pertains to the Medicare population.

Though CHSI variables are one of the more complete sources of information related to socioeconomic status, there are still instances where the data is not reported or cases are missing. The data file obtained from the United States Census Bureau contained cases where not all questions were answered, leaving blanks within the data set. In order for R to properly analyze the data set, all blanks must be removed as analysis will stop when the program encounters missing variables. If blanks were still in the dataset during analysis, the program will return an 'NA' error message and will not complete the analysis.

Inclusion and Exclusion Criteria

The case population were patients that were readmitted to the same hospital with a primary heart failure diagnosis within 30 days, either enrolled in Medicare or a VA beneficiary, aged 65 years and older, discharged from the hospital alive, were not sent to another acute care facility, and have been enrolled in Medicare Part A & Part B for the past year (CMS, 2014b). Patients who were discharged against medical advice were not included, as their rates would not be comparable to individuals who complied with medical orders (CMS, 2014b).

The control population were patients with a primary heart failure diagnosis, are a Medicare or a VA beneficiary, aged 65 years and older, discharged from the hospital alive, were not sent to another acute care facility, and have been enrolled in Medicare Part A & Part B for the past year. This population is identical to the case group, with the exception that the control group has not been readmitted within 30 days.

Patients who have been discharged from one hospital and readmitted to a different one, were excluded from this study. Between hospital readmissions are more difficult to track as medical record numbers, which are commonly used to identify same hospital readmissions, do not follow a patient between institutions. Algorithms used to track patients between different hospitals vary depending on the institution that is collecting and analyzing the data, but may include variables such as date of birth, last four digits of social security number, and zip code (J. Lee, personal communication, March 2015). Though this is a substantial step in being able to identify patients being admitted to a different hospital than the one they were in during their initial admission, MIDB does not allow for the identification of patients who were admitted to a different hospital.

Study Design

A case control study was used to examine the association between indicators of socioeconomic status and the likelihood of a hospital readmission. This type of study design allows for side-by-side comparison of the factors which were present in those who were readmitted compared to those who were not readmitted. Conducting a retrospective study to compare two groups of patients on how they differ with regards to the selected socioeconomic indicators, allows for a better understanding of which factors play the biggest role in predicting heart failure related readmissions for Medicare patients.

The nature of this case control study is slightly different from the way case control studies are normally designed. This case-control study limited the population of interest to those with heart failure, with the differences between the groups being their readmission status; not the disease status which is traditionally used in dividing the case and control groups.

CMS Readmissions Algorithm

In order to ensure comparability between hospitals, the following algorithm is used by CMS in order to report 30-day, all-cause, unplanned hospital readmission rates.

$$\frac{At\ Risk\ Discharges\ (ARD) with\ a\ qualifying\ unplanned\ acute\ care\ readmission\ within\ 30\ days}{At\ Risk\ Discharges\ (ARD)}$$

(Horwitz et al., 2011).

There are four important steps to computing an accurate readmissions model. First, the total number of discharges from a hospital in a given month is calculated, excluding rehabilitation readmissions and psychiatric discharges. At-risk discharges must then be calculated as these are the patients who will potentially be readmitted. The number of at-risk discharges is the number of total discharges minus labor and delivery patients, transplant patients, patients who are transferred to another facility, cancer patients, patients who die before discharge, and those who leave against medical advice (Horwitz et al., 2011). Third, all 30-day readmissions must be identified, which includes a patient's admission to the same hospital within 30 days of a previous at risk discharge, unless they were readmitted on day 0 (day of discharge) for the same condition (Horwitz et al., 2011). There is currently no way to identify patients who are readmitted to other institutions through MIDB, so readmission rates are calculated for readmissions to the same hospital (Horwitz et al., 2011). Lastly, planned readmissions must be identified so they can be subtracted from total number of readmissions, as they are not un-planned, which is the focus of this algorithm (Horwitz et al., 2011). Planned readmissions include: any procedure or diagnosis category that is always considered planned, such as discharge to a skilled nursing facility, or any potentially planned procedure, which is defined by the clinical classification software which groups patient diagnoses and procedures (CMS, 2014a). These clinical classifications software categories are defined as clinically meaningful and are based on the ICD-9 coding classification, which groups the codes in a way that makes reporting and analysis more understandable (AHRQ, 2012).

The algorithm used by CMS to classify patients who are admitted to the hospitals as a readmission was used for this research. Keeping the methodology consistent allows for accurate comparison between hospitals within Michigan, as well as between states, for ease of comparison and study replication in other states, if applicable.

Statistical Modeling

Utilizing two different modeling techniques with the same data set allows for comparison between final models, as well as identification of the variables that are the most important in predicting hospital readmissions. The two statistical models that were chosen were multivariate linear regression and binomial modeling.

The association between the independent socioeconomic factors and the outcome of interest, hospital readmission, can be determined through use of multivariate linear regression. Because the socioeconomic data is collected on county level, a multivariate linear model was best suited for predicting a patient's likelihood of being readmitted depending on the area where they reside. Patient level hospital data can be aggregated to a county level to allow the two data sets to be comparable and easier to work with in regression modeling.

Multivariate linear regression allows for independent variables to be added to the linear model of predicting hospital readmissions individually as well as in a variety of combinations. Each time a new model was created, with a different number or selection of variables included, model fit was assessed to determine how well it was able to predict hospital readmissions based on the independent variables which were used (Chen, Ender, Mitchell & Wells, n.d.).

Multivariate linear regression was chosen for data modeling due to the strong initial linear correlations that were seen between CHSI variables and hospital readmissions rates. Not all of the variables had a consistent linear relationship with the outcome however, which is why binomial modeling was used as well. Binomial models also allow for restriction of the outcome variable to 0 and 1; absence or presence of readmission, respectively. Final models were evaluated and compared to determine the outcome of each model and the discrepancies between them. The final model that was selected was the one that was best able to predict readmission rates based on a subset of socioeconomic variables which influence elderly Medicare patients with primary heart failure.

