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THE INFLUENCE OF SOCIAL CAPITAL ON SUCCESSFUL COMMUNITY DISCHARGE AFTER POST-ACUTE CARE AMONG MEDICARE BENEFICIARIES

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THE INFLUENCE OF SOCIAL CAPITAL ON SUCCESSFUL COMMUNITY DISCHARGE AFTER POST-ACUTE CARE AMONG MEDICARE BENEFICIARIES

by

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Dedication

This dissertation is dedicated to my family—Dylan, Lord and Lady Bumppo, Jacqui, and Christine. You have helped me fight the good fight, finish the race, and keep the faith.

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I acknowledge the dedication and commitment of my professors and colleagues to help me undertake and complete this endeavor.

The influence of social capital on successful community discharge after post-acute care among Medicare beneficiaries

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Health equity, in which high standards of care are provided to individuals regardless of individual characteristics, is a goal of the healthcare system. Social risk factors such as socioeconomic position, cultural contexts, and community factors may negatively affect health outcomes despite high standards of care. This dissertation focuses on structural social capital—the sum of resources available from the community structure—as a social risk factor in the community context that may affect health outcomes. This was done by examining the association between successful discharge to the community at 30 days and county-level social capital among Medicare beneficiaries who were discharged from post-acute care facilities for lower limb fracture and joint replacement services from 2013–2014. The analyses were retrospective and cross-sectional. Manuscript 1 looked at all patients in the United States, accounted for the nested structure of the data where patients were nested within counties, and regressed the binary outcome—successful discharge to the community—on patient- and county-level characteristics. Manuscript 2 was an ecological study in which the unit of analysis was

Texas Hospital Referral Regions (HRRs). We calculated the silhouette index, a proxy of how homogenous or disparate levels of social capital are among counties within Texas HRRs. We then regressed the percent of successful discharges to the community on the silhouette index and other HRR-level characteristics to see if there was an association between social capital disparity in Texas HRRs and the percent of beneficiaries with successful discharge to the community in each HRR. Manuscript 3 examined only patients with Texas HRRs, accounting for patients nested within HRRs. We used logistic regression to regress the outcome on the HRR-level silhouette index to see if social capital disparity was associated with successful discharge to the community. The findings of this dissertation show that the effect of social capital on health outcomes varies by diagnosis group and level of geographic analysis. Additional research should be cognizant of how the effect of social capital on health may vary depending on how social capital is defined, the amount of social capital that is available, and the geographic level of analysis.

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List of Abbreviations

CCU	Coronary Care Unit
CMS	Centers for Medicare and Medicaid Services
DTC	Discharge to Community
GSBS	Graduate School of Biomedical Sciences
HCC	Hierarchical Condition Categories
HRR	Hospital Referral Region
ICC	Intraclass Correlation Coefficient
ICU	Intensive Care Unit
IRF	Inpatient Rehabilitation Facility
IRF-PAI	Inpatient Rehabilitation Facility Patient Assessment Instrument
LOS	Length of Stay
LTCH	Long-term Care Hospital
MDS	Minimum Data Set
MedPAR	Medicare Provider Analysis and Review
PAC	Post-acute Care
RGFI	Rupasingha, Goetz, and Freshwater Social Capital Index
SI	Silhouette Index
SNF	Skilled Nursing Facility
US	United States
UTMB	University of Texas Medical Branch
VBP	Value-based Purchasing

Chapter 1: Introduction

Health care equity, in which high standards of care are provided to patients regardless of their individual demographics, diagnoses, severity, or geographic location, is a global issue that the American healthcare system is attempting to address.[1,2] For many payers including Medicare, payment modifiers distribute resources among market baskets that take into account differences in wages in order to address the needs, case mixes, and characteristics of varying regions and facilities. Additionally, the shift to value-based purchasing (VBP) incentivizes high quality care and quality outcomes over the volume of services.[2] However, these reimbursement strategies do not consider social risk factors that are known to influence health.

In 2016, the Health and Medicine Division of the National Academies published a report recognizing the importance of social risk factors such as socioeconomic position, race, ethnicity, cultural context, social relationships, and community context—among others—as key determinants of health (Figure 1.1).[2] As these social risk factors are not accounted for in VBP, the transition to a reimbursement system that incentivizes quality outcomes may be problematic if some regions have more patients with more prevalent social risk factors.[3] For example, “safety net” hospitals which serve a disproportionate share of low-income individuals may be unfairly penalized for treating a portion of individuals who may have substantially worse health outcomes than more affluent individuals, regardless of standards of care. One dimension that corresponds to residential and community context social risk factors is a person’s social structure, support, and connections—their social capital.

Minimal research has been conducted on the influence of the social capital of patients on health care outcomes in the post-acute care (PAC) setting, in part because of the difficulty of creating a precise definition of social capital. Whereas physical capital and human capital are objects and properties of individuals, social capital is a "soft" type of capital that is more difficult to define.[4] In fact, most researchers agree that it is unlikely that one definition can exist across all spheres, as the definition of the concept varies both within a field's analysis (e.g., economics, sociology, health, etc.) and between fields.[5] Although a single definition may not exist, most researchers agree that social capital is a "process" and not a thing[6] that can decay if it is not maintained.[7,8] Regardless of its complexity, the concept of social capital has been defined in several non-mutually exclusive ways over the past 100 years[7] by researchers in various fields.

Defining Social Capital

The term social capital was first introduced in 1916 by a state supervisor of rural schools who urged people to be involved in community activities as a way to improve the schools.[7] In the 1980s, Pierre Bourdieu focused on the individualistic aspect of social capital; he defined it as the sum of resources obtained from a person's social structure through mutual acquaintances, recognition, and institutional relationships.[7,9] For example, according to Bourdieu's definition, having a mutual acquaintance who is a car salesman would increase your social capital if you are in the market for a car; when a neighbor recognizes you or your colleague at work knows your name and greets you, your social capital increases. A few years later, James Coleman expanded the concept by focusing on social economy. He showed that social capital is not only a person's social structure but the advantages that accrue as a result of that social structure. If you have an acquaintance who is a car salesman, then you may save some money when purchasing a new car; if you have a neighbor who knows you, then he or she may watch out for suspicious activity around your house and consequently provide protection for your property. This concept also exists at higher levels, such as the neighborhood where neighbors depend on each other for advice, emotional support, and services such as babysitting or dog walking. Although Coleman's definition of social capital focuses on its positive aspects, social capital can also be disadvantageous. If you cease smoking and your colleagues or friends continue to smoke, then your social capital may decrease as a result of your connection to them.

The definition that is of interest to this project was given by Robert D. Putnam in 1993.[7] He viewed social capital as a community-centric concept based on social organization that facilitates coordinated action.[7,9] Putnam's view is that social capital is more than a person's connections or social network; it also includes the feelings of trust and reciprocity that occur when people are thus connected.[7] Therefore, Putnam's definition focuses on the importance of community organizations that connect individuals, foster a sense of trust and reciprocity (e.g., "I'll help him/her and in the future he/she or someone else will help me"), and coordinate people to make society more efficient. For example, a school's Parent–Teacher Association unites schoolchildren's parents and teachers to raise funds, discuss issues, and provide scholarships; these, in turn, help the school to improve and the community to thrive—all of which increase social capital. Although these definitions are certainly not exhaustive and the concept of social capital is a moving target that continues to fluctuate as times change, this study will focus on Putnam's community-centric vision of social capital as it applies to health care. It will focus on the "structural" aspects of social capital—i.e., what people do or do not have in their community.[7,10]

Types of Social Capital

Just as there are various definitions of social capital, researchers have identified numerous ways to operationalize the concept. Historically, two main typologies of social capital are 1) bonding, bridging, and linking social capital[11]; and 2) structural vs cognitive forms.[12]

Bonding and bridging social capital represent "horizontal" structures between individuals of similar social status. *Bonding social capital* is characterized by cooperation and trust and generally occurs between individuals who are similar with respect to their shared social identity,[13] such as between family members.[14] *Bridging social capital* refers to interactions between people who are dissimilar in some way—e.g., in their social identity or sociodemographic characteristics[13]—and manifests as shared feelings, actions, and respect, such as between colleagues or distant relatives.[14] On the other hand, *linking social capital* describes respect and trust in vertical relationships between individuals with institutionalized power from a formal hierarchical structure,[13] such as between bankers and clients or politicians and constituents. In the health field, this hierarchical relationship may exist between patients and providers, where providers hold a role of perceived power and authority and can manifest respect and trust from patients.

Using Putnam's community-centric definition of social capital (community organizations that facilitate coordinated action)[7], social capital can be divided into two different forms: cognitive social capital and structural social capital.[15] *Cognitive social capital* refers to people's subjective, intangible feelings of trust, shared norms, beliefs, and values.[12] This corresponds to Putnam's idea of the reciprocity and trust that occurs within organizations.[15] For example, cognitive social capital could be operationalized as how trusting a person is of people in their community. If a person feels he or she can trust their neighbor, their cognitive social capital would be high. In contrast, *structural social capital* refers to what people have or do in their local community, e.g., the collective actions, decisions, and information that is shared by people in their social network through positions with established procedures and rules.[12,16] Structural social capital is objective and externally observable, and it can be operationalized by describing the activities, number, and type of local-level institutions in an area.[7,12,16] For example, an area that has numerous religious, civic, and political organizations has higher structural social capital than an area that lacks these types of institutions. This project focuses on this type of social capital, which is represented by the structural social capital present in the county where an individual lives.

Measuring Social Capital

Social capital has numerous definitions and types, and it is not surprising that this complex concept is not directly measurable.[14] Although finding a definitive single measure of social capital is improbable,[17] comprehensive measures should encompass different levels and units of analysis and should adapt over time to allow for changes in formal institutions and informal groups.[17] Therefore, a proxy is necessary to measure social capital.[14]

Whereas years of education and work experience have served as effective proxies for human capital,[17] prominent proxies for social capital have been survey questions of generalized and specific trust, network densities, and Putnam's Instrument (the density of volunteer organizations in a population).[18,19] Instrumental variables have also been explored to increase understanding of the latent concept of social capital. The World Health Organization (WHO) Europe[20] used the following instruments in a survey to understand how social capital affects health: 1) if respondents had parents whose birth countries matched their country of residence, 2) if respondents had been burgled within a certain time frame, 3) the population density in the region, 4) road network lengths in the region, 5) the percent of people without internet in the region, and 6) the percent of residents holding citizen status in the region.

In 2006, Rupasingha, Goetz, and Freshwater developed a comprehensive structural social capital index[21] at the county level that has since been validated as a risk factor for population health outcomes.[22] This index (the Rupasingha, Goetz, and Freshwater Index, or RGFI) was developed using principle components analysis.[21] It combined the following four main variables: the number and types of membership organizations as captured by the *County Business Patterns* by the US Census Bureau, census and Housing Survey response rates from the census performed every 10 years by the US Census Bureau, the percentage of people who voted in presidential elections, and the number of per capita non-profit organizations as reported by the National Center for Charitable Statistics.[21] This index was validated by Lee and Kim in 2013.[22] Like the other county-level social indices examined in Lee and Kim's work, the RGFI was limited in face validity as the index may not be measuring social capital but may measure outcomes of social capital instead.[22] The index was also limited in content validity as it only considers one form of social capital (i.e., structural); however, it was better than Lee and Kim's other county-level measures in this sense, because the RGFI incorporates both formal (e.g., religious organizations) and informal membership organizations (e.g., golf clubs and fitness centers).[22] The social capital index was determined to be valid and negatively associated with the violent crime rate ($r = -0.27$, $P < 0.01$, $n = 2950$) and the Gini coefficient ($r = -0.24$, $P < 0.01$, $n = 3085$), which is a marker of income inequality.[22] Finally, using multivariable linear regression with RGFI as a predictor of population health outcomes, while controlling for county-level median household income and percentage of African Americans, the RGFI was weakly to moderately associated with all outcomes examined: premature death ($\beta = -0.22$, $P < 0.01$), average poor physical health days ($\beta = -0.43$, $P < 0.01$), average poor mental health days ($\beta = -0.40$, $P < 0.01$), and average self-rated health ($\beta = -0.47$, $P < 0.01$).[22] Lee and Kim's analyses show that increases in the structural social capital index are associated with improved population health outcomes. Therefore, we have chosen to use the 2014 version of this index in this project as a way to define individuals' structural social capital index based on the county they live in.

Degrees and Levels of Analysis of Social Capital

Regardless of the definition, three notions are common when conceptualizing social capital.[14] Firstly, social capital is intertwined with the sphere of economics[14] as it is the sum of resources that individuals have access to, and it can be characterized by the exchange of those resources.[14] Secondly, different amounts of social capital elicit different types of behavior.[14,23] This is expressed in the *social capital continuum* (Table 1.1).[23] For example, actions vary by quartile of social capital (i.e., "minimum," "elementary," "substantial," and "maximum" social capital).[23] For individuals with minimum levels of social capital, actions are self-serving at others' expense, and there is no interest in others' well-being (self-aggrandizement); at elementary levels individuals may cooperate in order to serve their own interests (efficiency of cooperation); at substantial levels of social capital individuals may exhibit cooperation that benefits others as well as the self, where people are committed to common activities (effectiveness of cooperation); at maximum levels, people are concerned with the public good and others' well-being (altruism).[23] Therefore, it is prudent to note that the effect—and sphere of influence—of social capital is not uniform and varies with the amount of capital available.

Additionally, the concepts, applied terminology, and consequences of social capital can change depending on the level at which the analysis is performed, from the micro (individual) to the macro (national or international).[24] This variability makes it challenging to decide where to focus analytical efforts. For example, at the individual level, terms such as "beliefs", "values", and "attitudes" are used, whereas at broader levels—e.g., regions—terms such as "regional culture" and "mentality" are used (Table 1.2).[25] Research in various spheres from business to economics to sociology has been performed at each level: individuals,[20] groups,[7] neighborhoods,[26-28] communities,[13,29] counties,[21] regions,[14] and national comparisons have been made.[30]

Therefore, a priority of this project was to explore the effect of social capital at different levels of analysis to better understand the association between social capital and health outcomes: Chapter 3 examines it at the county level, and Chapter 4 and 5 examine it at the level of the Hospital Referral Region (HRR). This project uses the social capital index at the county level as proposed by Rupasingha et al. to incorporate the community-centric definition of social capital. This objective and externally observable measure accounts for the notion that different behaviors can manifest at different levels of analysis. The index also allows for different degrees or categories of social capital since it can be broken into quartiles, such as minimum, elementary, substantial, and maximum levels.[23] Additionally, the index incorporates different units of analysis such as business patterns and voter turnout.[17]

The county-level RGFI was chosen as the index of social capital in this dissertation as it is a broader concept of social capital than other individual- or lower-level indicators. For example, individual-level characteristics of senior housing are types of social capital that are associated with health outcomes.[31,32] In fact, housing variables may be more proximal to those that directly affect health. For example, if a senior citizen does not have access to appropriate and livable housing, they may be less likely to participate in many activities of daily living both inside and outside the house and may have worse health.[31,32] However, this dissertation will examine the effect of the RGFI (referred to as the "social capital index") on health outcomes as it is a broader and potentially more robust definition due to its combination of different aspects of structural social capital.

Geographic Variation in Post-Acute Care

Geographic variation exists in healthcare; use, practices, outcomes, and costs continue to vary significantly across the United States, and increased spending does not always equate to improved outcomes.[33-35] In the acute setting, studies have shown that variation exists across all levels of care. Differences in patients, provider preferences, facility practices, and regional attitudes all contribute to a wide range of spending and outcomes.[33] A 2013 Institute of Medicine Report estimated that only 27% of the variation in total Medicare spending occurs in the acute setting, whereas a vast 73% of the variation occurs in the post-acute care (PAC) setting;[33] this setting includes stays in long-term acute care hospitals (LTCHs), inpatient rehabilitation facilities (IRFs), skilled nursing facilities (SNFs), and visits by home health agencies. Although Medicare spending may be predictable in the hospital setting, more research is needed to identify what factors—such as social risk factors—drive such high variation in the PAC setting.