Data analysis was conducted using R statistical software. Initial correlation models from R provided an indication of the variables which created the best and strongest models for predicting hospital readmissions, but did not provide any summary statistics on which to evaluate these models to determine which one best fit the data. These initial models were taken into consideration when building final models, as this was a starting point for determining which variables made the most contribution to the overall model fit. The resulting output from R listed each variable which was inputted into the model, and identified the ones which were the strongest predictors in combination with other variables to predict the likelihood of hospital readmission. This file listed each variable with either 'TRUE' or 'FALSE' depending on whether that variable was used in the specified model, containing x number of variables. The best formulas were then extrapolated based on the 'TRUE' variables for each model. These formulas indicated the best variables to use for predicting a hospital readmission, based on the variables which in combination were most accurately able to model the outcome of interest.

Due to the non-random categories where patients were placed (i.e. geographic location), weighted distributions become important in order to generalize data. Weighted distributions account for and adjust probabilities of actual occurrence, as the number of patients in a county in a densely populated urban area will be very different from a county with a much lower population density (Patil, 2002). With the weighted independent variables the readmissions *rate* was calculated, representing a more accurate account of variances within the population. Being able to account for the total patient population per county, allows for more consistent comparison between counties as appropriate weights adjust for differences in the size of populations. In counties where there was a large number of patients, the weight was higher as this data accounts for a larger proportion of data within the model, as larger sample sizes are generally more representative of the true rate as compared to smaller ones.

When conducting the generalized linear model in R, the bestglm package was utilized, however unsuccessfully. An error message prevented the program from executing correctly, and indicated that successes plus failures (readmissions + non-readmissions) must be constant between counties. This would never occur due to population variances throughout the state and their corresponding differences in readmission. The bestglm model is an exhaustive search of each variable and gives an all-subset linear regression, however due to the errors in this package, the leaps package was utilized instead.

Model Selection and Evaluation

The leaps package was utilized as a method of model selection and through use of 'regsubsets' command the program ran a stepwise model selection (University of Hawaii, n.d.). The resulting matrix which was produced, indicated which variables were included in the varying models, and listed the models according to size; with the smallest models first (University of Hawaii, n.d.). Leaps package allows for the creation of many different size models, and finds the variables which together have the strongest predictive power for predicting the outcome of interest. Thus, each model includes the best selection of variables for each model, making the combination the strongest possible predictor from all of the variables of interest.

Use of the Binomial Model is appropriate due to the three criteria it satisfies: the two binary outcomes (readmitted or not readmitted), the probability of each outcome remaining constant between patients, and each patient remaining independent of the others (Jones, 2015). This model used the patient's readmission status, whether or not they were readmitted, as the binomial outcome for which the analysis was conducted and the model was built. In the binomial model, the 'successes' or 'failures' indicates the presence or absence of the outcome of interest. The binomial distribution formula is as follows, with N being the number of patients that each have π probability of occurring

$$P(x) = \frac{N!}{x!\,(N-x)!}\pi^{x}(1-\pi)^{N-x}$$

(Lane, n.d.).

P(x) is the probability of x successes out of N trials, with $\pi = 0.5$ as the chance of being readmitted is set at 50% - either you are or you are not (Lane, n.d.).

Model evaluation relied on AIC, Akaike's Information Criterion, to indicate the fit of the model. AIC estimates the difference between the predicted data and the actual data which it is trying to model, as it evaluates the relative distance between the model and the 'truth'. When the AIC value is closer to zero, it indicates that the model created is closer to the truth, meaning it more accurately predicts the outcome of interest. AIC was used to evaluate the strength of each binomial model and was indicated in the output for each model through the glm package within R (Wagenmakers & Farrell, 2004).

Another method utilized for the linear model was the Variance Inflation Factor (VIF). This statistic was used to determine the presence of multicollinearity within each model. When a model has a $\sqrt{VIF}$ larger than 2, it indicates that there were two variables within the model that are highly correlated to one another. In this situation, one of the variables should be removed from the model, as the inclusion of both variables adds a large amount of variance to the model (Penn State University, 2015). When two variables are highly correlated to each other, more so than to the outcome of interest, it artificially inflates how well the model is able to predict the outcome of interest, adding significance to the model which is not actually present.

Human Subject Protection

The Michigan Health and Hospital Association requires a Data Request submission which must be approved prior to conducting research on protected health information stored in MIDB. After MHA approval of the Data Request was received, the MIDB data set was cleaned by MHA personnel to remove protected health information (PHI). Appendix 1 contains the approval of the MHA data request. Approval was also given by Grand Valley State University's Human Research Review Committee (HRRC). The HRRC determination letter can be found in Appendix 2.

IV. Results

Results

Determining which socioeconomic factors have the biggest impact on hospital readmissions for Michigan Medicare beneficiaries with primary heart failure was achieved through assessment of Census Bureau Data in addition to hospital level administrative data. Varying health outcomes have been linked to lifestyle factors such as education level, insurance status, and employment status, making socioeconomic factors a useful baseline on which to compare differences in health outcomes. Through comparisons of health outcomes for individuals with similar socioeconomic characteristics, readmissions rates can be analyzed and interpreted to determine which factors influence these rates.

The U.S. Census data contained nearly 600 socioeconomic variables, all of which were not anticipated to be associated with hospital readmissions for patients with heart failure. Determining which variables were more likely to relate to increased readmission rates was the first step in building a model. 78 variables were selected which were believed to influence the overall health as well as heart failure status within the elderly heart failure population. Of these, 10 were discarded due to missing observations, which prevents R from running properly. The variables which were discarded are listed in Table 1. The remaining 68 variables were then utilized to build both models, multivariate linear regression and binomial modeling.

Table 1.

Variables Excluded from Analysis due to Missing Observations

Brst_Cancer_Ind	Col_Cancer_Ind	MVA_Ind	Suicide_Ind
RHI_Brst_Cancer_Ind	RHI_Col_Cancer_Ind	RHI_MVA_Ind	RHI_Suicide_Ind
RHI_Injury_Ind	Injury_Ind		

Note. Variable definitions can be found in Appendix 3.

Initially, a Spearman Correlation test was performed to assess the strength of the relationship between each CHSI variable and its impact on the rate of heart failure related hospital readmissions. The resulting correlation coefficient was indicative of the strength and direction of the relationship between these two variables. Those with a positive correlation coefficient indicate that as number of diabetics increases, for example, the rate of hospital readmissions within the population of interest would increase as well. The variables that had a significant correlation ($p < 0.05$) with heart-failure associated readmissions in Michigan Medicare beneficiaries are listed in table 2.

Table 2.

Variables which were Significantly Correlated with Hospital Readmission Rates as indicated by Spearman Correlation Test.

Variable Name	**P-value**	**Correlation Coefficient**
Population_Density	0.0044	0.3098
Age_65_84	0.0068	-0.2945
White	0.0186	-0.2578
Black	0.0023	0.3300
E_Wh_Cancer.age.45.64.	0.0010	-0.3535
F_Wh_Cancer.age.65..	0.0138	-0.2692
Homicide	0.0055	0.3021
Total_Births	0.0077	0.2904
Total_Deaths	0.0081	0.2887
FluB_Rpt	0.0112	0.2772
HepA_Rpt	0.0215	0.2522
HepB_Rpt	0.0440	0.2217
Pap_Smear	0.0488	0.2170
High_Blood_Pres	0.0165	0.2625
Uninsured	0.0076	0.2911
Elderly_Medicare	0.0059	0.2996
Disabled_Medicare	0.0079	0.2899
Average.Life.expectancy	0.0069	-0.2944
All_Cause.of.Death	0.0442	0.2215
No_HS_Diploma	0.0080	0.2893
Unemployed	0.0065	0.2966
Major_Depression	0.0053	0.3035
Recent_Drug_Use	0.0056	0.3018
Salm_Rpt	0.0059	0.2999
Shig_Rpt	0.0204	0.2542

Note. Variable definitions can be found in Appendix 3.

After initial correlations were established, only those variables with independent significance were used moving forward, to conduct additional data modeling. Some of these variables, even though they were significant, were not included in subsequent analyses due to the relevance of their impact on heart failure. The 78 variables which were initially chosen for inclusion in modeling heart failure readmissions, were those which could be linked to overall health status, heart conditions, comorbid conditions which could impact heart disease, as well as social and economic indicators which were suspected to have a relationship with prevalence of heart failure and subsequent hospitalizations.

Some of the variables which were removed, even though they were significant within initial correlations were removed due to lack of clear impact on generalized health status and more specifically, heart failure. For example, there was a significant correlation between lung cancer and rate of hospital readmissions regarding heart failure. Lung cancer, though a comorbidity, will not directly impact the prevalence of heart-failure specifically. Thus, not all of the variables which were significant in the Spearman's Correlation test were used to conduct additional modeling due to their relationship with heart failure related readmissions. The ones which were kept for additional data modeling were those which were believed to have the largest impact on the readmissions specifically as it pertains to heart failure.

Variables relating to most chronic health conditions were eliminated from additional modeling as they were not anticipated to have a large impact on heart failure. There were a few chronic conditions which were kept however; heart disease, cancer, and major depression. These variables were kept specifically due to their link with either heart failure or the higher frequency with which patients are visiting their healthcare providers. These patients are less likely to be readmitted as they are more likely to have appropriate follow up care after a hospitalization. Patients who saw their primary care physician frequently were 10 times less likely to be readmitted compared to those who did not have adequate physician follow-up; equating to readmission rates of 3% and 21%, respectively (Healthcare Information and Management Systems Society, 2012).

With the elimination of variables which were not related to heart failure or frequency of care, it allowed the model to select from variables which are most relevant and strongly related to predicting the patients who were most at risk for heart failure related readmissions.

Linear Model

Linear modeling was used first for building a model to predict heart failure related hospital readmissions. The initial linear model included weights, which were added to correct for the data being aggregated; not at the patient level.

Strictly comparing a rate would not be an accurate assessment of the readmission status, as counties with larger populations will similarly have higher rates of readmissions. Using the weighted linear model, there were 25 variables which were significantly related to heart failure related readmissions ($p < 0.05$) and are shown in Table 3.

Table 3.

CHSI Variables Significantly Related to Hospital Readmissions based on Weighted Linear Modeling

Variable Name	Overall P-value
Population_Density	0.0044
Age_65_84	0.0068
White	0.0186
Black	0.0023
E_Wh_Cancer.age.45.64.	0.0010
F_Wh_Cancer.age.65..	0.0138
Homicide	0.0055
Total_Births	0.0077
Total_Deaths	0.0081
FluB_Rpt	0.0112
HepA_Rpt	0.0215
HepB_Rpt	0.0440
Pap_Smear	0.0488
High_Blood_Pres	0.0165
Uninsured	0.0076
Elderly_Medicare	0.0059
Disabled_Medicare	0.0079
Average.Life.expectancy	0.0069
All_Cause.of.Death	0.0442
No_HS_Diploma	0.0080
Unemployed	0.0065
Major_Depression	0.0053
Recent_Drug_Use	0.0056
Salm_Rpt	0.0059
Shig_Rpt	0.0204

Note. Variable definitions can be found in Appendix 3.

Utilizing these 25 significant variables to construct a weighted linear model, the 13 best models were created. These 13 models were predicted by R to best model hospital readmission rates within Michigan Medicare patients based on the initial variables which were significant.