Researching social determinants of health, such as social capital, within the community context may help explain some of the variation that occurs in post-acute care. This project focuses on two of the most common conditions occurring in Medicare beneficiaries: lower limb fracture (an emergent condition) and joint replacement (a planned procedure).[36,37] Different levels of analyses that nest patients within counties and patients within Hospital Referral Regions are used to determine the amount of variation that can be explained by accounting for patient characteristics within administrative and healthcare boundaries.

To measure differences in health care between regions, regional boundaries that relate to health care must be defined that may or may not correspond with administrative boundaries (e.g., zip codes or counties). For the world of acute care, this breakdown into regions was accomplished by the Dartmouth Atlas of Health Care group in 1996. The group broke the United States into multiple "naturally occurring health care markets," such as Hospital Service Areas (HSAs).[38] Hospital Referral Regions are generally larger in area than HSAs and correspond to regions in which Medicare patients received tertiary care, such as neurosurgery and major cardiovascular surgery.[38] These boundaries have since been validated and adopted by the Centers for Medicare and Medicaid (CMS)[33] to identify regional differences in resources, spending, and usage. The current project uses an administrative boundary—the county—and the larger healthcare regions—HRRs—each of which includes one or more Texas counties. The goal is to understand if accounting for the nested structure of the data where patients are nested within counties or patients nested within HRRs can account for a substantial amount of variation seen in successful community discharge.

Applying Social Capital to Healthcare Outcomes

This project will focus on how Medicare beneficiaries' RGFI influences their likelihood of discharge to the community, which is the goal of PAC rehabilitation. This is presented in the conceptual model in Figure 1.2 which is based on the conceptual framework of social risk factors by the National Academies presented in Figure 1.1.[2] Returning to the community is a multi-dimensional measure of a person's functional status. Community discharge requires individuals to be cognitively and physically able to meet the demands of returning to community life, and the decision regarding discharge can be affected by access to caretakers, family, and friends. Successful discharge to community (DTC) at 30 days in this dissertation refers to the claims-based measure defined by CMS as discharge home (Patient Discharge Status codes 01, 06, 81, and 86), and no unplanned readmissions to a hospital or LTCH or death within 31 days after discharge.[39] Therefore, this project builds upon the PAC research that has focused on patient, clinical, and facility characteristics normally captured in Medicare data. It enhances the current literature by adding the dimension of social risk factors—an individual's structural social capital—that has previously been associated with improved health outcomes, but has previously been ignored in PAC rehabilitation research.

The overall objective of this project is to contribute to an improved understanding of the influence of social risk factors on PAC outcomes. This will be accomplished by examining the influence of Medicare beneficiaries' structural, collective social capital on successful community discharge for patients with joint replacement and hip fracture across two PAC settings: inpatient rehabilitation facilities (IRFs) and skilled nursing facilities (SNFs). Patients receiving post-acute care in long-term care hospitals were not included in the analyses because individuals receiving care in such facilities have significantly lower community discharge rates than those in other post-acute care facilities. Additionally, home health services were excluded because of significant market instability and variation in types and quality of services provided by home health agencies.[40] The goal is to understand if the structural social capital index is associated with the healthcare outcome of interest, successful community discharge, and to understand at what level (e.g., individual, county, or HRR) it was most impactful. The objective was accomplished with three aims.

AIM 1. Explore how different implementations of the structural social capital index influence patients' odds of successful community discharge.

The 2014 county-level social capital index created by Rupasingha et al.[21] for each county in the United States was explored as a continuous, a binary, and a categorical variable. Using 100% Medicare data, hierarchical logistic regression models were performed with each implementation of the social capital index, nesting patients within counties. The outcome measured was successful community discharge at the patient level. Nested models were compared using likelihood ratio tests to determine whether more complex models were significantly different from less complex models.

Hypothesis 1: Higher social capital is significantly associated with a higher likelihood of community discharge across all rehabilitative settings.

AIM 2. In an ecological analysis of Texas, explore variation in the social capital index at the level of the Hospital Referral Region (HRR) using the silhouette index and model its influence on successful community discharge at the HRR level.

The disparity in social capital between healthcare regions was examined with the silhouette index (SI),[41] a type of clustering measure. The 2014 county-level social capital index was grouped at the HRR level in Texas, and the SI—a numeric value—was assigned to each HRR.[41] The more similar the social capital between the counties within each HRR, the higher the SI and the less disparity for that HRR. Linear regression was used to model the association between SI and the percentage of successful community discharge at the HRR level.

Hypothesis 2: Higher SI, indicating more similarity in social capital among counties within an HRR and less disparity, is associated with a higher percentage of successful community discharge at the HRR level.

AIM 3. Explore the association between silhouette index, a marker of social capital disparity, and the odds of successful community discharge in a multi-level structure with patients nested within HRRs.

Hierarchical logistic models accounting for the nested data structure (patients nested within HRRs) were used to examine the influence of social capital disparity, described using the social capital SI at the HRR level, on successful community discharge.

Hypothesis 3: More variation is explained when the HRR-level social capital SI is added to the model, controlling for other patient- and HRR-level variables.

Although it is difficult to reach a consensus on the definition of social capital, this complex concept is a process, a moving target, that can manifest in different ways depending on the level of capital available. Therefore, this lack of understanding of this influential concept can make policies to increase social capital a challenge.[42] As with the "chicken and the egg" example, social and human capital are intertwined.[42,43] Social capital can increase education and health, which ultimately increases human capital[14]; human capital—through good education—increases community engagement, and good health increases the likelihood of community cooperation and participation.[14] Only by beginning to understand what may be associated with health outcomes can we affect future policies. This project is an attempt to lend structure and clarity to this complex concept.

Figure 1.1. The conceptual framework of social risk factors and performance indicators for value-based payment. Taken from *Accounting for Social Risk Factors in Medicare Payment: Identifying Social Risk Factors.* Washington, D.C: National Academies Press; 2016.

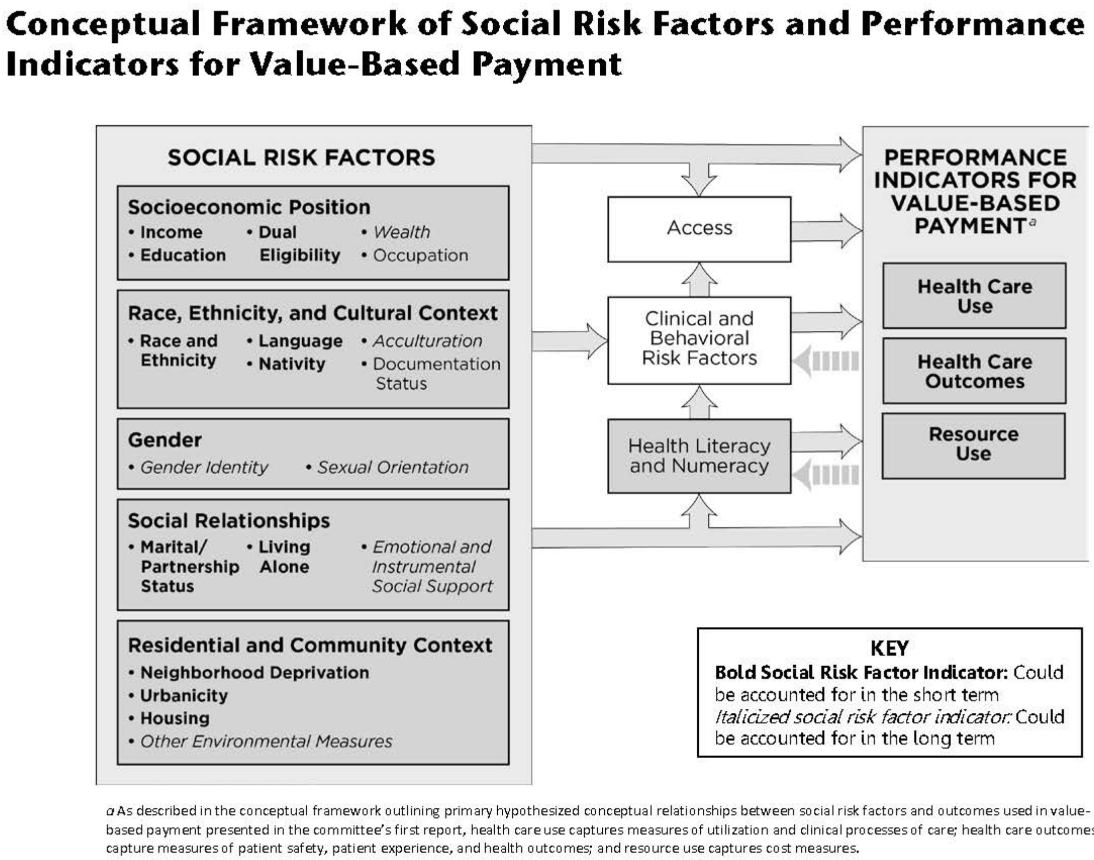


Figure 1.2. Conceptual model mapping the association between social capital and discharge to community.

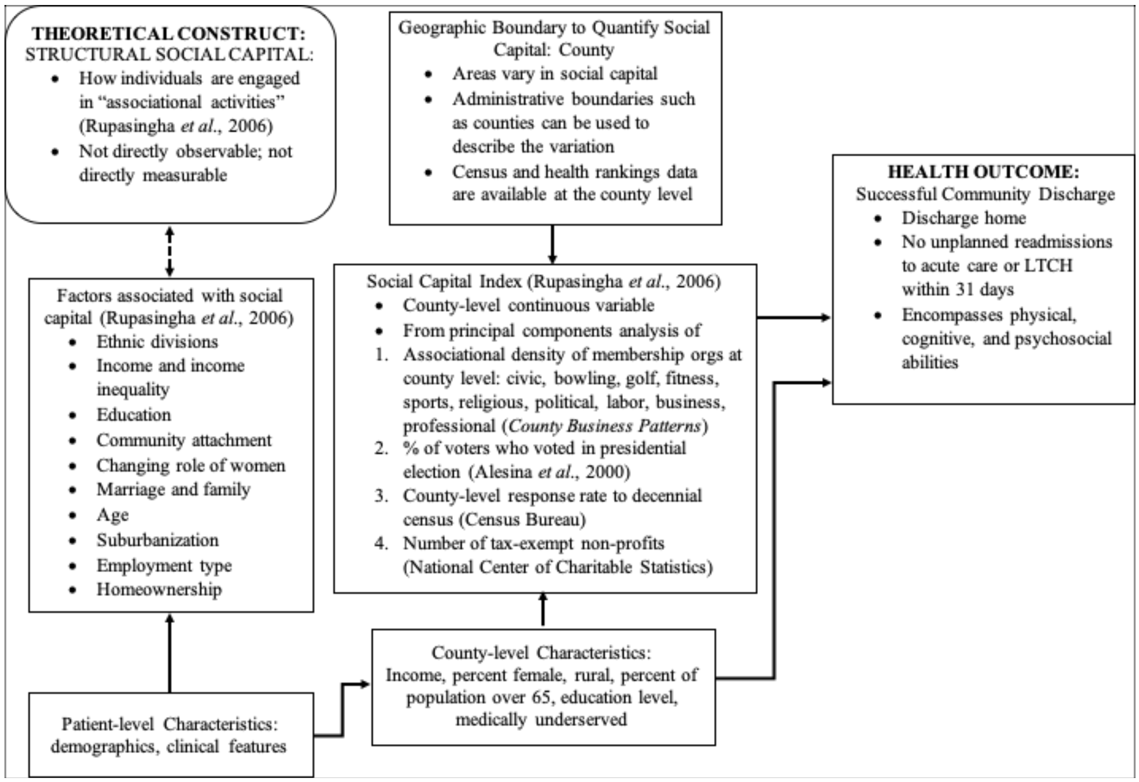


Table 1.1. The social capital continuum showing different behaviors at different levels of social capital. Taken from *Uphoff N. Understanding social capital: learning from the analysis and experience of participation. Social capital: A multifaceted perspective. 2000:215–249.*

Minimum social capital	*Elementary social capital*	*Substantial social capital*	*Maximum social capital*
No interest in others' welfare; seek self-interest maximization at others' expense	Interest primarily in own welfare; cooperation occurs only to the extent that it serves one's own advantage	Commitment to common enterprises; cooperation occurs to a greater extent when it is beneficial also for others	Commitment to others' welfare; cooperation is not limited to seeking one's own advantage; concern for public good
Values:			
Self-aggrandizement respected	*Efficiency* of cooperation	*Effectiveness* of cooperation	*Altruism* regarded as something good in itself
Issues:			
Selfishness—how can this be kept from being socially quite destructive?	*Transaction costs*—how can these be reduced to increase people's respective net benefits?	*Collective action*—how can cooperation (that is, pooling of resources) succeed and be sustained?	*Self-sacrifice*—how far should this be taken: for example, patriotism? religious zealotry?
Strategy:			
Autonomy	Tactical cooperation	Strategic cooperation	Merger or submergence of individual interests
Mutual benefits:			
Not considered	Instrumental	Institutionalized	Transcendent
Options:			
Exit whenever dissatisfied	*Voice*, try to improve terms of exchange	*Voice*, try to improve overall productivity	*Loyalty*; acceptance of results if good for all in total

Table 1.2. Social capital at different levels of analysis. Found in *Malecki EJ. Regional Social Capital: Why it Matters. Regional Studies. 2012;46(8):1023–1039*. Adapted from *Westlund H. Social capital in the knowledge economy: Theory and empirics. Springer; 2006. Figure 3.1.*

Level	Terms used for social capital
Nation	National cultures
Region	Regional culture, regional mentality
Local level (place)	Local relations, spirit of place
Group	Relations, norms, networks
Individual	Behaviour, preferences, opinions, values, attitudes

Chapter 2: Common Methods

There are methods that are common to each of the three manuscripts presented in this dissertation. They are the method of patient selection from the Medicare analytical files and the operationalization of the social capital index.

DATA SOURCES

The following Medicare files were linked to obtain claims information, demographics, discharge destinations, and facility characteristics: Medical Provider Analysis and Review (MedPAR), Beneficiary Summary, Minimum Data Set (MDS 3.0), Inpatient Rehabilitation Facility-Patient Assessment Instrument (IRF-PAI), and Provider of Services (POS) files.

PATIENT SELECTION

Patients in the study were fee-for-service Medicare beneficiaries aged 66 years or older who were discharged from a skilled nursing facility or inpatient rehabilitation facility after a first acute episode discharge from January 1, 2013 to December 31, 2014, with a diagnosis of lower limb extremity fracture (MS-DRG 480–482) or joint replacement (MS-DRG 469–470) (Figure 4.1). Patients were excluded if they did not have an IRF stay within three days or a SNF stay within 8 days of discharge from the index acute episode, were younger than 66 years, were discharged from PAC after December 31, 2014, or if they lacked continuous Medicare coverage one year before hospital discharge and 90 days after PAC discharge. Patients were also excluded if they were transferred to another hospital after PAC, or if they were transferred to PAC from a

SNF or LTCH. Only patients whose acute admission was elective, urgent, or emergent were included.

SOCIAL CAPITAL INDEX

The 2014 social capital index was a continuous variable at the county level. The index was originally created in 2006 by Rupasingha et al.[21] from a principle components analysis of four main variables (with various data sources): 1) the number of non-profit organizations per capita (National Center for Charitable Statistics); 2) the type and number of membership organizations (*County Business Patterns* of the US Census Bureau); 3) decennial census and Housing Survey response rates (US Census Bureau); and 4) the percent of voters in presidential elections. The index can range from negative to positive infinity, where negative values indicate low social capital and positive values indicate high social capital.