- Heart Failure Readmissions = Wh_Cancer.age.45.64
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84

- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Wh_HeartDis.age.45.64
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Asian
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Wh_HeartDis.age.45.65 + Asian
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Wh_HeartDis.age.45.65 + Asian + Prim_Care_Phys_Rate
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Wh_HeartDis.age.45.65 + Asian + Prim_Care_Phys_Rate + Wh_Cancer.age.65
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Wh_HeartDis.age.45.65 + Asian + Prim_Care_Phys_Rate + Wh_Cancer.age.65
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Uninsured + Asian + Prim_Care_Phys_Rate + Pneumo_Vax + HepA_Rpt
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Uninsured + Asian + Prim_Care_Phys_Rate + Wh_Cancer.age.65 + HepA_Rpt + Hispanic + Disabled_Medicare
- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Uninsured + Asian + Prim_Care_Phys_Rate + Wh_Cancer.age.65 + HepA_Rpt + Hispanic + Flu_Vac + No_HS_Diploma

- Heart Failure Readmissions = Wh_Cancer.age.45.64 + Age_65_84 + Average.Life.expectancy + Uninsured + Asian + Prim_Care_Phys_Rate + Wh_Cancer.age.65 + HepA_Rpt + Hispanic + Disabled_Medicare + Major_Depression + Recent_Drug_Use

Final Analysis – Linear

Utilizing forward stepwise model building procedures, based on variables suggested by the best models from initial analysis, final linear models were built and evaluated. The variables that appeared frequently in initial linear models were used as the starting point for building the final linear models. The ones which appeared more often were those that were most important in being able to accurately predict the outcome of interest. The 6 variables which were selected from initial linear models included Wh_Cancer.age.45.64, Age_65_84, Average.Life.Expectanct, Uninsured, Asian, and Wh_HeartDis.age.45.64.

The variable Cancer in White patients aged 45-64 was seen in all 13 initial models, and was highly significant on its own when added to the linear model ($p < 0.01$). This variable was kept and average life expectancy and population aged 65-84 was added to the model. Upon adding these variables to the model, all three variables remained significant ($p < 0.05$).

Heart Disease in White Patients aged 45-64 was then added to the model, but was not statistically significant ($p = 0.94$), and was subsequently removed prior to adding any additional variables. After removing this variable, Asian ethnicity was added to the model, but was not statistically significant either ($p = 0.13$). Due to this variable being seen in many initial linear models however, it was kept in the model temporarily while testing other combinations of variables to find significance. Upon addition of Uninsured and Primary Care Physician Rate variables, Asian ethnicity became significant ($p < 0.05$). Though this variable became significant, it was replaced by another insignificant variable: Uninsured population ($p = 0.44$). Primary Care Physician Rate was significant within this model ($p < 0.05$).

Upon adding back Heart disease in White patients aged 45-64 to test for significance based on other variables which had been successfully added to the model, this variable was still insignificant ($p = 0.91$), and was permanently removed from additional models.

With the addition of Pneumonia Vaccine and Reported Hepatitis A variables to the model, the Uninsured population became significant ($p < 0.05$), and each of the added variables had an individual, significant effect on model fit ($p<0.05$). All of these variables (Pneumonia Vaccine, Hepatitis A, and Uninsured) were consequently kept in the model due to their significance and their contribution to overall model strength.

When assessing the different models which were constructed, variance inflation factors were examined in order to test for multicollinearity. Uninsured population and Hepatitis A, when used in the same model, added a large amount of variance to the model, as indicated by a $\sqrt{VIF} > 2$. Thus, in order to minimize the variance due to the interaction between the two variables, it is best if only one of these variables was used in each model. The same was true for Cancer in White patients aged 65+ and Cancer in White patients aged 45-64, and Flu vaccine and Pneumonia Vaccine. Thus, in the final model, only one of each of these variable pairs with high correlations was included.

The final linear model, however did include two variables with a large VIF value; Uninsured population and Hepatitis A. This is assessed in further detail in the discussion section. The final linear model was built with the following variables: Wh_Cancer.age.45.64., Age_65_84, Average.Life.Expectancy, Asian, Prim_Care_Phys_Rate, Uninsured, Pneumo_Vax, and HepA_Rpt, and is shown below:

Heart Failure Readmissions = 1.245 + (Wh_Cancer.age.45.64. x -3.85e-3) + (Age_65_84 x -3.78e-3) + (Average.Life.Expectancy x -1.12e-2) + (Asian x 1.93e-2) + (Prim_Care_Phys_Rate x -3.43e-4) + (Uninsured x 1.63e-6) + (Pneumo_Vax x -5.38e-4) + (HepA_Rpt x -1.72e-3).

Binomial Model

The initial, unweighted, binomial model resulting from R was not significant, as all variables in the model had $p > 0.05$. Because of the insignificance of the unweighted binomial model, a weighted binomial model was used to determine if there was a difference between the weighted and unweighted models. The weight that was used was the number of patients in each county divided by the total number of patients in Michigan, restricting the population to Medicare beneficiaries over the age of 65, with a primary diagnosis of heart failure. By adding this weight to the model, all of the variables subsequently became highly significant, $p < 0.01$. Through the use of weighted variables to the model, it was with the intention that some of the variables would become significant while others would not, providing a subset of variables to use moving forward. This, however, did not help to narrow down a subset of variables to be used within the final model, as all variables were now highly significant.

Final Analysis – Binomial

Due to the lack of variable subsets from initial binomial modeling, the variables which were used in the final linear model were used as a starting point for building the binomial model. The unweighted model had no significant variables and the weighted model had all significant variables. Thus, use of the variables within the final linear model will prevent a complete redesign of the model, as some variables have already shown their ability to impact the model in predicting hospital readmissions; though not in binomial form.

When evaluated in a binomial model, the only variables from the final linear model which remained significant were Average.Life.expectancy, Primary_Care_Phys_Rate, and Asian, and were all highly significant ($p < 0.01$). This was the first binomial model which was constructed, and had an AIC of 768.05; the highest of all models evaluated.

Keeping these three variables in the model, and adding Disabled Medicare and Cancer in White Patients aged 45-64, all variables were significant ($p < 0.05$) with the exception of Cancer in White Patients 45-64 years. AIC for this model decreased to 763.19. Due to the insignificance of Cancer in White Patients aged 45-64, this variable was removed from further modeling.

The addition of vaccination status was not significant for either influenza or pneumonia vaccines ($p > 0.05$), and their inclusion in the model increased AIC to 764.9. After additional models were constructed with these two vaccination variables, where they never provided a significant contribution to overall model fit ($p > 0.1$), they were removed from further analysis.

Adding Hispanic and No_HS_Diploma variables to the model changed which variables remained significant. The addition of these variables resulted in only two variables, out of the six in the model, remaining significant; average life expectancy and Asian ($p < 0.05$). In this model, Hispanic had a p-value of 0.06 and No_HS_Diploma had a p-value of 0.96, both of which were insignificant, although Hispanic was on the verge of significance. Through the changes made to the models, addition or removal of variables, Hispanic variable became significant in subsequent models and remained in the model. No_HS_Diploma however remained insignificant and was removed from further models.

The final binomial model included Average life expectancy, Asian, Primary Care Physician Rate, Disabled Medicare, and Hispanic indicators, and had the lowest AIC of all models evaluated: 761.2. The model is shown below.

Heart Failure Readmissions = 2.09 + (Average.Life.Expectancy x -4.46e-2) + (Asian x 5.90e-2) + (Prim_Care_Phys_Rate x -7.31e-4) + (Disabled_Medicare x 2.98e-6) + (Hispanic x -1.03e-2).

V. Discussion

Assessing the differences in hospital readmission rates for Medicare patients with primary heart failure, the two models created were able to indicate which components of socioeconomic status were most influential on repeated hospital admissions. Comparing the linear model to the binomial model, there were variables that were seen in both; Asian ethnicity, Average Life Expectancy, and Primary Care Physician Rate. This indicates that these three variables, in conjunction with others, are critical components of being able to accurately predict heart failure readmission rates in Medicare patients. For reference, the final models are listed below:

Final Linear Model:

Heart Failure Readmissions = 1.245 + (Wh_Cancer.age.45.64. x -3.85e-3) + (Age_65_84 x -3.78e-3) + (Average.Life.Expectancy x -1.12e-2) + (Asian x 1.93e-2) + (Prim_Care_Phys_Rate x -3.43e-4) + (Uninsured x 1.63e-6) + (Pneumo_Vax x -5.38e-4) + (HepA_Rpt x -1.72e-3).

Final Binomial Model:

Heart Failure Readmissions = 2.09 + (Average.Life.Expectancy x -4.46e-2) + (Asian x 5.90e-2) + (Prim_Care_Phys_Rate x -7.31e-4) + (Disabled_Medicare x 2.98e-6) + (Hispanic x -1.03e-2).

The final linear model contained eight variables, six of which were negatively correlated with hospital readmissions; Cancer in white patients aged 45-64, average life expectancy, patients aged 65-84, rate of primary care physician visits, pneumonia vaccination rates, and reported Hepatitis A. As these variables increase, the number of heart failure related hospital readmissions decreased, indicating the inverse relationship between the two. The rate of pneumonia vaccination seemed to be the strongest variable included in the linear model, as this variable had the largest coefficient regardless of direction. This is promising however, as the strongest variable included in prediction of heart failure related readmissions is easily mitigated through effective public health prevention efforts. Additionally, the preventive health measures which continually appeared in the final linear model indicate that better management of chronic conditions in the outpatient setting coupled with patients who are engaged in their care, will prevent a large number of readmissions as patients are aware of the steps they need to take in order to stay healthy (AHRQ, 2013).

The final model that was selected to best predict hospital readmissions with regard to heart failure was the binomial model. Due to violation of normality assumptions with the linear model, the binomial model will be better able to predict the outcome of interest. This is because the non-normal distribution of the data does not make it easy for a model to predict – especially in the form of a linear model.

There were two variables in the final linear model which had a direct positive relationship to predicting hospital readmissions for Michigan Medicare patients with heart failure: population of Asian descent and number of uninsured patients. Thus, as these two variables increased, so did the likelihood of an associated heart failure related hospital readmission.

Within the linear model, average life expectancy had the smallest coefficient, indicating that it is the variable with the smallest impact on the outcome. This result must be interpreted critically however, because this variable is a compilation of other factors. Average life expectancy is an amalgamation of factors such as co-morbid conditions, overall health status, ethnicity, age, and many other health and sociodemographic factors– all of which were included in statistical modeling.

In contrast, the final binomial model only contained five variables, compared to the eight which were included in the final linear model. The variables contained in the binomial model had much stronger coefficients than those from the linear model, indicating that they have a larger impact on the rate of change for mean hospital readmissions. Within the final binomial model, the variables were divided fairly evenly in the direction of their relationship with the outcome variable as two had a direct relationship, while the other three had an inverse relationship. Rate of primary care physician visits was the variable with the largest coefficient, indicating the strongest inverse relationship with the outcome. As the rate of primary care physician visits increased, the mean of heart failure related hospital readmissions decreased by 0.0073.