Lee et al. showed that the index was reliable and valid and that it outperformed other less-comprehensive measures. For example, other county-level measures of social capital include the Petris Social Capital Index (PCSI) and the Behavioral Risk Factor Surveillance System (BRFSS) measure.[22] In terms of content validity, the BRFSS measure does not include structural social capital and the PCSI and Rupasingha et al. index do not include cognitive social capital.[22] Additionally, while the Rupasingha index encompasses formal and informal organizations, the PCSI only includes formal memberships.[22] In terms of associations with health outcomes, the Rupasingha et al. index and the BRFSS index showed weak to moderate associations with all outcomes in the study: “premature death”, “average poor physical health days,” “average poor mental health days," and average self-rated health."[22] These associations were also more pronounced for the RGFI and BRFSS than for the PCSI.[22] Therefore, the structural social capital index from Rupasingha et al. was chosen because its broad index encompasses both formal and informal measures of structural social capital and because it outperformed other less inclusive or other types of county-level social capital measures.[22] Each patient who lived in the same county was assigned the same social capital index at the county level.

Chapter 3: Manuscript 1

INTRODUCTION

Health care equity, a goal of the American healthcare system, is the concept of providing high standards of care to patients regardless of individual demographics, environment, or location.[1,44] In Medicare, changes in reimbursement strategies are aimed at making this goal achievable; payment modifiers distribute resources to address the needs of certain areas, and value-based purchasing (VBP) incentivizes quality outcomes.[44] However, social risk factors (e.g., socioeconomic position, cultural context, social relationships, etc.) can influence health outcomes and are ignored in these strategies.

In 2016, the Health and Medicine Division of the National Academies published a report recognizing the importance of social risk factors such as socioeconomic position, race, ethnicity, cultural context, social relationships, community context, and other risk factors, as key determinants of health.[44] Social risk factors in the community context may be of particular importance for post-acute care (PAC) outcomes.[45] Rates of successful discharge to the community are now being measured in PAC facilities[46] and are important quality indicators and outcomes for PAC. However, discharge to the community is a complex decision that takes into account physical, mental, and psychosocial skills, as well as the environment that the patient returns to.[47,48] Without accounting for the influence of community/social risk factors on successful discharge to the community (DTC), facilities that treat patients returning to communities with higher risk factors may be unfairly penalized when the discharges are unsuccessful.

One potential social risk factor in the community context is social capital, broadly defined as resources available from the community structure.[7,9,10] Social capital can be further divided into cognitive or structural forms.[10] Cognitive social capital is a more subjective notion—what an individual thinks and feels about the support available to them—and trust and reciprocity are examples of this concept. For example, you may trust your neighbor to bring you a meal after a hospitalization or offer the same to him/her. This study focuses on the more physical components of social capital—the objective, quantitative form of structural social capital, defined as what people have or do in their community.[16] This refers to the activities, number, and types of local-level institutions in an area that an individual can participate in or draw resources from.[7,16] For example, a community that has numerous religious, civic, and political organizations has higher structural social capital than a community lacking these. From these organizations, individuals can find physical, mental, financial, and other types of support that can help them remain in the community after PAC discharge. Therefore, we hypothesize that individuals with higher structural social capital at the county level—i.e., those with more opportunities from which to draw resources and support—are more likely to experience DTC. Quartiles of the social capital index used in this study (the RGFI discussed in Chapter 1) are mapped for all counties in the United States in Figure 3.1. Darker red indicates lower levels of social capital and darker green indicates higher levels. Southern regions of the United States tended to have lower values whereas the Midwest presented with higher levels of the structural social capital index.

In this study we study Medicare beneficiaries with joint replacement and lower limb extremity fracture, as these groups represent two of the most common conditions treated in IRF and SNF PAC facilities.[36,37] They also represent planned and unplanned diagnoses and are commonly used to test payment strategies such as the Bundled

Payments for Care Improvement (BPCI) Initiative[49-51] and MedPAC site-neutral payments.[52,53] The purpose of this study is to identify a potential association between Medicare beneficiaries' county-level social capital and the likelihood of being successfully discharged to the community following post-acute care in skilled nursing facilities and inpatient rehabilitation facilities after lower limb fracture or joint replacement.

METHODS

Study Design and Data Sources

We performed a retrospective cross-sectional study of Medicare beneficiaries who received PAC to see if there was an association between the social capital in the county in which the beneficiary resided and the likelihood of DTC. The process of linking Medicare files was detailed in Chapter 2. We then determined the beneficiaries' county of residence by linking their zip code of residence to the U.S. Housing and Urban Development zip code to county crosswalk corresponding to the year of the patient's PAC admission (https://www.huduser.gov/portal/datasets/usps_crosswalk.html). Finally, we linked beneficiaries' county of residence to the 2014 social capital index developed by Rupasingha et al.[21] We used a one-year look-back before hospital discharge and 90-day look-forward period after PAC discharge to determine continuous coverage. This study was approved by the University's Institutional Review Board and the authors had a CMS data use agreement.

Population

Inclusion criteria for beneficiaries was presented in Chapter 2. Exclusion criteria were younger than 66 years, other acute episode diagnoses, no IRF stay within three days or SNF stay within eight days, non-continuous Medicare enrollment for the one year prior to and 90 days after admission to the PAC facility, entitlement reason other than age, missing profit status or teaching status of the PAC facility, and zip code of residence not mapping to a U.S. county (e.g., patients who lived in American territories or other countries) (Figure 3.2). Patients were also removed if they were missing any data from any linked variables. The final sample consisted of 114,108 beneficiaries in the lower limb fracture group and 237,474 in the joint replacement group.

Outcome

The outcome was a composite outcome of successful discharge to the community (DTC, yes/no) at 30 days, a claims-based measure defined by CMS as discharge home from patient discharge status codes (i.e., 01, 06, 81, and 86), and no unplanned readmissions to a hospital or LTCH or death within 31 days after discharge.[39] These codes are found in inpatient and skilled nursing fee-for-service files and are defined as 01(home/self care), 06 (home with home health services), 81 (home/self care with planned acute readmission), and 86 (home with home health services with planned acute readmission).

Social Capital

County-level structural social capital was the main variable of interest and was described in detail in Chapter 2, and it was coded as a continuous variable for each county in the U.S. The index has been shown to be reliable and valid.[22] Since the variable is at the county level, all beneficiaries from one county were assigned the same social capital index.

Covariates

Covariates were chosen by content experts with statistical considerations of multicollinearity[54] that might arise in our model building process.

Patient-Level Characteristics. Sociodemographic variables at the patient level were categorical: age (66–69, 70–74, 75–79, 80–84, 85+), sex (male, female), race (non-Hispanic White, non-Hispanic Black, Hispanic, Other), PAC length of stay (quartiles), and dual status (yes/no). Clinical characteristics at the patient level were categorical: post-acute care type (IRF, SNF), hospital length of stay (LOS) (quartiles), PAC LOS (quartiles), ICU/CCU (yes/no), and hospitalizations in the past year (yes/no). The top 15 most prevalent Hierarchical Condition Categories (HCCs) were also included as markers of comorbidities.[55] Facility characteristics (POS file) at the patient level were categorical: hospital bed count (0–25, 25–49, 50–99, 100–199, 200–299, 300–399, 400–499, 500+), hospital control status (profit, non-profit, government), and hospital teaching status (yes/no).

County Characteristics. All characteristics at the county level were from County Health Rankings & Roadmaps 2014 data (www.countyhealthrankings.org) and were split into quartiles. Variables were median household income, percent female, percent rural, percent over 65 years old, percent of residents with some college, and the rate of primary care physicians defined as the ratio of the population to primary care physicians.

Statistical Analysis

We analyzed the joint replacement group and lower limb fracture group separately. We performed univariate descriptions for each group and checked the continuous social capital variable for normality using a boxplot and q–q plot, and grand-mean centered social capital. Collinearity of the social capital index was assessed using linear models to regress the continuous form of the index on each of the covariates. Cramer's V was calculated to assess the measure of association between all pairs of categorical variables, and Spearman's correlations were used to assess the correlation between all pairs of ordinal variables.

We hypothesized that hierarchical modeling would be necessary to account for the nested structure of the data, in which patients were nested within counties. Conceptually, we hypothesized that the likelihood of DTC may have varied between counties, and the effect of patient-level variables on the likelihood of DTC may have also varied by county. Therefore, to test the necessity of hierarchical modeling we first ran an empty generalized linear mixed-effects model with Laplace estimation that contained only a random intercept grouped by county, and we calculated the intraclass correlation coefficient (ICC). The ICC is the amount of variation that can be attributed to the county grouping structure and is calculated as ρ:

$$\rho = \tau^2/(\tau^2 + \pi^{2/3}),$$

where τ^2 is the between-county variance, and $\pi^{2/3}$ represents the logistic distribution variance.[56] Negligible values (those close to 0) of the ICC may suggest that complex hierarchical models nesting patients within counties should be abandoned in favor of simpler single-level logistic regression models. Therefore, if the empty model with a random intercept had an ICC < 2%, analyses using single-level models were performed for all further logistic regression models detailed below.

All patient- and county-level covariates were entered into a single-level logistic regression model together to determine a subset of covariates that met a threshold of $P < 0.1$. These covariates were then entered into a sequence of four models regressing 30-day DTC on 1) patient-level covariates, 2) patient-level covariates + social capital index, 3) patient- and county-level covariates, and 4) patient- and county-level covariates + social capital index. Likelihood ratio tests were performed to compare more complex models to similar, less complex models; C statistics were used to determine goodness of fit of each of the models.

Sensitivity analyses were performed in which social capital was coded as quartiles and as a binary variable. As literature suggests that different behaviors may manifest at different levels of social capital,[23] the effect of social capital on DTC may also vary by the amount of social capital available. This may mean that there could be a different effect of social capital when there is an abundance compared to when there is a scarcity. Therefore, ICCs for empty models with only a random intercept grouped by county were performed on subsets of patients whose social capital fell in the top quartile, second, third, and bottom quartiles, and also for patients residing only in Texas. All analyses were performed using R Version 3.5.3 “Great Truth” in RStudio Version 1.1.456. Significance was set at $P < 0.05$.

RESULTS

Population Characteristics

Univariate descriptions of patient characteristics are shown in Table 3.1, categorized by diagnosis group. The majority of patients in both groups received post-acute care in SNFs (LLFx: 76.3%, JR: 81.7%), were female (77.0%, 72.9%), white (90.6%, 89.32%), were not dual eligible (85.8%, 90.5%), had no ICU/CCU stay (79.8%, 89.6%), and had no hospitalizations in the past year (71.3%, 79.7%). Whereas over half (54%) of LLFx patients were 85 years and older, patient age in the JR group was more evenly distributed with less than a quarter of these patients (24.7%) 85 years or older. For those with LLFx, 66.3% (n = 75,690) had an acute length of stay of 4–7 days; 60% (n = 144,416) of those with JR had an acute stay lasting 0–3 days. Concerning facility characteristics that were coded at the patient level, a high proportion of patients in each group came from acute hospitals with 500 or more beds (24.0%, 24.6%), were for-profit (71.5%, 71.6%), and non-teaching (56.6%, 55.7%) hospitals.

Table 3.2 presents bivariate relationships of each variable with the outcome, 30-day DTC, using chi-squared tests for categorical variables and a t-test for the continuous social capital index. Dashes indicate that the variable was not included in the top 15 HCCs for the diagnosis group.

For both lower limb fracture and joint replacement, grouping patients by county did not account for a sufficient amount of variation to warrant the use of hierarchical models (LLFx ICC = 0.0091; JR ICC = 0.0138); less than 1% of the variation in the odds of DTC could be attributable to county differences for LLFx patients and only 1.4% for those with JR. Single-level logistic regression models were pursued and final models for each group with adjusted odds ratios and 95% confidence intervals are presented in Table 3.3. In this table, dashes indicate the variable was either collinear or did not meet the *a priori* $P < 0.10$ threshold when all covariates were entered into a single-level model and therefore was not used for modeling purposes.

Variables associated with higher odds of DTC :

Both groups: Being female was associated with higher odds of DTC (LLFx: adjusted odds ratio (AOR) 1.095, 95% CI 1.067–1.122, $P < 0.001$; JR: AOR 1.076, 95% CI 1.054–1.098, $P < 0.001$). There were significantly higher odds of DTC for Hispanics (LLFx: AOR 1.371, 95% CI 1.293–1.454, $P < 0.001$; JR: AOR 1.220, 95% CI 1.154–1.289, $P < 0.001$) and other races (LLFx: AOR 1.460, 95% CI 1.363–1.564, $P < 0.001$; JR: AOR 1.308, 95% CI 1.227–1.395, $P < 0.001$) compared to whites. Receiving care in an IRF compared to a SNF was associated with significantly higher odds of DTC (LLFx: AOR 1.745, 95% CI 1.694–1.797, $P < 0.001$; JR: AOR 1.143, 95% CI 1.115–1.172, $P <$

0.001). Although quartiles of PAC length of stay were associated with higher odds of DTC, compared to the lowest quartile, the highest odds were associated with the third quartile.

Joint replacement only: For those with joint replacement, receiving care in a teaching hospital compared to a non-teaching hospital was associated with 3.8% higher odds of DTC (AOR 1.038, 95% CI 1.017–1.060, $P = 0.003$). Each one-unit increase in social capital was associated with a 3% increase in the odds of DTC (AOR 1.030, 95% CI 1.016–1.044, $P < 0.001$).

Variables associated with lower odds of DTC:

Both groups: In comparison to the youngest age group, there was a decreasing trend in the odds of DTC as age increased. Dual eligibility status was associated with lower odds of DTC (LLFx: AOR 0.567, 95% CI 0.549–0.586, $P < 0.001$; JR: AOR 0.567, 95% CI 0.550–0.585, $P < 0.001$). Longer length of stay in an acute hospital was associated with lower odds of DTC. Compared to for-profit hospitals, not-for-profit hospital status was associated with significantly lower odds of DTC (LLFx: AOR 0.959, 95% CI 0.931–0.987, $P = 0.017$; JR: AOR 0.950, 95% CI 0.926–0.975, $P < 0.001$). Having a hospitalization in the past year was significantly associated with lower odds of DTC (LLFx: AOR 0.848, 95% CI 0.827–0.869, $P < 0.001$; JR: AOR 0.802, 95% CI 0.784–0.821, $P < 0.001$). All comorbidities were associated with lower odds of DTC. Compared to the lowest quartile of the percent of residents in a county who were female, being in the higher quartiles (areas with more females) was associated with generally lower odds of DTC. Similarly, living in more rural counties was generally associated with lower odds of DTC compared to living in the lowest quartile of the percent of the county that is rural.

Joint replacement only: Being non-Hispanic black was significantly associated with 8.3% lower odds of DTC (AOR 0.917, 95% CI 0.878–0.958, $P = 0.001$). Compared to for-profit hospitals, government hospitals were associated with 3.6% lower odds of DTC (AOR 0.964, 95% CI 0.936–0.993, $P = 0.039$). Compared to hospitals with 0–99 beds, receiving care in a hospital with 100 or more beds was associated with lower odds of DTC.

Lower limb fracture only: Each one-unit increase in social capital was associated with a 3.2% decrease in the odds of DTC (AOR 0.968, 95% CI 0.953–0.983, $P = 0.001$).

As a sensitivity analysis, stepwise selection was performed to verify the final models for both groups. This analysis yielded essentially the same models for both groups as built above, with the quartiles of county-level median household income no longer being significant for those with joint replacement.

Sensitivity analyses with social capital coded as a binary variable and as quartiles with variables from the chosen model are shown in Appendix Tables A3.1 and A3.2, respectively. For binary social capital, the relationship was significant and similar to that of continuous social capital for both groups. For quartiles of social capital, for JR the association with DTC was significant and similar to that of continuous social capital. However, for LLFx, only the third and fourth quartiles in comparison to the first was associated with significantly lower odds of DTC. These sensitivity analyses did not result in substantially higher C statistics for each group compared to the chosen model with social capital coded as a continuous variable (Appendix Table A3.3). Additionally, subsetting to patients who had social capital that fell within the first and second quartiles did not substantially impact the ICC when running an empty model (Table 3.4). However, the highest ICC among the empty models was found when analyzing the lowest quartile for each group (LLFx ICC = 0.0125; JR ICC = 0.0178), indicating that county grouping may explain more, albeit still little, variation when social capital is at its lowest.