Heart disease in White patients aged 45-64 was one variable which was included in all 13 initial linear models suggested by R, however this variable was not seen in either final model. Though one could have predicted that heart disease in a younger age group could predict the frequency of heart failure readmissions in another, it is important that this variable be evaluated due to the significance given to it by R-software during the initial modeling phase. There are a few reasons why this variable may have been included; the care these patients are receiving is frequent, and they are more engaged with their providers and with the overall process of their care. Because it was not included in either final model but was present in every model built by R, it is important that the models generated by the computer are re-evaluated because there may be better, stronger options available which were not presented solely by the statistical analysis. Using the initial suggestions which were generated by the R software is a good start to model building, however through trial and error with manual model building and evaluation, better models may be obtained. Furthermore, relying solely on the variables which were statistically significant based on initial linear correlations may not result in the strongest models being generated, as two of the three variables seen in both final models (Asian, Average Life

Expectancy and Primary Care Physician Rate) were insignificant during the initial model building process.

Differentiating between statistical significance and clinical significance is important to adequately ensure that results of the research are applicable to the patient population they were intended to effect. Noting that some of the variables that were statistically significant cannot be utilized as a target for preventive measures as they are non-modifiable risk factors. Ethnicity and presence of a chronic disease are not mitigated, while rate of physician visits or vaccine status are easily targeted and can have a substantial impact on overall health of the community. Two additional variables which were seen in the final linear model, pneumonia vaccine status and reported Hepatitis A, are modifiable risk factors which can be targeted in prevention of hospital readmissions. Through targeted campaigns to increase vaccination rates of all kinds, these variables can trend downward, in turn reducing heart failure associated hospital readmissions.

Three variables which proved to be useful in helping predict hospital readmissions for elderly Medicare patients with primary heart failure (Asian, Average Life Expectancy and Primary Care Physician Rate), they are not all risk factors which can be altered through programs aimed at reducing readmissions. Due to the complex interaction between social factors and health outcomes there is no standardized way to measure the impact one has on the other. This conclusion is similar to previously conducted research indicating that some uncontrollable sociodemographic characteristics that influence readmission rates are a critical component for identifying patient populations who are at increased risk (Librero et al., 1999; Williams & Fitton, 2014). Thus, being able to better understand the relationship between socioeconomic variables and health outcomes through looking at models that predict a patient’s likelihood of being readmitted, hospitals will be able to better target their resources to prevent readmissions.

Additionally, Hispanic and Asian ethnicities were both included in a final model, indicating that minorities are more likely to be readmitted, which was the same conclusion reached in a 2001 study conducted by Philbin et al.

There are few validated readmission risk-prediction models which incorporate variables associated with social determinants of health, and without them, hospitals lack data about patient populations who are most vulnerable (Nagasako, Reidhead, Waterman, & Dunagan, 2014). Inclusion of socioeconomic factors in models which predict hospital readmissions is an important way for hospitals to use social factors for the patient population they serve to better determine the underlying cause for continued hospital readmissions. With a better understanding, these can be targeted and hopefully prevented entirely. Currently, the CMS risk-standardized model for hospital readmission does not include socioeconomic factors, however it is clear that hospital readmissions are not a direct function of quality of care provided, but that socioeconomic factors of the patient population they serve is just as important (Nagasako et al., 2014). Based on the results of this study, it is possible to conclude that indicators of socioeconomic status do affect the likelihood of predicting hospital readmission rates of Michigan Medicare patients with primary heart failure, and that all individual components of the broader SES concept are important in influencing likelihood of hospital readmissions.

Socioeconomic status indicators are indicative of the likelihood that a patient will be readmitted, though some of these risk factors are non-modifiable, such as age, ethnicity, or chronic disease status. However, when attempting to decrease rate of readmissions, the risk factors which are modifiable, will be the best option as they will have the biggest impact. Due to the complexity of readmissions with all of the interwoven components, preventing readmissions in their entirety is an overwhelming task (Fontanarosa & McNutt, 2013).

Location of patients' residence also has the capability to impact health status, as lived environment is able to help or hinder the ability of its' residents to stay healthy. This can be seen through access to grocery stores and gyms, availability of healthcare services, the presence of toxins and pollutants, and poor infrastructure. Thus, hospital location, whether urban or rural, and the population which it serves, seems to be indicative of the readmission rate of that hospital; regardless of care quality. Not only have readmission rates been correlated with the treatment of low-income patients, but those suffering from congestive heart failure as well (Williams et al., 2014). Due to the impact of various socioeconomic factors on the residents in the surrounding community, readmission rates serve as a reflection of the level of wealth and prosperity for that location. A yearlong collaborative was aimed at improving heart failure related readmissions in the metro-Detroit area, and was successfully able to reduce readmissions by 9.5% in this area, as compared to a 4.9% reduction in other Michigan hospitals who were not participating ("Michigan Hospitals", 2014). Thus, being aware of shortcomings make it easier to reduce unwanted hospital admissions.

Strengths & Limitations

The datasets that were utilized to conduct this study were complete and reliable sources of the respective information they contain. Due to the comprehensive nature of the data and the detail contained within these datasets, it can easily be utilized for research as it is has very few missing observations, especially MIDB. Using datasets which have complete information is important for drawing conclusions which are consistent with measuring the true rates within the population of interest. Additionally, due to the publically available nature of the census data, and the standardization of state inpatient databases, it makes replicating this study in other states possible. In doing so, the results can be compared between states to see where consistency lies with regards to what socioeconomic status indicators have an impact on heart failure readmissions rates.

Another strength of the study is the creation of two different models, each having their individual strengths, allowing for hospitals and health systems to utilize the models which were created to best target their patient population. Furthermore, it provides contrast between which variables were significant in each model, allowing for comparisons between the factors that remained significant and those that did not. Because the multivariate linear regression model violated normality assumptions, it indicates that this final model may not contain the best combination of independent variables to predict the outcome of interest (Northwestern University, 1997).

One of the variables that was found in both the binomial and the linear final models, rate of visits to a primary care physician, can be a potential target for most effective prevention efforts. Targeting the modifiable risk factors will result in the best improvement with regards to heart failure related readmissions.