DISCUSSION

Social risk factors such as socio-economic status, social relationships, and cultural context can significantly affect health outcomes.[1,2] Structural social capital, i.e., resources available from the community structure, is a social risk factor in the community context that might affect the odds of successful community discharge from post-acute care. This study is the first of its kind to examine the association between structural social capital and the odds of DTC among Medicare beneficiaries. For beneficiaries who received PAC services in SNFs and IRFs, 80.0% of those with joint replacement and 56.3% with lower limb fracture were successfully discharged to the community at 30 days. Our study found directional differences in the association of social capital with DTC between diagnosis groups, non-significant geographic impact on DTC at the county level, and higher odds of community discharge for those treated in IRFs.

There was a fundamental difference in the association of structural social capital with the odds of DTC between diagnosis groups. For those with lower limb fracture, there was a negative association, where an increase in one-unit of social capital was associated with 3.2% lower odds of DTC. Conversely, for those with joint replacement, the same one-unit increase in social capital was positively associated with 3.0% higher odds of discharging successfully. This directional difference in association between the two groups may be due in part to the urgency status (urgent/emergent vs elective)[51] of the two diagnoses and related decisions in the aftermath of the diagnoses. The Lewin group reported that outcomes of quality and utilization may differ depending on whether an event is elective or emergent.[51] For example, fractures are usually emergent, which may influence the decision of caretakers and stakeholders to reconsider the ability of a patient to live in his/her community; after a fracture, some may be more likely to seek facility care. On the other hand, joint replacements are usually planned, elective procedures where stakeholders may believe the patient to be in good enough health to use and benefit from the new joint.

Although there was a negligible amount of variation that could be attributed to county grouping, the map (Figure 3.2) shows the distribution of county-level social capital across the U.S. This may indicate a pattern at different geographic units of analysis. From the map, a general pattern can be seen where southern states experience lower quartiles of social capital and the Midwest reports higher levels. These notion of varying social capital at different geographic units of analysis coincide with findings from studies at numerous levels: individuals,[20] groups,[7] neighborhoods,[26-28] communities,[13,29] counties,[21] regions,[14,57] and national comparisons.[30] For example, Iyer et al. broke the U.S. into 9 multi-state regions of 40 states and ranked them according to the amounts of different types of social capital such as social trust; racial trust; civic-, group-, and faith-based participation.[57] In that study, although southern regions generally ranked low in most types of social capital, some regions such as the South Atlantic (e.g., Atlanta, GA) ranked highly in specific types of social capital, e.g., group- and faith-based involvement.[57] This means that although structural social capital in the present study may be generally low in southern US counties, other definitions of social capital as well as a different level of analysis (such as larger regions or smaller neighborhoods) may yield different findings. This is known as the "modifiable areal unit problem," where variation changes depending on how data is aggregated into different areal units.[58,59]

In these models adjusting for the selected variables, compared to patients treated in SNFs, those in IRFs had about 1.75 times higher odds of successful DTC for those with LLFx and 1.14 times higher for those with JR. However, we interpret this significant finding cautiously because this study does not account for differences in access to IRF and SNF facilities. For example, there are many more SNFs than IRFs in the United States, and IRFs may be built in areas that are systematically different from others (e.g., higher income areas). A study from Buntin et al. adjusted for access issues and compared outcomes for hip fracture and stroke patients by PAC setting (IRF vs SNF).[60] Their findings suggested that the IRF setting was associated with improved health outcomes for hip fracture patients.[60] In that study, whereas 28.4% of SNF patients died or were in a custodial nursing home within 120 days, this occurred in only 9.1% of patients who received care in an IRF. Therefore, the intense rehabilitation required by IRF stays may increase the odds of successfully discharging to the community. Although this study does not focus on comparative effectiveness between PAC settings and does not take into account patient differences in access to IRF and SNF facilities, this finding is similar to that of the Buntin study, controlling for our set of study variables.

There are several limitations to this study. Social capital is a complex concept that may not be possible to define with one measure; any index must rely on proxies for measurement. Therefore, the structural social capital index is not a complete, exhaustive measure of social capital, and it does not address cognitive aspects of the concept such as trust. The index is a county-based measure, not an individually-derived measure, meaning the social capital index associated with each Medicare beneficiary may not actually represent that individual's social capital. Each person who lived in the same county was assigned the same social capital index, an assumption that may not be reflective of the true situation. The index was also a 2014 variable, and it was assumed that 2013 and 2014 estimates were similar enough that patients treated in 2013 were assigned the 2014 index. Finally, beneficiary zip codes of residence were linked to counties using a crosswalk. In cases where a zip code spanned more than one county, the county chosen was the one with the highest percentage of residential area, which may have resulted in a negligible percentage of incorrect county assignments.

Despite the limitations, this study spotlights social capital as a social risk factor in the community context that our findings suggest is associated with successful community discharge from PAC. For patients with lower limb fracture, higher social capital is associated with significantly lower odds of DTC, whereas for those with joint replacement, higher social capital is associated with higher odds of DTC. However, this effect of social capital may vary depending on the geographic unit of analysis. Finally, for both lower limb fracture and joint replacement, care in IRFs compared to SNFs was associated with higher odds of DTC. These findings call for more research on the effect of different types of social capital at varying levels of geographic analysis to better understand the effect of social risk factors on health outcomes.

Figure 3.1. Quartiles of the social capital index across contiguous US counties in 2014. Green indicates higher values of social capital and red indicates lower. Quartile cutoffs are as follows from highest to lowest: 1.875–9.149; 0.326–1.874; −0.724–0.325; −3.183–−0.723.

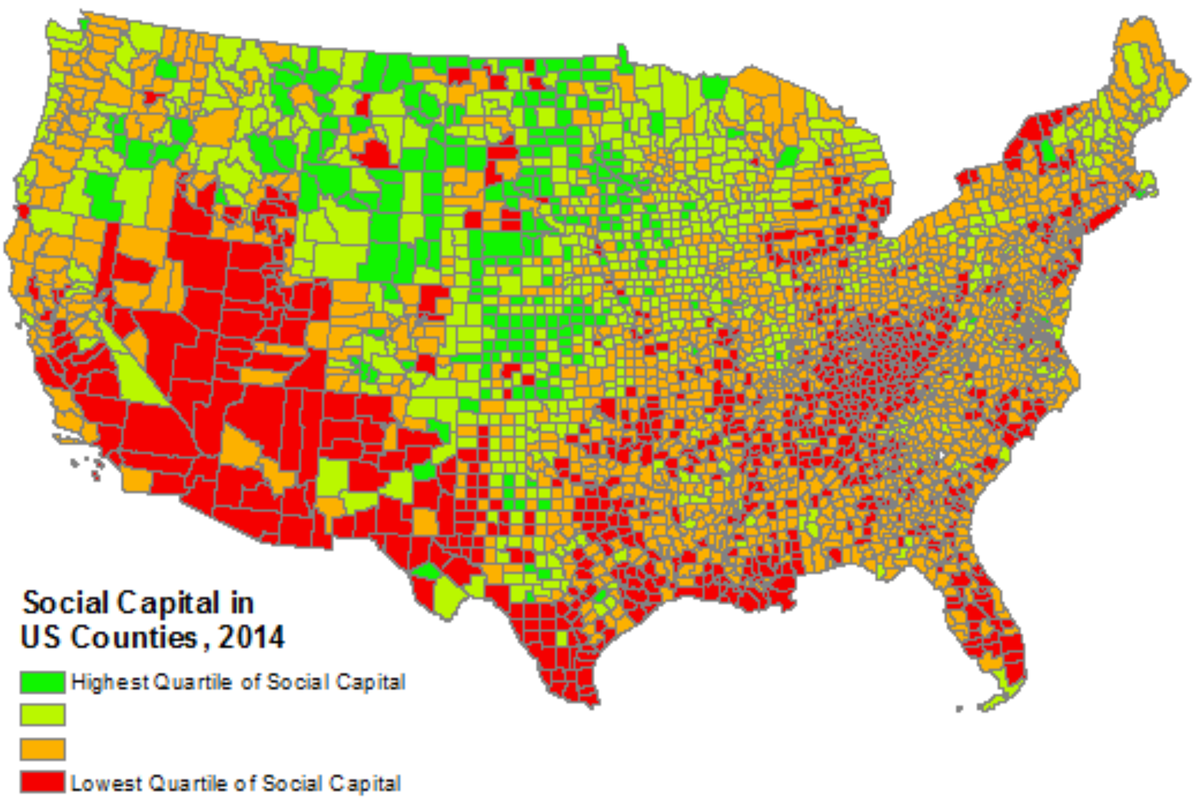


Figure 3.2. Flowchart of cohort selection for lower limb fracture (LLFx) and joint replacement (JR) groups (N = number remaining after previous step; % = percent of previous step).

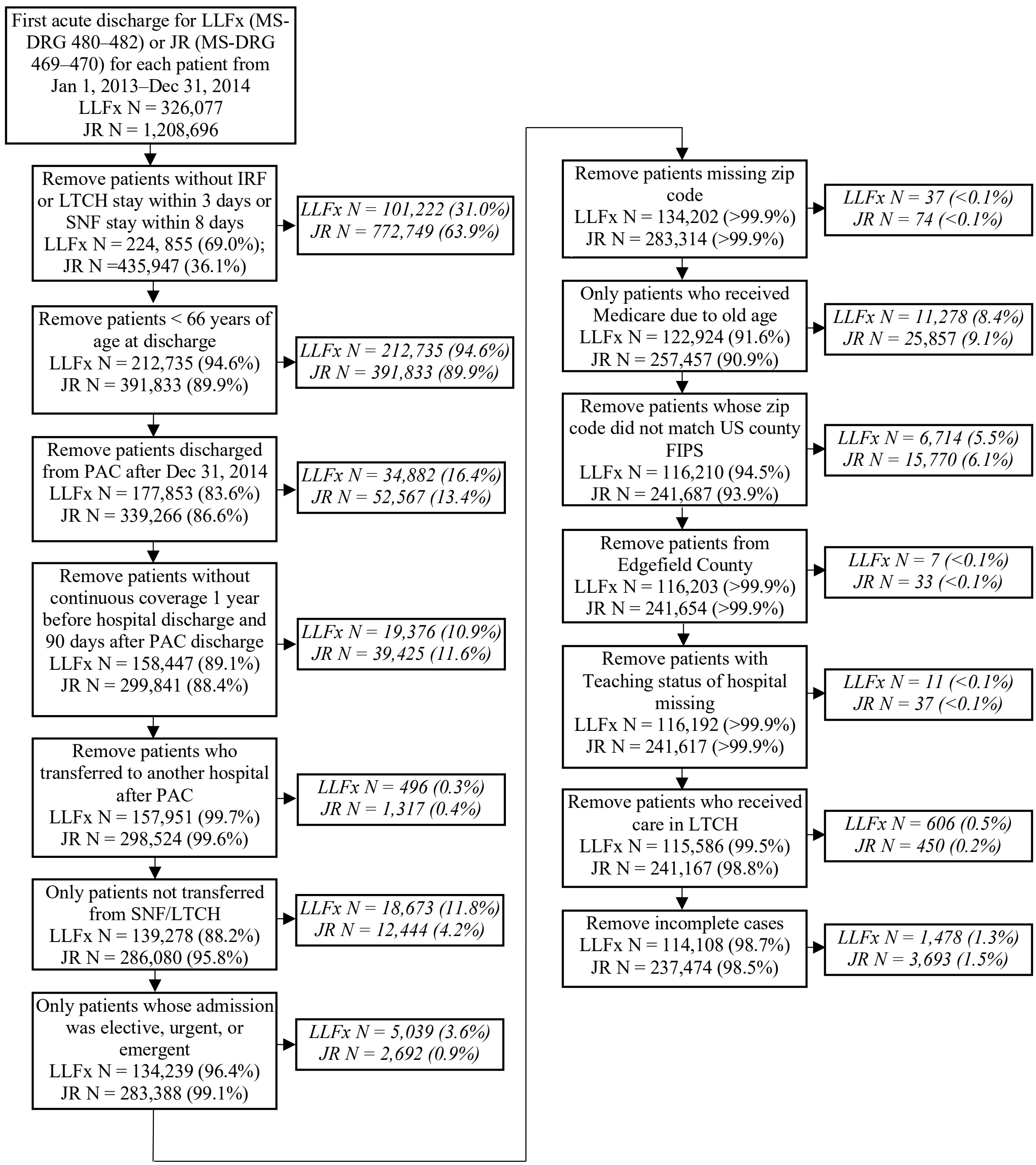


Table 3.1. Univariate descriptions of patients by diagnosis group.

Variable	Lower Limb Fracture (N = 114,108)		Joint Replacement (N = 237,474)	
	(n or mean)	**(% or SD)**	**(n or mean)**	**(% or SD)**
PATIENT-LEVEL				
Sex				
Male	26277	23.028	64362	27.103
Female	87831	76.972	173112	72.897
Age				
66-69	3902	3.4200	25359	10.679
70-74	9002	7.889	46565	19.608
75-79	15252	13.366	54589	22.987
80-84	24153	21.167	52274	22.013
85+	61799	54.158	58687	24.713
Race				
Non-Hispanic White	103418	90.632	211885	89.225
Non-Hispanic Black	3359	2.944	11841	4.986
Hispanic	4327	3.792	7877	3.317
Other race	3004	2.633	5871	2.472
Dual Eligibility				
No	97868	85.768	215021	90.545
Yes	16240	14.232	22453	9.455
Acute LOS				
0–3	24052	21.078	144416	60.813
4–7	75690	66.332	3251	1.369
8–11	10650	9.333	80808	34.028
12+	3716	3.257	8999	3.789
Acute Hospital Control Status				
Profit	81565	71.481	170101	71.629
Non-profit	18678	16.369	39457	16.615
Government	13865	12.151	27916	11.755
Acute Hospital Teaching Status				
No	64600	56.613	132196	55.668
Yes	49508	43.387	105278	44.332
Hospital Bed Count				
0–99	10120	8.869	30288	12.754
100–199	21334	18.696	40961	17.249

200–299	22940	20.104	45008	18.953
300–399	19097	16.736	37861	15.943
400–499	13246	11.608	24971	10.515
500+	27371	23.987	58385	24.586
ICU/CCU Stay				
No	91083	79.822	212887	89.646
Yes	91083	20.178	24587	10.354
Hospitalized in Last Year				
No	81409	71.344	189339	79.730
Yes	32699	28.656	48135	20.270
Diabetes Without Complication				
No	91978	80.606	189207	79.675
Yes	22130	18.419	48267	20.325
Specified Heart Arrhythmias				
No	83037	72.771	195137	82.172
Yes	31071	27.229	42337	17.828
Chronic Obstructive Pulmonary Disease				
No	93091	81.581	208296	87.713
Yes	21017	18.419	29178	12.287
Congestive Heart Failure				
No	89229	78.197	209904	88.390
Yes	24879	21.803	27570	11.610
Acute Renal Failure				
No	96499	84.568	218451	91.989
Yes	17609	15.432	19023	8.011
Vascular Disease				
No	103138	90.386	222720	93.787
Yes	10970	9.614	14754	6.213
Morbid Obesity				
No	-	-	223204	93.991
Yes	-	-	14270	6.009
Coagulation Defects and Other Specified Hematological Disorders				
No	102705	90.007	224354	94.475
Yes	11403	9.993	13120	5.525