One limitation of this research is the reliance on census data and its division of the population by location through the use of zip-codes. It is difficult to rely solely on geographic location (zip code or census data) as a link to health outcomes due to issues with heterogeneity within these areas. "Census tracks are defined by the US Census Bureau as small, relatively permanent statistical subdivisions of a county, which are relatively homogenous with respect to population characteristics, economic status, and living conditions while zip codes are administrative units designated by US Postal Service" (Krieger et al., 2002, p. 1100). The entire zip code may look drastically different than one suburb within that area which is problematic when trying to draw overarching generalizations regarding socioeconomic factors and health outcomes (Krieger et al., 2002). Thus, aggregate measures should not be interpreted at the patient level, nor should specific measures be aggregated to represent the entire population (Geronimus & Bound, 1998). Though the spatiotemporal zip code-census mismatch is a well-understood problem with census level data and it's link to health outcomes, there is no better way of finding such detailed patient level demographics on a large population scale (Geronimus & Bound, 1998). Utilizing socioeconomic data by geographic area has been criticized in prior research due to validity of these assumptions, however it is the best data available as there is not an identifiable data set which can be used to link directly to subsequent health outcomes. Thus, being aware of the shortcomings with using census data while still utilizing the results to improve patient care must be carefully balanced.

Differences in health status cannot be attributed entirely to differences in socioeconomic status, as there are many factors besides socioeconomic status which impact population health. Though there has been an association established between socioeconomic factors and health status, which was confirmed through this study, it is not a direct relationship between these factors and the outcome. Confounding of variables within this study is noteworthy as socioeconomic status variables are not independent of each other, as indicated by multicollinearity, which ultimately contributes to overall variance within the model. This is true of any collection of closely related variables all aimed at measuring one common theme. Thus, use of this type of data is a potential draw-back of the study and should be noted when utilizing these models for prediction.

The use of case-control study design for this study was done so in a non-traditional manner. A traditional case-control study would suggest that this study be comprised of the cases which would have heart failure, while the control group would not, and then would compare the readmission rates between the two. In this study however, both groups of patients have heart failure, however the difference between the case group and the control group was the presence of a hospital readmission. Using a patient group, all of whom have the disease of interest, and dividing them based on their readmission status, will indicate which socioeconomic variables are different between the two groups. Ultimately this will show which factors are more prevalent in the group who was readmitted compared to the group who was not, and will provide insight to actionable items which can reduce the readmission rate.

Recommendations for Future Research

Replication of the study is made possible through the identical information collection conducted by other state organizations through their inpatient databases as well as publically available U.S. Census data. Due to consistency between states on the type of information collected through their inpatient databases, it is possible for the study to be replicated.

The "See You in 7" campaign, as mentioned previously, was shown to be an effective way to reduce hospital readmissions, especially as it pertains to heart failure ("Michigan Hospitals", 2014). Through specific recommendations of areas of need, hospitals are able to identify patients who may need additional help to stay healthy; in turn reducing their readmission rates through improving patient care.

Utilizing the models provided within this research and applying them to intervention programs to determine if these are an effective way to reduce readmissions among this patient population will be beneficial for both patients and providers. Some of the variables within the models cannot be modified but the ones which can should be targeted through community outreach and public health campaigns to reduce the rate of readmissions for Medicare patients with heart failure. The modifiable socioeconomic variables from the final models which can be targeted include rate of visits to a primary care provider, uninsured status, receipt of pneumococcal vaccine, and reported cases of Hepatitis A. In alleviating some of this health burden, the models presented suggest that this will result in a decrease number of hospital readmissions due to heart failure within the Michigan Medicare population.

VI. Conclusion

The purpose of this study was to determine which socioeconomic status indicators were associated with hospital readmissions for Medicare patients with heart failure. Hospital readmission rates are being linked to the quality of care provided as well as reimbursement rates to physicians and hospitals. Mitigating readmission risks can be done through a foundational understanding of the conditions that place a large burden on the American health care system. In addition to these health conditions, knowledge of socioeconomic factors which influence the likelihood of patients to be readmitted is another way that patients can be effectively targeted to reduce risk of readmission.

Due to the progressive nature of heart failure, the majority of patients who suffer from more serious, chronic heart failure are in the Medicare age range. Linking health outcomes and hospital readmission of this population to the socioeconomic status indicators collected by the United States Census Bureau allowed this research to determine which factors most heavily impact heart failure readmissions among Medicare patients. Primary care physician rate, which was seen in the binomial model and the linear model, is a good starting point as its inclusion in both models suggests that it has a strong impact on heart failure readmission rates. Through increased patient engagement in their care as well as increased frequency of care, hospitalizations due to readmissions may decrease.

Utilizing the modifiable socioeconomic status indicators that were included in final models to construct prevention efforts is the next step to begin reducing heart failure readmissions among Medicare patients. Through targeted interventions, both prior to hospital discharge as well as shortly after, provided by a primary care physician, patients are able to receive the medical attention they need in order to prevent a subsequent readmission.

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Appendix 1. MHA Data Request Approval

MHA Keystone Center

2112 University Park Drive
Okemos, MI 48864
(517) 323-3443
www.mha.org

May 12, 2015

To whom it may concern:

Kelsey Peterson does not need Institutional review board approval through Michigan Health and Hospital Association to conduct research on the data used for her thesis. Per the approved Data Request (attached), MHA has been granted permission by any providers submitting data to share for specific approved public health purposes. Any necessary IRB approval would only need approval through Grand Valley State University.

Please contact me with any questions.