Diabetes with Chronic Complications					
	No	109420	95.892	230570	97.093
	Yes	4688	4.108	6904	2.907
Protein-Calorie Malnutrition					
	No	106437	93.277	231510	97.489
	Yes	7671	6.723	5964	2.511
Parkinson's and Huntington's Diseases					
	No	110582	96.910	232632	97.961
	Yes	3526	2.973	4842	2.039
Hip Fracture/ Dislocation					
	No	105639	92.578	232696	97.988
	Yes	8469	7.422	4778	2.012
Other Significant Endocrine and Metabolic Disorders					
	No	110715	97.027	232906	98.076
	Yes	3393	2.973	4568	1.924
Cardio-Respiratory Failure and Shock					
	No	106494	93.327	229242	96.534
	Yes	7614	6.673	8232	3.466
Rheumatoid Arthritis and Inflammatory Connective Tissue Disease					
	No	108922	95.455	225249	94.852
	Yes	5186	4.545	12225	5.148
Septicemia, Sepsis, Systemic Inflammatory Response Syndrome/ Shock					
	No	110312	96.673	-	-
	Yes	3796	3.327	-	-
PAC Type					
	IRF	26990	23.653	43380	18.267
	SNF	87118	76.347	194094	81.733
PAC LOS, quartiles					
	1	28487	24.965	58871	24.791

	2	28208	24.720	59040	24.862
	3	28487	24.965	59415	25.020
	4	28926	25.350	60148	25.328
COUNTY-LEVEL					
Social Capital		−0.500	0.730	−0.468	0.745
Median Household Income, quartiles					
	1	27384	23.998	56837	23.934
	2	28481	24.960	59074	24.876
	3	28822	25.259	60094	25.306
	4	29421	25.783	61469	25.885
Percent Female, quartiles					
	1	27935	24.481	58077	24.456
	2	28630	25.090	59669	25.127
	3	28648	25.106	59753	25.162
	4	28895	25.323	59975	25.255
Percent Rural, quartiles					
	1	29329	25.703	61302	25.814
	2	29203	25.592	60955	25.668
	3	28723	25.172	59912	25.229
	4	26853	23.533	55305	23.289
Percent Over 65 Years, quartiles					
	1	29007	25.421	60637	25.534
	2	28918	25.343	60476	25.466
	3	28724	25.173	59547	25.075
	4	27459	24.064	56814	23.924
Percent Some College, quartiles					
	1	27582	24.172	57478	24.204
	2	28470	24.950	59315	24.977
	3	28731	25.179	59873	25.212
	4	29325	25.699	60808	25.606
Percent PCP Rate, quartiles					
	1	27603	24.190	57287	24.123
	2	28403	24.891	59365	24.999
	3	28930	25.353	60108	25.311
	4	29172	25.565	60714	25.567

All variables are presented as n (%) except social capital which is mean (SD); social capital was grand-mean centered; DTC = discharge to community; LOS = length of stay; ICU/CCU = intensive care unit/coronary care unit; PAC = post-acute care; PCP = primary care physician

Table 3.2. Bivariate analyses for the relationship of each individual covariate with the outcome, 30-day successful community discharge. Missing values indicate the variable did not reach the initial $P < 0.1$ threshold for entrance into hierarchical models.

	Lower Limb Fracture (N = 114108)					Joint Replacement (N = 237474)				
Variable	**DTC: No**	**%**	**DTC: Yes**	**%**	***P***	**DTC: No**	**%**	**DTC: Yes**	**%**	***P***
PATIENT-LEVEL										
Sex										
Male	12264	0.467	14013	0.533	<0.001	14346	0.223	50016	0.777	<0.001
Female	37631	0.428	50200	0.572		33163	0.192	139949	0.808	
Age										
66–69	995	0.255	2907	0.745	<0.001	2569	0.101	22790	0.899	<0.001
70–74	2613	0.290	6389	0.710		5438	0.117	41127	0.883	
75–79	5141	0.337	10111	0.663		8164	0.150	46425	0.850	
80–84	9721	0.402	14432	0.598		10636	0.203	41638	0.797	
85+	31425	0.509	30374	0.491		20702	0.353	37985	0.647	
Race					<0.001					<0.001
Non-Hispanic White	45375	0.439	58043	0.561		42745	0.202	169140	0.798	
Non-Hispanic Black	1565	0.466	1794	0.534		2310	0.195	9531	0.805	
Hispanic	1829	0.423	2498	0.577		1469	0.186	6408	0.814	
Other race	1126	0.375	1878	0.625		985	0.168	4886	0.832	
Dual Eligibility					<0.001					<0.001
No	41263	0.422	56605	0.578		41056	0.191	173965	0.809	
Yes	8632	0.532	7608	0.468		6453	0.287	16000	0.713	
Acute Hospital LOS					<0.001					<0.001
0–3	8644	0.359	15408	0.641		18239	0.126	126177	0.874	
4–7	32750	0.433	42940	0.567		23106	0.286	57702	0.714	
8–11	6077	0.571	4573	0.429		4265	0.474	4734	0.526	
12+	2424	0.652	1292	0.348		1899	0.584	1352	0.416	
Acute Hospital Control Status					0.881					0.003
Profit	35629	0.437	45936	0.563		33736	0.198	136365	0.802	
Non-profit	8195	0.439	10483	0.561		8087	0.205	31370	0.795	
Government	6071	0.438	7794	0.562		5686	0.204	22230	0.796	
Acute Hospital Teaching Status					0.357					<0.001
No	28324	0.438	36276	0.562		26779	0.203	105417	0.797	
Yes	21571	0.436	27937	0.564		20730	0.197	84548	0.803	

Acute Hospital Bed Count					0.205					<0.001
0–99	4494	0.444	5626	0.556		5431	0.179	24857	0.821	
100–199	9295	0.436	12039	0.564		8533	0.208	32428	0.792	
200–299	10067	0.439	12873	0.561		9241	0.205	35767	0.795	
300–399	8426	0.441	10671	0.559		7717	0.204	30144	0.796	
400–499	5687	0.429	7559	0.571		4968	0.199	20003	0.801	
500+	11926	0.436	15445	0.564		11619	0.199	46766	0.801	
ICU/CCU Stay					<0.001					<0.001
No	38004	0.417	53079	0.583		38674	0.182	174213	0.818	
Yes	11891	0.516	11134	0.484		8835	0.359	15752	0.641	
Hospitalized in Last Year					<0.001					<0.001
No	33410	0.410	47999	0.590		33605	0.177	155734	0.823	
Yes	16485	0.504	16214	0.496		13904	0.289	34231	0.711	
Diabetes Without Complication					<0.001					0.374
No	39847	0.433	52131	0.567		37783	0.200	151424	0.800	
Yes	10048	0.454	12082	0.546		9726	0.202	38541	0.798	
Specified Heart Arrhythmias					<0.001					<0.001
No	33893	0.408	49144	0.592		34523	0.177	160614	0.823	
Yes	16002	0.515	15069	0.485		12986	0.307	29351	0.693	
Chronic Obstructive Pulmonary Disease					<0.001					<0.001
No	39818	0.428	53273	0.572		39237	0.188	169059	0.812	
Yes	10077	0.479	10940	0.521		8272	0.284	20906	0.716	
Congestive Heart Failure					<0.001					<0.001
No	36256	0.406	52973	0.594		37447	0.178	172457	0.822	
Yes	13639	0.548	11240	0.452		10062	0.365	17508	0.635	
Acute Renal Failure					<0.001					<0.001
No	40244	0.417	56255	0.583		40374	0.185	178077	0.815	
Yes	9651	0.548	7958	0.452		7135	0.375	11888	0.625	
Vascular Disease					<0.001					<0.001
No	44509	0.432	58629	0.568		43095	0.193	179625	0.807	
Yes	5386	0.491	5584	0.509		4414	0.299	10340	0.701	
Morbid Obesity					-					<0.001
No	-	-	-	-	-	45293	0.203	177911	0.797	

Yes	-	-	-	-	-	2216	0.155	12054	0.845	
Coagulation Defects and Other Specified Hematological Disorders					<0.001					<0.001
No	44457	0.433	58248	0.567		43677	0.195	180677	0.805	
Yes	5438	0.477	5965	0.523		3832	0.292	9288	0.708	
Diabetes with Chronic Complications					<0.001					<0.001
No	47464	0.434	61956	0.566		45575	0.198	184995	0.802	
Yes	2431	0.519	2257	0.481		1934	0.280	4970	0.720	
Protein-Calorie Malnutrition					<0.001					<0.001
No	45957	0.435	59682	0.565		44694	0.193	186816	0.807	
Yes	3938	0.465	4531	0.535		2815	0.472	3149	0.528	
Parkinson's and Huntington's Diseases					<0.001					<0.001
No	48183	0.436	62399	0.564		45788	0.197	186844	0.803	
Yes	1712	0.486	1814	0.514		1721	0.355	3121	0.645	
Hip Fracture/ Dislocation					<0.001					<0.001
No	45957	0.435	59682	0.565		45682	0.196	187014	0.804	
Yes	3938	0.465	4531	0.535		1827	0.382	2951	0.618	
Other Significant Endocrine and Metabolic Disorders					<0.001					<0.001
No	48180	0.435	62535	0.565		46070	0.198	186836	0.802	
Yes	1715	0.505	1678	0.495		1439	0.315	3129	0.685	
Cardio-Respiratory Failure and Shock					<0.001					<0.001
No	45603	0.428	60891	0.572		44210	0.193	185032	0.807	
Yes	4292	0.564	3322	0.436		3299	0.401	4933	0.599	
Rheumatoid Arthritis and Inflammatory Connective Tissue Disease					0.002					0.758
No	47738	0.438	61184	0.562		45050	0.200	180199	0.800	
Yes	2157	0.416	3029	0.584		2459	0.201	9766	0.799	

Septicemia, Sepsis, Systemic Inflammatory Response Syndrome/ Shock						<0.001				-	
	No	47832	0.434	62480	0.566		-	-	-	-	
	Yes	2063	0.543	1733	0.457		-	-	-	-	
PAC Type						<0.001					<0.001
	IRF	10446	0.387	16544	0.613		38347	0.198	155747	0.802	
	SNF	39449	0.453	47669	0.547		9162	0.211	34218	0.789	
PAC LOS, quartiles						<0.001					<0.001
	1	15750	0.553	12737	0.447		14555	0.247	44316	0.753	
	2	11538	0.409	16670	0.591		8851	0.150	50189	0.850	
	3	10464	0.367	18023	0.633		9372	0.158	50043	0.842	
	4	12143	0.420	16783	0.580		14731	0.245	45417	0.755	
COUNTY-LEVEL											
Social Capital		-0.005†	-	−0.030	-	<0.001††	-0.033	-	−0.024	-	0.015
Median Household Income, quartiles						<0.001					<0.001
	1	12176	0.445	15208	0.555		11901	0.209	44936	0.791	
	2	12728	0.447	15753	0.553		11987	0.203	47087	0.797	
	3	12577	0.436	16245	0.564		11822	0.197	48272	0.803	
	4	12414	0.422	17007	0.578		11799	0.192	49670	0.808	
Percent Female, quartiles						<0.001					<0.001
	1	12010	0.430	15925	0.570		11184	0.193	46893	0.807	
	2	12382	0.432	16248	0.568		11887	0.199	47782	0.801	
	3	12577	0.439	16071	0.561		12287	0.206	47466	0.794	
	4	12926	0.447	15969	0.553		12151	0.203	47824	0.797	
Percent Rural, quartiles						<0.001					0.050
	1	12526	0.427	16803	0.573		12125	0.198	49177	0.802	
	2	12701	0.435	16502	0.565		12082	0.198	48873	0.802	
	3	12752	0.444	15971	0.556		12188	0.203	47724	0.797	
	4	11916	0.444	14937	0.556		11114	0.201	44191	0.799	
Percent Over 65 Years, quartiles						<0.001					0.6017
	1	12507	0.431	16500	0.569		12181	0.201	48456	0.799	
	2	12496	0.432	16422	0.568		11997	0.198	48479	0.802	

	3	12797	0.446	15927	0.554		11982	0.201	47565	0.799	
	4	12095	0.440	15364	0.560		11349	0.200	45465	0.800	
Percent Some College, quartiles						0.039					<0.001
	1	12254	0.444	15328	0.556		11731	0.204	45747	0.796	
	2	12450	0.437	16020	0.563		11985	0.202	47330	0.798	
	3	12440	0.433	16291	0.567		12089	0.202	47784	0.798	
	4	12751	0.435	16574	0.565		11704	0.192	49104	0.808	
Percent PCP Rate, quartiles						<0.001					<0.001
	1	12266	0.444	15337	0.556		11528	0.201	45759	0.799	
	2	12493	0.440	15910	0.560		12093	0.204	47272	0.796	
	3	12365	0.427	16565	0.573		12116	0.202	47992	0.798	
	4	12771	0.438	16401	0.562		11772	0.194	48942	0.806	

Social capital was grand-mean centered; *P* values are from chi-squared test of independence; †t-statistic from two-sample t-test; ††*P* value from two-sample t-test; DTC = discharge to community; LOS = length of stay; ICU/CCU = intensive care unit/coronary care unit; PAC = post-acute care; PCP = primary care physician

Table 3.3. Adjusted odds ratios (OR) and 95% confidence intervals (CI) from single-level logistic regression modeling the odds of successful community discharge at 30 days.

		Lower Limb Fracture				Joint Replacement		
Variables		**OR**	**95% CI**		***P***	**OR**	**95% CI**		***P***
COUNTY-LEVEL									
Social Capital		0.968	0.953	0.983	0.001	1.030	1.016	1.044	<0.001
Median Household Income, quartiles									
	1	Ref.							
	2	0.964	0.935	0.995	0.056	1.006	0.979	1.034	0.712
	3	0.983	0.952	1.016	0.398	1.023	0.994	1.053	0.187
	4	1.029	0.994	1.066	0.172	1.027	0.996	1.058	0.151
Percent Female, quartiles									
	1	Ref.							
	2	0.979	0.950	1.008	0.238	0.954	0.929	0.980	0.003
	3	0.959	0.931	0.989	0.024	0.927	0.903	0.952	<0.001
	4	0.937	0.907	0.967	0.001	0.932	0.905	0.959	<0.001
Percent Rural, quartiles									
	1	Ref.							
	2	0.925	0.897	0.953	<0.001	0.976	0.950	1.002	0.131
	3	0.896	0.868	0.925	<0.001	0.955	0.929	0.983	0.009
	4	0.945	0.910	0.980	0.011	0.979	0.947	1.012	0.294
PATIENT-LEVEL									
Sex									
	Male	Ref.							
	Female	1.095	1.067	1.122	<0.001	1.076	1.054	1.098	<0.001
Age, years									
	66–69	Ref.							
	70–74	0.816	0.758	0.879	<0.001	0.862	0.826	0.900	<0.001
	75–79	0.629	0.587	0.674	<0.001	0.665	0.639	0.693	<0.001
	80–84	0.440	0.412	0.471	<0.001	0.474	0.455	0.494	<0.001
	85+	0.268	0.251	0.286	<0.001	0.248	0.239	0.259	<0.001
Race									
	Non-Hispanic White	Ref.							
	Non-Hispanic Black	1.074	1.009	1.144	0.062	0.917	0.878	0.958	0.001
	Hispanic	1.371	1.293	1.454	<0.001	1.220	1.154	1.289	<0.001
	Other	1.460	1.363	1.564	<0.001	1.308	1.227	1.395	<0.001
Dual Eligibility									
	No	Ref.							
	Yes	0.567	0.549	0.586	<0.001	0.567	0.550	0.585	<0.001

Acute LOS, days									
	0–3	Ref.							
	4–7	0.800	0.779	0.822	<0.001	0.495	0.485	0.505	<0.001
	8–11	0.546	0.524	0.570	<0.001	0.304	0.292	0.317	<0.001
	12+	0.431	0.403	0.461	<0.001	0.224	0.209	0.239	<0.001
Acute Hospital Control Status									
	For-Profit	Ref.							
	Not-For-Profit	0.959	0.931	0.987	0.017	0.950	0.926	0.975	<0.001
	Government	0.999	0.967	1.033	0.969	0.964	0.936	0.993	0.039
Acute Hospital Teaching Status									
	No	Ref.							
	Yes	-	-	-	-	1.038	1.017	1.060	0.003
Acute Hospital Bed Count									
	0–99	-	-	-	-	Ref.			
	100–199	-	-	-	-	0.939	0.907	0.972	0.003
	200–299	-	-	-	-	0.925	0.893	0.958	<0.001
	300–399	-	-	-	-	0.944	0.910	0.978	0.008
	400–499	-	-	-	-	0.935	0.898	0.975	0.007
	500+	-	-	-	-	0.927	0.894	0.961	<0.001
ICU/CCU Stay									
	No	Ref.							
	Yes	0.875	0.851	0.899	<0.001	0.820	0.797	0.843	<0.001
Hospitalized in the Last Year									
	No	Ref.							
	Yes	0.848	0.827	0.869	<0.001	0.802	0.784	0.821	<0.001
Specified Heart Arrhythmias		0.884	0.862	0.906	<0.001	0.860	0.840	0.881	<0.001
Congestive Heart Failure		0.812	0.789	0.835	<0.001	0.774	0.753	0.796	<0.001
Diabetes Without Complication		0.863	0.840	0.887	<0.001	0.902	0.881	0.923	<0.001
Chronic Obstructive Pulmonary Disease		0.935	0.909	0.962	<0.001	0.809	0.788	0.830	<0.001
Acute Renal Failure		0.788	0.765	0.812	<0.001	0.792	0.768	0.816	<0.001
Hip Fracture/ Dislocation		0.951	0.914	0.990	0.039	0.753	0.712	0.796	<0.001
Protein-Calorie Malnutrition		0.744	0.713	0.776	<0.001	0.597	0.568	0.627	<0.001

Cardio-Respiratory Failure and Shock	0.888	0.849	0.930	<0.001	-	-	-	-
Diabetes with Chronic Complications	0.719	0.681	0.759	<0.001	0.783	0.744	0.824	<0.001
Parkinson's and Huntington's Diseases	0.707	0.666	0.751	<0.001	0.496	0.470	0.525	<0.001
Other Significant Endocrine and Metabolic Disorders	0.898	0.845	0.956	0.004	0.842	0.794	0.893	<0.001
Vascular Disease	-	-	-	-	0.887	0.857	0.918	<0.001
Morbid Obesity	-	-	-	-	0.895	0.858	0.934	<0.001
Coagulation Defects and Other Specified Hematological Disorders	-	-	-	-	0.935	0.902	0.970	0.003
PAC Type								
SNF	Ref.							
IRF	1.745	1.694	1.797	<0.001	1.143	1.115	1.172	<0.001
PAC LOS, quartiles								
1	Ref.							
2	1.918	1.862	1.976	<0.001	2.189	2.131	2.247	<0.001
3	3.245	3.141	3.353	<0.001	2.482	2.417	2.549	<0.001
4	2.908	2.814	3.004	<0.001	2.204	2.146	2.264	<0.001

Odds ratios are adjusted for all other covariates; social capital was grand-mean centered; DTC = discharge to community; LOS = length of stay; ICU/CCU = intensive care unit/coronary care unit; PAC = post-acute care; PCP = primary care physician

Table 3.4. Intraclass correlation coefficients of empty hierarchical models with a random intercept grouped by county for each diagnosis group. Each model represents a subset of patients whose social capital falls into the specified quartiles or Texas. For example, the second row for each diagnostic group represents the ICC from a model containing only individuals whose social capital is in the first quartile (LLFx N = 28,527 across 449 counties; JR N = 59,369 across 504 counties).

	ICC	
Empty Model	**LLFx**	**JR**
All Quartiles	0.0091	0.0138
1st Quartile	0.0052	0.0112
2nd Quartile	0.0085	0.0134
3rd Quartile	0.0102	0.0117
4th Quartile	0.0125	0.0178
1st and 2nd	0.0068	0.0125
3rd and 4th	0.0111	0.0149
Texas Only	<0.0001	0.0084

Chapter 4: Manuscript 2

INTRODUCTION

The concept of health equity was discussed in Chapter 3. However, disparity in the healthcare system remains; access, treatment, and health outcomes can vary drastically between certain demographics, socioeconomic positions, and geographic areas. Social risk factors were also presented in Chapter 3; regardless of high standards of care, patients' social risk factors may be detrimental to their health outcomes. Therefore, it is necessary to identify and describe how disparities in these social risk factors affect health in order to effect change in payment strategies and improve health equity in the healthcare system.

Structural social capital as a social risk factor in the community context was discussed in Chapters 1 and 3. It is hypothesized that low social cohesion, a measurement of social capital, can affect health through its strong relationship with income inequality.[61-63] There is a large body of literature on the relationship between income inequality and health,[64] where regions with disparate wealth experience worse health outcomes than more homogenous areas. Research indicates that in areas with income disparity, individuals are less trusting and less likely to participate in social organizations.[61,62] However, inequality in social capital may also exist and affect health, but it is not thoroughly studied.

One way to measure disparity in social capital is by examining geographic clusters, where geographic areas are grouped within a predetermined boundary and the social capital is compared within the group. This study examines the healthcare boundaries defined by Hospital Referral Regions (HRRs), which are larger than counties and smaller than states, and we cluster county-level social capital into HRR groups. We hypothesize that HRRs with more social capital disparity, as shown by more heterogeneous levels of social capital, may negatively affect health outcomes. The purpose of this study is to 1) quantify the degree of clusteredness (similarity) of county-level social capital within a larger boundary—HRRs—in Texas, and 2) to measure the association between the degree of clusteredness of county-level social capital within HRRs and the percent of patients successfully discharged to the community at the HRR level in Texas. The HRR boundary was chosen as the grouping structure for county-level social capital as it is a boundary that is larger than an individual county and contains two or more counties.

METHODS

Study Design and Data Sources

We performed an observational, retrospective, cross-sectional ecological study using 100% Medicare claims from 2013 to 2014 for beneficiaries living in Texas HRRs to quantify how well county-level social capital was clustered within Texas HRRs and to see if this clusteredness was associated with the percent of 30-day successful DTC from PAC at the HRR level. The Medicare files that were linked were described in Chapter 2. As this was an ecological study, the unit of analysis in models was the Texas HRR.

Beneficiary zip code of residence was then linked to the Housing and Urban Development 2014 zip to county crosswalk (https://www.huduser.gov/portal/datasets/usps_crosswalk.html) to obtain a Federal Information Processing System (FIPS) county. However, some zip codes do not perfectly match to one county. For zip codes that lie in multiple counties, the HUD crosswalk provides ratios of residential, business, other, and total addresses in each county for that zip code.[65] Therefore, for zip codes without an exact county match, we matched the zip code to the county that had a total ratio of > 0.5 of the zip code's total addresses of any type, and in the case where for each county the total ratio was < 0.5, the county with the highest ratio of residential addresses was assigned to the zip code. This resulted in one county assignment for each zip code. Next, the beneficiary's zip code of residence was linked to the Dartmouth Atlas zip code–HSA–HRR crosswalk to obtain each beneficiary's HRR. Finally, the beneficiary's FIPS county was linked to the county-level social capital index.

The process of linking provided a way to assign each county to an HRR. However, just as zip codes and counties are not mutually exclusive boundaries, some counties fell within more than one HRR. This occurred for 42 of the 267 total counties with Texas HRRs, which includes some non-Texas counties. Therefore, for a county with multiple possible HRRs, we assigned to the county the HRR that had the highest number of patients in that HRR. When calculating the silhouette index, we also performed a sensitivity analysis by assigning to the county the HRR with the fewest patients, to see if this impacted the clustering of county-level social capital in HRRs. This study was approved by the University's Institutional Review Board, and the authors had a data use agreement with CMS.

Population

The process of patient selection was detailed in Chapter 2. After linking the Medicare files to the crosswalks, patients who were missing zip codes, who had zip codes that did not match a US Federal Information Processing Standard Publication (FIPS) county code, or who had non-Texas HRRs were removed. To calculate the silhouette index, lower limb fracture and joint replacement cohorts were combined (N = 29,131) (Figure 4.1). This allowed for the maximum number of possible counties to be represented in the crosswalk used to link county-level social capital to HRR.

For linear modeling, the unit of analysis was the HRR, and additional patients were removed if they were entitled to Medicare due to any reason other than old age, such as due to disability or end-stage renal disease. These patients were not initially removed in order to create a county to HRR crosswalk that was as robust as possible. The final sample consisted of 8,993 patients with lower limb fracture and 17,556 with joint replacement.

Social Capital Index

The social capital index was defined in Chapter 2. Each patient who lived in the same county was assigned the same social capital index at the county level.

Silhouette Index

After linking one county to one Texas HRR, the silhouette index (SI) was calculated for each county using the R package "cluster."[66] A "distance matrix" was computed using the function "dist()" to obtain a "distance" or difference between each county's social capital index.[66] In this study, we use differences in the social capital index as our "distance" measure. For example, if County A had a social capital index of 0.3 and County B had a value of 0.2 for its social capital index, then 0.1 would be the "distance" between the two counties. This matrix contained 267 rows and 267 columns representing the number of counties with a Texas HRR, with a 0 diagonal. The function “silhouette()” calculated a silhouette width s(i) for each object (i) (i.e., county-level social capital), based on the formula by Rousseeuw[41]:

$$s(i) = (b(i) - a(i)) / \max(a(i), b(i)),$$

where a(i) is the average dissimilarity (i.e., distance; in this case difference in social capital) between (i) and all other objects in the cluster (i.e., HRR) to which (i) belongs, and b(i) is the minimum distance from (i) to all other observations in other clusters.[41,66] This study groups 267 observations of county-level social capital indices into 22 clusters that are the 22 Texas HRRs. The index ranges from −1 to 1, where 1 means the object fits well within its cluster, 0 means it is unclear whether the object has been correctly assigned to its cluster (i.e., it may fit equally well in another cluster), and −1 means it fits poorly and has been incorrectly clustered. All silhouette indices for each object (i.e., county) were then averaged to create an average silhouette index for each cluster (i.e., HRR).

The SI is an internal validation technique which assesses clusters of data based on intrinsic information contained in the data; e.g., it accounts for each object’s placement in its own cluster. This is in contrast to external validation techniques where clusters are chosen based on previous knowledge about the data.[67] The SI has been validated as a way to appropriately cluster data and assess clustering of data.[67] For this study, in HRRs with higher, positive silhouette statistics (i.e., greater than 0 and approaching 1) the objects—

county-level social capital indices—are more similar to each other than to social capital indices in other HRRs. This indicates that there is little dissimilarity of social capital within the HRR and suggests less variation. Higher, positive silhouette indices for an HRR means the counties that make up that HRR have similar social capital, whereas neutral (i.e., 0) or negative indices mean the counties have dissimilar social capital. It is important to note that silhouette indices do not indicate the magnitude of social capital among the objects in the cluster. For example, silhouette indices close to one do not necessarily indicate that the counties in the cluster have high social capital, they simply indicate that the objects in the cluster are similar (i.e., the counties could have similarly high values [e.g., 0.8] or similarly low values [e.g., −0.2]).

Outcome

The outcome of the linear regression models was the percent of 30-day successful DTC for lower limb fracture or joint replacement at the HRR level. This was created by aggregating the binary patient-level outcomes, 30-day successful community discharge, and taking the mean for each HRR. Thirty-day successful community discharge is a claims-based measure that CMS requires post-acute care facilities to report. It is defined as discharge home with no death or unplanned readmissions to long-term care hospitals within 31 days of post-acute care discharge (Patient Discharge Status codes 01, 06, 81, and 86 as defined in Chapter 3).[39]

Covariates

Covariates in the linear regression models were chosen by content experts. They were all continuous, at the HRR-level, and were obtained from the 2014 CMS Public Use File HRR Table for Beneficiaries 65 and Older (https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/GV_PUF.html). They were the average age of fee-for-service Medicare beneficiaries, percent of beneficiaries who are female, percent of beneficiaries who were eligible for Medicaid for at least one month of the year, percent of beneficiaries who used SNF and IRF services with at least one covered stay, and the average Hierarchical Condition Category (HCC) Score. The CMS-HCCs are made up of 70 categories of 189 conditions that CMS weights to create a single score for each beneficiary as a method of risk adjustment.[68] Finally, the CMS Public Use File lists the percent of various races in each HRR. We created the variable "percent minority" in each HRR by subtracting the percent of non-Hispanic whites and percent unknown race from one.

Statistical Analysis

We performed univariate descriptive and bivariate analyses of HRR-level characteristics. The lower limb fracture and joint replacement groups were analyzed separately in regression models. Normality of the continuous variables including the outcome, percent of 30-day successful DTC at the HRR-level, was assessed using q–q plots and boxplots. Collinearity of continuous covariates was assessed using Pearson correlations on each pair of covariates; if the r was > 0.40, the variables were deemed potentially collinear. Variance inflation factors (VIFs) were obtained for each variable in the multivariable linear model regression % successful DTC at the HRR level on the variables listed above; those with VIF > 10 were potentially problematic and assessed conceptually for removal. Ordinary least squares regression was performed for each group, regressing the percent of 30-day successful DTC at the HRR level on the silhouette index and additional HRR-level covariates. All analyses were performed using R Version 3.5.3 "Great Truth"[69] in RStudio Version 1.1.456.[70] Significance was set at $P < 0.05$.

RESULTS

Univariate descriptions of HRR characteristics are shown in Table 4.1. For Texas HRRs comprised of Medicare fee-for-service individuals, the average age was around 75.5 years (range 74–76 years), a little more than half were females, approximately one quarter were a minority race, around 19% were dual eligible for Medicaid, and they had on average one HCC (range 0.86–1.26).

From our patient-based crosswalk linking zip code of residence to county and zip code of residence to HRR, there were 267 counties that corresponded to a Texas HRR. Additionally, there were 42 counties in Texas that linked with one or more HRRs. Therefore, the algorithm described above was used to assign the county to the HRR with the most patients. There were 21 total non-Texas counties with Texas HRRs according to this algorithm (Appendix Table A4.1). For counties that corresponded to a Texas HRR, social capital indices ranged from −2.95 to 7.16, indicating diverse amounts of structural social capital (Appendix Tables A4.2 and A4.3). The ten lowest social capital indices were found among all the counties in the McAllen (2 counties, social capital indices −2.95 and −2.50) and Harlingen HRRs (2 counties, social capital indices −2.41 and

−2.31), five counties within the San Antonio HRR (5/28 counties, social capital index range −2.88 to −2.22), and one county within the El Paso HRR (1/7, social capital index −2.39) (Appendix Table A4.2). The ten highest social capital indices were among two of the 29 counties in the Lubbock HRR (7.17, 2.62), two of the 12 counties in Wichita Falls (3.21, 2.41), one of the 13 counties in Odessa (2.92), three of 31 counties in Amarillo (2.74, 2.29, 2.20), one of the 28 counties in San Antonio (2.16) and one of the 15 counties in the Abilene HRR (2.16) (Appendix Table A4.3).

The silhouette statistics for each of the 22 Texas HRRs are presented in Table 4.2 and are mapped in Figure 4.2. Harlingen, Texas was the only HRR to have a high silhouette index (0.72), indicating strong clustering and similar county-level social capital between the counties making up that HRR, in comparison to other counties in the remaining HRRs. Although Beaumont (SI = 0.05) and Longview (SI = 0.02) have positive silhouette indices, they are still close to 0, which represents neither strong nor weak clustering. All other 19 HRRs had negative silhouette indices (range −0.17 to −0.73) indicating inappropriate clustering within the HRR, meaning the county-level social capital was dissimilar between the counties in the HRR compared to other counties. The overall silhouette width for Texas was −0.48, meaning in general the counties were poorly clustered by social capital index and dissimilar, indicating disparity within and between Texas HRRs.

A sensitivity analysis reversed the algorithm described above concerning HRR assignment for counties with two or more possible HRRs; HRRs for these counties were chosen based on the fewest number of individuals residing there. The strong clustering of social capital in counties within the Harlingen, Texas HRR remained (0.76), and all other

HRR silhouette indices dropped below zero, indicating similarly poor clustering and continued disparity.