Danielle Barnes
dbarnes@mha.org
517-256-2332

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Appendix 2. GVSU HRRC Letter of Determination

DATE:	June 3, 2015
TO:	Kelsey Peterson
FROM:	Grand Valley State University Human Research Review Committee
STUDY TITLE:	[756553-1] Sociodemographic Characteristics of Heart Failure Associated Hospital Readmissions in Michigan Medicare Patients
SUBMISSION TYPE:	New Project
ACTION:	RESEARCH - NOT HSR
EFFECTIVE DATE:	June 3, 2015
REVIEW TYPE:	Administrative Review

Thank you for your submission of materials for your planned research study. It has been determined that this project:

DOES NOT meet the definition of covered human subjects research* according to current federal regulations. The project, therefore, *DOES NOT* require further review and approval by the HRRC.

This determination was made after discussing the proposal with the PI and clarifying several contradictions within the submitted materials. Discussion points worth mentioning:

- the limited focus of this public health research proposal, funding reimbursement practices for a select population (Medicare or VA patients age 65 or older with a primary diagnosis of heart disease) based on readmission rates, does not meet the definition of research as described at 45 CFR 46.102 (see below)
- neither the use of publicly available data obtained from the Census Bureau, nor the deidentified data set obtained from MHA (where the researcher has no current or future access to identifiers) constitutes research on living human subjects (no interaction/intervention/observation) or their private, identifiable information
- the PHI mentioned in the protocol referred to obtaining zip codes; however, when clarified with the PI these zip codes are for the admitting hospital, rather than the patients' addresses, and does not constitute PHI

If you have any questions, please contact the Research Protections Program, Monday through Thursday, at (616) 331-3197 or rpp@gvsu.edu. The office observes all university holidays, and does not process applications during exam week or between academic terms. Please include your study title and reference number in all correspondence with our office.

Appendix 3. CHSI Indicator Dictionary

Age_65_84

- Number of residents between ages 65 and 84 years of age.

Asian

- Population by Race/Ethnicity — Race- and ethnicity-specific population sizes are from "Annual estimates of the resident population by age, sex, race, and Hispanic origin for counties: April 1, 2000 to July 1, 2008." These data are mid-year estimates of the resident population of 2008, and reflect standard race and ethnicity categories in use by the U.S. Census Bureau.

Average.Life.expectancy

- Average Life Expectancy — This measure represents the average number of years that a baby born in a particular year is expected to live if current age-specific mortality trends continue to apply. Calculations for the 5-year life expectancies (1997–2001) were made by Chris Murray and colleagues at the Harvard School of Public Health.

Disabled_Medicare

- Number of Medicare beneficiaries reporting some type of disability, including sensory, physical, mental, self-care, go-outside-home, or employment disabilities.

Flu_Vac

- <u>Flu</u> —The percentage of adults aged 65 years and older who have had a flu shot within the past year. Influenza is more likely to lead to serious complications, such as pneumonia, in older adults. Much of the illness and death caused by influenza can be prevented by yearly vaccination.

HepA_Rpt

- Number of reported Hepatitis A cases.

Hispanic

- Hispanic Ethnicity — This classification is a description of persons, separate from their categorization by race. The reader is encouraged to use race cross-classified by ethnicity (e.g., non-Hispanic white; non-Hispanic black, etc.) and not to treat race and ethnicity as mutually exclusive. Currently all states report ethnicity data, although this has not been the case in the past. Ethnicity is most complete for the most recent years, since 1997 for deaths and since 1993 for births.

Major_Depression

- Major Depression — An estimate of the number of individuals aged 18 years and older experiencing a major depressive episode during the past year, was calculated by multiplying 2006–2007 Annual Averages Major depression prevalence by state for age 18 and older by 2008 mid-year county population estimates for people aged 18 years and older.

No_HS_Diploma

- No High School Diploma— The number of individuals aged 25 years and older who have not graduated from high school. Prevalence estimates of no high school diploma (from the 2000 Census of Population and Housing Demographic Profile: 2000)

Pneumo_Vax

- Pneumonia — The percentage of adults aged 65 years and older who have ever had a pneumococcal vaccination. Pneumonia is a leading cause of death among older Americans; many pneumonia deaths can be prevented through increased use of this vaccine.

Prim_Care_Phys_Rate

- Area Primary Care Physicians— The total number of active, non-federal physicians per 100,000 population in 2007. This figure includes those who practice in one of the four primary care specialties — general or family practice, general internal medicine, pediatrics, and obstetrics and gynecology.

Recent_Drug_Use

- Recent Drug Use — An estimate of the number of individuals aged 12 years and older using illicit drugs within the past month was calculated. The figure was calculated by multiplying 2006–2007 Percentages Reporting Past Month Use of Any Illicit Drug by Age Group and State for age 12 and older by 2008 county population estimates for ages 12 and older. Illicit drug use includes use of one or more of the following: marijuana, cocaine (including crack), heroin, hallucinogens (including LSD and PCP), inhalants, or non-medical use of psychotherapeutics, Substance Abuse and Mental Health Services Administration (SAMHSA, Office of Applied Statistics, Table B.1 Illicit Drug Use in Past Month, by Age Group and State: Percentages, Annual Averages Based on 2006-2007 NSDUHs).

Uninsured

- Uninsured Individuals — The estimated number of uninsured individuals under age 65 in the county in 2006 is from the U.S. Census Bureau, Small Area Health Insurance Estimates Program (SAHIE). The SAHIE program models county-level health insurance coverage by combining survey data with population estimates and administrative records.

Wh_Cancer.age.45.64

- Cancer — Malignant neoplasm, ICD-9 codes: 140-208. ICD-10 codes: C00-C97. Population – White, ages 45-64.

Wh_Cancer.age.65.

- Cancer — Malignant neoplasm, ICD-9 codes: 140-208. ICD-10 codes: C00-C97. Population – White, ages 65 and older.

Wh_HeartDis.age.45.64

- Heart Disease — Diseases of the heart, ICD-9 codes: 390-398, 402, 404-429. ICD-10 codes: I00-I09, I11, I13, I20-I51. Population – white, ages 45-64.

(United States Department of Health and Human Services, 2009).