Bivariate analyses are presented in Table 4.3. The individual variables significantly associated with the percent of 30-day successful DTC were the percent of Medicare beneficiaries who were female in the lower limb fracture group (unadjusted P = 0.012) and the average age of Medicare beneficiaries in the HRR in the joint replacement group (unadjusted P = 0.021). The following pairs of covariates were potentially collinear: minority race and dual eligible (r = 0.931), minority race and average HCC score (r = 0.768), dual eligible and average HCC score (r = 0.847), dual eligible and silhouette index (0.550), and silhouette index and average HCC score (r = 0.695). As many of the collinear variables may have overlapping concepts and may function as proxies for each other, only three variables were chosen for the final linear model: percent of the Medicare beneficiaries who were female, the percent of beneficiaries who were dual eligible, and the silhouette index. Neither the lower limb fracture nor joint replacement model had significantly high VIFs (all were < 5), and therefore the selected variables do not have multicollinearity issues. Findings from ordinary least squares regressions for the lower limb fracture and joint replacement groups showed no significant associations between the silhouette index or any other HRR-level covariate and the percent of 30-day successful DTC at the HRR level (P > 0.05 in all cases, Table 4.4), except for percent female for the lower limb fracture group (Beta = 4.463, SE = 1.590, P = 0.012).

DISCUSSION

Geographic disparities in social risk factors can affect health outcomes. Structural social capital—resources that are available because of the structure of the community—is a social risk factor in the community context, and areas with more disparate social capital may have different health outcomes than areas with similar levels of social capital. This study is the first to examine social capital disparity between counties in Texas HRRs and its potential association with the percent of 30-day successful DTC from PAC. There were 267 counties that linked to the 22 Texas HRRs. Our findings suggest there is disparity among counties in Texas HRRs, except for one southern HRR—Harlingen, Texas. Finally, findings from this study suggest there was not a significant association between the county-level social capital disparity within Texas HRRs and percent of 30-day successful DTC at the HRR level.

There was a high prevalence of negative silhouette indices in Texas HRRs (19/22, 86.4%), indicating poor clustering and high dissimilarity and disparity among county-level social capital in those HRRs. This finding coincides with those of Iyer et al. who found the West South Central region (TX, OK, AR, LA) to rank simultaneously among the lowest and highest communities in different types of social capital in the U.S. The authors examined eight types of social capital in nine regions using the Social Capital Benchmark Survey 2000 of 24,000 individuals in 40 communities. The authors found that the Houston, Texas/Harris county community ranked among the lowest communities for all types of social capital examined, including social trust (37/40), racial trust (22/40), civic participation (40/40), diversity of friendship networks (37/40), group involvement (39/40), and organized interactions (40/40). However, although the Baton Rouge, LA community in the same West South Central region ranked similarly low among social

(33/39) and racial trust (39/40), it ranked second in group involvement and faith-based social capital. This means that while some types of social capital in the West South Central may rank very low, some may also rank highly, indicating dissimilarity in the region.

The only HRR in Texas with strong clustering of county-level social capital was Harlingen, Texas, located on the southern Texas-Mexico border. It was also the second-lowest ranking HRR in regard to the social capital indices of its two counties, higher only than the county-level social capital in McAllen, Texas. The counties that comprise the Harlingen HRR—Cameron and Willacy—are similar in regard to the sociodemographic characteristics that are associated with social capital production in counties, such as income and education. In 2014 Cameron and Willacy counties, in comparison to the Texas average, had more than twice the poverty rate (34.8% in Cameron and 38.0% in Willacy vs 17.7% in Texas), over a quarter more individuals with less than high school education (24.1% and 25.7% vs 17.9%), and about a third more uninsured individuals (33.2% and 31.2% vs 21.9%) (https://factfinder.census.gov). The high silhouette index found in the Harlingen HRR is likely not an artifact of having only two counties that clustered within it. Even when the alternate algorithm was used to assign possible HRRs to one county (the HRR with the fewest patients was assigned to the county), the Harlingen HRR absorbed a third neighboring county and still had strong clustering (SI = 0.76, Appendix Table A4.4).

The county-level social capital disparity within HRRs in Texas and other HRR-level characteristics of all beneficiaries aged 65 and older in the HRR were not significantly associated with the percent of 30-day successful DTC at the HRR level, except for the percent of the beneficiaries who were female for the lower limb fracture group. For every 1% increase in the percent of beneficiaries who were female in the HRR, the percent of beneficiaries successfully discharged to the community decreased approximately 4.5%. However, we are cautious of this statistically significant finding due to the limited number of observations (i.e., HRRs) in the model. It is possible that a different clustering structure may be more appropriate; in order to group the county-level measure, a region larger than the county was necessary. Hospital Referral Regions are health market boundaries based on where the majority of Medicare beneficiaries received tertiary care such as neurosurgery and cardiovascular surgery.[38] Studies have shown that the effects of social capital may change depending on the geographic level of analysis such as at the community[13,29] or regional level,[14] and more granular or macro measures of social capital should be explored. Finally, Texas may not have high enough levels of social capital to make an impact on successful community discharge. As shown in Figure 3.1, Texas and other southern states fall in the lowest quartiles of social capital, whereas the midwestern states experience some of the highest quartiles. Research has shown that different amounts of social capital have different effects on behaviors and outcomes[23]; minimum levels reflect a lack of interest in others' well-being and maximal levels indicate altruism and commitment to improving others' lives. Whereas the Texas region in general has low levels social capital,[57] other regions with more substantial levels of social capital may have different associations with 30-day successful community discharge.

The main limitation in this ecological study is that geographic and administrative boundaries do not always cleanly align. For numerous zip codes and counties, we had to create algorithms to decide which zip codes belong to which counties and which HRR belongs to each county. However, sensitivity analyses performed with variants of the algorithms yielded similar results. Additionally, the social capital index used in this study is not an exhaustive measure of social capital. There are many ways to define and measure social capital,[57] and different definitions may lead to different associations. Finally, as with all ecological studies, generalizations to individuals cannot be made; any association (or lack thereof) observed at the HRR level does not necessarily reflect the association that may exist at the individual level.[71]

In conclusion, this study is the first to quantify the disparity of county-level social capital within HRRs in Texas. For 19 out of 22 of the Texas HRRs, there was poor clustering, indicating disparity in those areas. Harlingen was the only HRR with strong clustering, indicating similar levels of social capital for the two counties in that HRR. There was no association found between county-level social capital disparity and the percent of 30-day successful DTC at the HRR level. The study of the effect of social capital on health is complex and resembles an intricate and advanced Rubik's cube of three dimensions: 1) numerous definitions of social capital, 2) different geographic levels of analysis, and 3) varying effects based on the amount of social capital available. This study examines one small block in that cube as it relates to healthcare, and additional studies should explore different definitions of social capital and different levels of analysis that are meaningful to the health care industry.

Figure 4.1. Flowchart of cohort selection for lower limb fracture (LLFx) and joint replacement (JR) groups for calculating 1) the silhouette index and 2) the outcome, percent of successful community discharges in each Texas HRR.

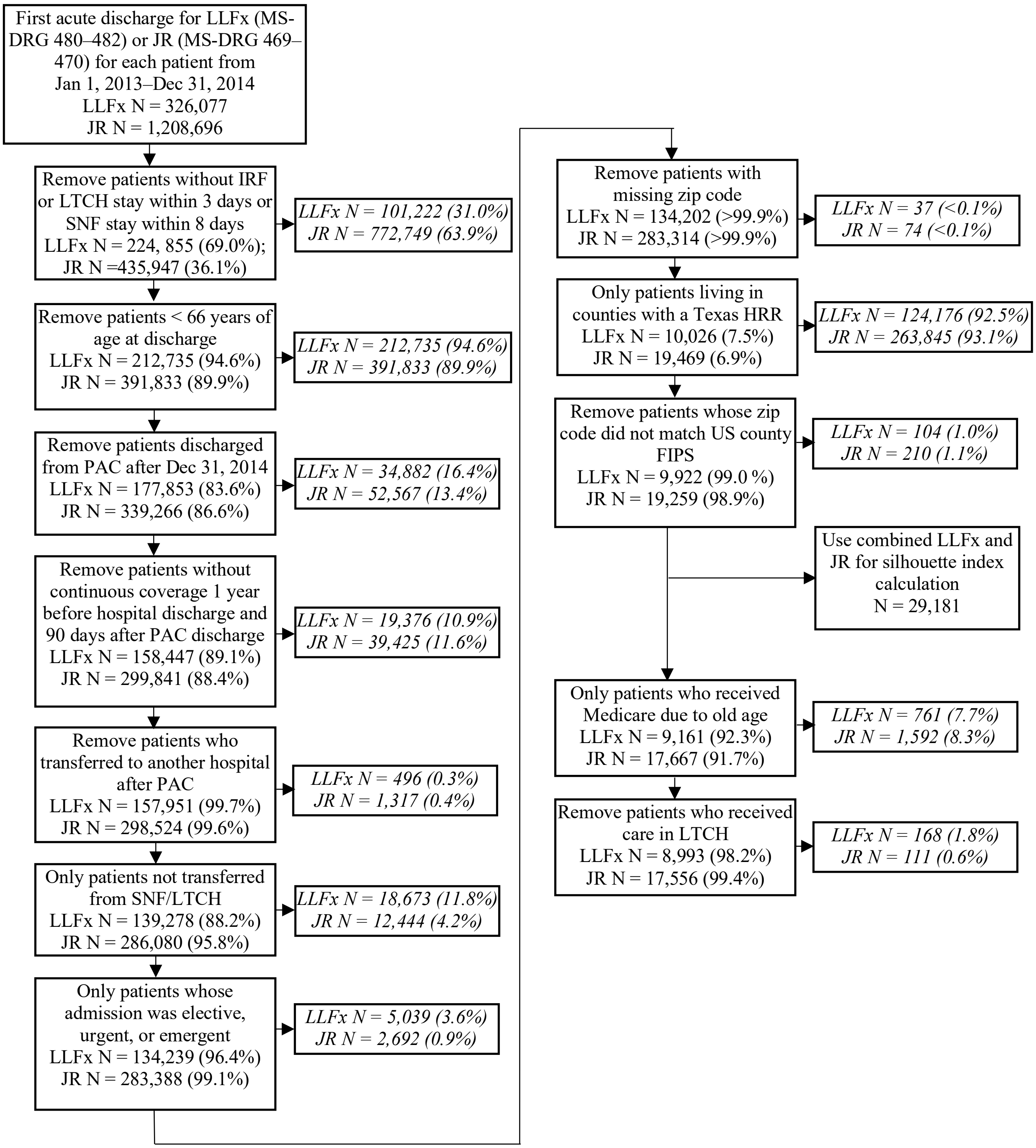


Figure 4.2. Quintiles of social capital in counties with Texas HRRs in 2014. The average silhouette index for each HRR is listed below each HRR name.

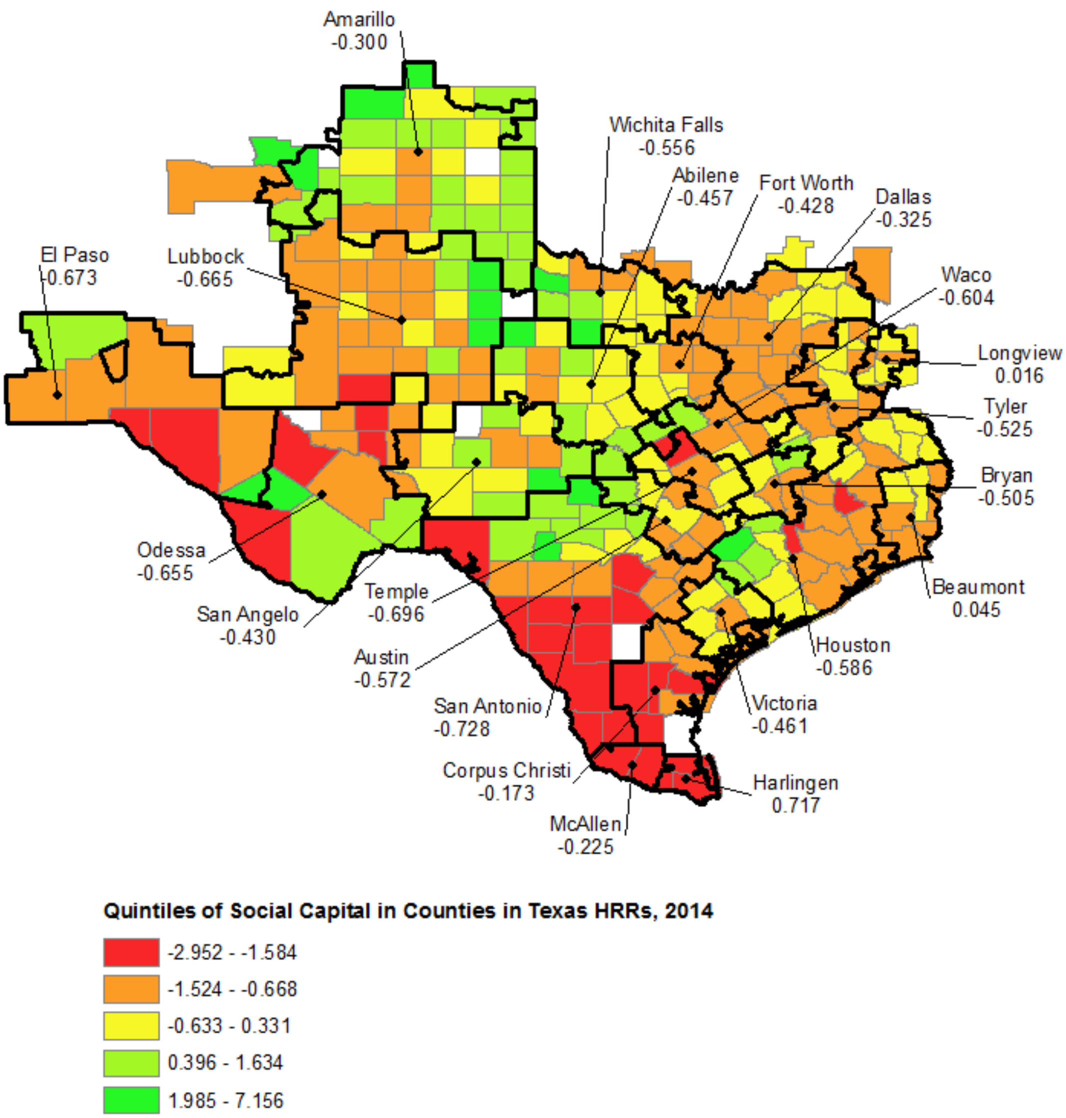


Table 4.1. Univariate HRR characteristics.

HRR-Level Variable	Mean	SD
Average Age, yrs	75.545	0.596
Female, %	56.015	0.006
Minority, %	25.955	0.183
Dual Eligible, %	17.885	0.102
SNF Use, %	5.261	0.009
IRF Use, %	1.858	0.007
Average HCC Score	1.002	0.093
30-day DTC, %		
LLFx	55.138	0.042
JR	79.770	0.032

HRR = Hospital Referral Region; HCC = Hierarchical Condition Category; SNF Use = percent of beneficiaries using SNF with at least one covered stay; DTC = discharge to the community; LLFx = lower limb fracture; JR = joint replacement

Table 4.2. The silhouette index for each HRR in Texas from any county (n = 267) with a Texas HRR.

HRR City	HRR State	HRR Number	Number of Counties in HRR Cluster	Silhouette Index
Harlingen	TX	396	2	0.717
Beaumont	TX	386	6	0.045
Longview	TX	399	5	0.016
Corpus Christi	TX	390	9	−0.173
McAllen	TX	402	2	−0.225
Amarillo	TX	383	31	−0.300
Dallas	TX	391	22	−0.325
Fort Worth	TX	394	8	−0.428
San Angelo	TX	411	11	−0.430
Abilene	TX	382	15	−0.457
Victoria	TX	417	6	−0.461
Bryan	TX	388	5	−0.505
Tyler	TX	416	13	−0.525
Wichita Falls	TX	420	12	−0.556
Austin	TX	385	8	−0.572
Houston	TX	397	24	−0.586
Waco	TX	418	7	−0.604
Odessa	TX	406	13	−0.655
Lubbock	TX	400	29	−0.665
El Paso	TX	393	7	−0.673
Temple	TX	413	4	−0.696
San Antonio	TX	412	28	−0.728

HRR = Hospital Referral Region

Table 4.3. Bivariate analyses for lower limb fracture and joint replacement.

	LLFx			JR		
Variable	**Beta**	***P***	**R^2**	**Beta**	***P***	**R^2**
Average Age, yrs	0.003	0.862	0.002	0.026	0.021	0.240
Female, %	3.553	0.012	0.274	1.768	0.120	0.116
Minority Race, %	0.060	0.241	0.068	0.025	0.521	0.021
Dual Eligible, %	0.070	0.450	0.029	0.077	0.271	0.060
Average HCC Score	0.042	0.681	0.009	0.092	0.227	0.072
SI	0.002	0.957	<0.001	0.021	0.337	0.046
IRF Use, %	1.097	0.384	0.038	1.223	0.198	0.081
SNF Use, %	1.948	0.050	0.179	0.806	0.304	0.053

P value from regressing the outcome, percent of 30-day successful DTC, on each covariate.

Table 4.4. Linear model regressing percent of 30-day successful DTC at the HRR-level on the silhouette index and other HRR-level covariates.

	LLFx			JR		
Variable	**Beta**	**SE**	***P***	**Beta**	**SE**	***P***
(Intercept)	3.075	0.907	0.003	0.617	0.746	0.419
Female, %	4.463	1.590	0.012	2.470	1.307	0.075
Dual Eligible, %	0.040	0.106	0.714	0.132	0.087	0.148
SI	0.040	0.035	0.270	0.019	0.029	0.513

All variables are at the HRR level; LLFx = lower limb fracture; JR = joint replacement; HCC = hierarchical condition category; SI = silhouette index

Chapter 5: Manuscript 3

INTRODUCTION

In Chapters 3 and 4, the effect of the social risk factor—structural social capital—on DTC was discussed. These chapters also defined social capital, and in particular structural social capital. Hospital Referral Regions (HRRs)—a geographic healthcare boundary—were defined in Chapter 4. That chapter examined social capital disparity as represented by the silhouette index of county-level social capital within Texas HRRs.

Social capital can affect outcomes differently depending on the geographic level of analysis: individuals,[20] counties,[21] regions,[14] or nations.[30] Therefore, social capital may be seen to affect healthcare outcomes differently when analyzed at a macro level, such as at the HRR level, rather than at the county level as was done in Chapter 3. This study uses Texas HRRs as geographic boundaries to analyze the association of the silhouette with DTC.

Texas is unique with respect to the magnitude and range of social capital present in the state. As shown in the map of social capital in US counties in Chapter 3, Texas has generally low social capital, and previous research on the region of Texas, Oklahoma, Arkansas, and Louisiana showed it to have some of the lowest social capital in the nation.[57] However, Texas also has a mix of counties with extremely high and extremely low social capital indices as shown in the Chapter 4 map. For example, Motley County in the Lubbock, TX HRR has the highest social capital index in Texas at 7.156, whereas Starr County in the McAllen, TX HRR has the lowest at −2.952. This broad range of social capital present in Texas makes the state of particular interest in understanding the effect social capital may have on health outcomes.

Although increased spending does not necessarily equate to higher quality care and improved outcomes[33,72] (and in fact may result in worse care[33,72-74]), Texas HRRs are certainly unique in regard to healthcare spending and use. In his famous 2009 *New Yorker* article, Atul Gawande highlighted that the city of McAllen, Texas in the McAllen HRR was second only to Miami in healthcare spending per capita,[74] and Cooper et al. noted that increased Medicare spending was associated with poorer quality of care in Texas.[75] Harlingen is another unique Texas HRR in regard to its overall high Medicare spending. In 2006 it was one of the highest price-adjusted per capita Medicare spending HRRs in the nation,[76] and it had 58% higher Medicare PAC spending per enrollee than the Texas average in 2008.[77] Additionally, Harlingen was one of the top three HRRs in the country for use of low-value diagnostic services (DXA) and low-value treatments (feeding tubes in dementia patients).[78] With such diverse social capital in Texas and the state's particular Medicare usage characteristics, Texas HRRs were chosen as the geographic region in which to analyze DTC for comparison to the effect of social capital within counties.

The purpose of this study is to examine the effect social capital disparity has on 30-day successful community discharge within Texas HRRs. We hypothesize that the HRR grouping will account for significant variation in the outcome, DTC, and that higher social capital disparity at the HRR level will be associated with decreased odds of DTC.

METHODS

Study Design and Data Sources

The study design is the same as presented in Chapter 3. The process of linking Medicare files to crosswalks, the social capital index, and CMS Public Use Files were presented in Chapter 2. The authors had a CMS data use agreement. This study was approved by the University's Institutional Review Board.

Population

The population selection was the same as presented in Chapter 3. However, patients were also removed if they did not live in a Texas HRR. This resulted in 8,983 beneficiaries in the lower limb fracture group and 17,540 beneficiaries in the joint replacement group.

Outcome

The outcome is the same as that presented in Chapter 3, namely, successful discharge to community at 30 days (yes/no).

Silhouette Index

The silhouette index (SI) is the variable of interest in this study. It was presented, defined, and calculated for each HRR in Texas in Chapter 4. In this study it remains as a continuous variable at the HRR level.

Covariates

Patient-level covariates are the same as presented in Chapter 3. HRR-level covariates are the same as those presented in Chapter 4, and were chosen by content experts.

Statistical Analysis

Lower limb fracture and joint replacement groups were analyzed separately. Univariate descriptions and bivariate analyses were performed for all patient- and HRR-level characteristics. Normality of continuous variables was assessed using boxplots and q–q plots. Multicollinearity of covariates[54] was assessed with Pearson correlations on all pairs of continuous variables, Cramer's V for all pairs of nominal variables, and with Spearman's rho for all pairs of ordinal variables. Following what was done in Chapter 3, variables were deemed potentially collinear if they appeared with any other variable with $0.4 <$ Pearson's $r < -0.4$, Cramer's $V > 0.4$, or $0.4 <$ Spearman's rho < -0.4, and were assessed for removal.[54] After removing collinear covariates, we performed logistic regression regressing the outcome, 30-day successful DTC, on the remaining covariates. Covariates that did not meet a significance threshold of $P < 0.1$ were removed from further models.

As in Chapter 3, we hypothesized that the nested structure of the data (patients nested within HRRs) may account for significant variation in the outcome and therefore may warrant the use of hierarchical modeling. Therefore, we calculated the intraclass correlation coefficient (ICC) for each group to determine if hierarchical modeling would be necessary. The ICC was introduced and defined in Chapter 3. As done in Chapter 3, if the ICC was < 2%, we proceeded with single-level models. Such a low ICC would mean that the grouping structure (patients grouped in HRRs) does not account for a significant enough amount of variation in the outcome to warrant the use of hierarchical models. We used R Version 3.5.3 “Great Truth” in RStudio Version 1.1.456 to perform all analyses, and we set significance at $P < 0.05$.

RESULTS

Population Characteristics

Univariate descriptions of patient- and HRR-level characteristics stratified by diagnosis group are presented in Table 5.1. Among beneficiaries living in Texas HRRs, 78.5% with joint replacement and 54.7% with lower limb fracture were successfully discharged to the community at 30 days. A little over half received PAC in SNFs (LLFx: 56.0%; JR: 54.0%). Almost half of beneficiaries with lower limb fracture were 85 and older (49.4%), and for joint replacement, almost a quarter were 75–79 (24.0%) or 85 years and older (23.6%). Approximately three quarters of beneficiaries in each group were female (LLFx: 76.3%; JR: 72.6%), and the majority were non-Hispanic White (LLFx: 81.7%; JR: 83.8%), had a hospital LOS of 4–7 (LLFx: 67%) or 0–3 days (JR: 58.7%), were not dual eligible (LLFx: 83.6%; JR: 89.3%), did not have an ICU/CCU stay (LLFx: 79.5%; JR: 89.6%), and were not hospitalized in the last year (LLFx: 71.2%; JR: 78.8%). About a third of beneficiaries received care in hospitals with 500+ beds (LLFx: 32.2%; JR: 29.7%), and these facilities tended not to be teaching hospitals (LLFx: 63.2%; JR: 61.7%). For those with lower limb fracture, the most prevalent HCCs were Specified Heart Arrhythmias (25.6%), Diabetes without Complications (21.3%), and Congestive Heart Failure (20.6%). For those with joint replacement, the most prevalent HCCs were

Diabetes without Complications (21.6%), Specified Heart Arrhythmias (17.3%), and Chronic Obstructive Pulmonary Disease (12.5%). Concerning characteristics of Texas HRRs for beneficiaries in both groups, the average age of beneficiaries was 75 years, about 56% were female, approximately 23% were minority, 15% were eligible for Medicaid, about 310,000 had Part A and Part B Medicare, and the average HCC score was around 0.99.

Table 5.2 shows the bivariate relationship of each variable with the binary outcome, DTC at 30 days; *t*-tests were used for continuous variables and chi-squared tests were performed for categorical variables. In this table, dashes indicate that the variable was not in the top 15 HCCs for the diagnosis group. For both diagnosis groups, the ICCs were negligible (LLFx: 0; JR: 0.004) when accounting for the HRR grouping structure of the data, and therefore hierarchical models were abandoned in favor of single-level logistic regression models. The final models for each group with adjusted odds ratios and 95% confidence intervals are detailed in Table 5.3. All HRR-level covariates except the SI were removed from the models. This was done due to the limited number of possible unique values for those variables—with only 22 HRRs in Texas, there were only 22 possible unique values for any variable.

Multivariable Models

For both groups, the silhouette index—the proxy for social disparity among counties within Texas HRRs—was not significantly associated with the odds of DTC. Variables associated with higher and lower odds of DTC are detailed below.

Variables associated with higher odds of successful DTC

Both groups: Receiving care in an IRF compared to a SNF multiplied the odds of DTC by 1.8 times for LLFx (adjusted odds ratio [AOR] 1.804, 95% CI 1.641–1.984, $P < 0.001$), and by 1.4 times for JR (AOR 1.386, 95% CI 1.285–1.496, $P < 0.001$).

Lower limb fracture only: Females had approximately 1.1 times higher odds of DTC (AOR 1.129, 95% CI 1.034–1.233, $P < 0.023$).

Variables associated with lower odds of successful DTC

Both groups: Whereas older age groups were associated with lower odds of DTC compared to those 66–69 years of age for those with JR, for those with LLFx only the two oldest age groups 80–84 and 85+ years) were significantly associated with lower odds of DTC compared to the youngest age group. Compared to those without an ICU/CCU stay, for those with lower limb fracture an ICU/CCU stay was associated with 20% lower odds of DTC (AOR 0.799, 95% CI 0.817–0.974, $P < 0.001$), and for those with joint replacement an ICU/CCU stay was associated with 17% lower odds of DTC (AOR 0.826, 95% CI 0.746–0.915, $P = 0.002$). Compared to those who were not hospitalized in the last year, the odds of DTC were lower for those who were hospitalized (LLFx: AOR 0.892, 95% CI 0.817–0.974, $P = 0.032$; JR: AOR 0.790, 95% CI 0.728–0.857, $P < 0.001$). Compared to not having the HCCs, having the HCCs included in the models was significantly associated with lower odds of DTC, except for Parkinson's and Huntington's Disease in LLFx.

Joint replacement only: Although dual eligibility was not included in the LLFx model, for those with JR the odds of DTC were 17.4% lower if the beneficiary was dual eligible (AOR 0.826, 95% CI 0.619–0.759, *P* < 0.001). The teaching status of the hospital was also not included in the LLFx model, but for those with joint replacement being in a teaching hospital was associated with 1.1 times higher odds of DTC compared to non-teaching hospitals (AOR 1.145, 95% CI 1.054–1.244, *P* = 0.007).

DISCUSSION

Disparities in social risk factors can affect health outcomes, regardless of uniformly high standards of care. Structural social capital is a social risk factor in the community context, where individuals with more resources available from the community structure may have improved health outcomes. This study is the first to examine disparities in county-level social capital within HRRs in Texas as operationalized by the silhouette index, a proxy of how similar or disparate social capital is among counties within HRRs. We hypothesized that patients in HRRs that were more homogenous in regard to social capital—indicating lower levels of disparity—would have significantly higher odds of DTC for both lower limb fracture and joint replacement diagnoses. However, findings from this study suggest no significant association between the silhouette index (the proxy for social capital disparity) and odds of DTC, negligible variation as explained by the grouping structure of patients grouped within Texas HRRs, and increased odds of DTC when receiving care in IRFs compared to SNFs, for both lower limb fracture and joint replacement groups.

In this study, the silhouette index was not significantly associated with odds of successful discharge to the community in LLFx (AOR 0.915, 95% CI 0.786–1.064, *P* = 0.332) or JR (AOR 1.172, 95% CI 1.018–1.349, *P* = 0.063), controlling for other patient-level characteristics in single-level logistic regression models. This may be due to a true absence of an association, or to the overall low silhouette indices that are seen across Texas HRRs and generally low social capital in the Texas region.[57] In Chapter 4, silhouette indices were presented for the 22 HRRs in Texas; all but three were negative, and only one was close to 1 (0.717 in Harlingen). Therefore, this variable may not have enough variation to significantly affect the outcome. Additionally, the silhouette index is a complex variable that may overlap in concept with some covariates not present in the models. For example, HRR-level variables such as dual eligibility and percent of beneficiaries that were minority or female were removed from models due to substantial collinearity with the SI.[54] However, although we removed parts of concepts that mathematically overlapped with the SI, we may have also removed aspects of the variables that were distinct from the SI. Also, Rupasingha et al. detailed many variables that are significantly associated with social capital such as age, education, income and income inequality, among others;[21] therefore, it is possible that some variables that remained in the model may continue to overlap with the concept of the SI. It is more likely, however, that the silhouette index was not significant due to the fact that it could take on only 22 possible unique values corresponding to the 22 HRRs in Texas, most of which were negative, as shown in Chapter 4.

Our study found that hierarchical models that account for the nested structure of the data, where patients were nested with HRRs were not necessary, as the ICCs were approximately 0 in both the lower limb fracture and joint replacement groups. This means that practically no variation in DTC was attributable to the grouping structure of patients within HRRs. Leland et al. found similar low variation in DTC (0.5%) attributable to grouping by patients within PAC facilities within states in an analysis of hip fracture patients.[79] We first pursued the use of hierarchical models because we hypothesized that patients in Texas HRRs may not be independent of each other—patients in the same HRR may somehow be more similar to each other than patients from different HRRs, therefore violating the assumption of independence for logistic regression.[54,80] The lack of explained variation that we observed may have been due to the limited number of level-two variables. Swaminathan et al. showed that the number of second level variables (i.e., clusters, or in this case HRRs) may be more important than the number of patients within those clusters.[80,81] Research by Schoeneberger recommends at least 40 level-two clusters to identify a small effect size (OR 1.70) with a small intercept variance (approximately 0.1).[80,82] Therefore, future analyses of social capital disparity among counties within HRRs could focus on broader regions that include multiple states.

Finally, our findings suggest increased odds of DTC when beneficiaries received care in IRFs compared to SNFs. However, we are cautious in interpretation of this significant finding as we did not control for issues of access to IRF and SNF facilities. As mentioned in Chapter 3, there are more SNFs in Texas than IRFs, and IRFs may be located in areas that are systematically different from other areas. Therefore, this may affect individuals' access to these facilities. This finding among beneficiaries living in Texas HRRs is similar to the findings in Chapter 3 regarding all beneficiaries living in the US. Additionally, Leland et al. found a similar relationship in three-level hierarchical models nesting patients within PAC facilities, within states when examining predictors of DTC. She found that patients discharged from acute care to a SNF were 69% less likely (AOR 0.31, 95% CI 0.31–0.32) to experience DTC compared to being discharged not to a

SNF. Although the purpose of this study is not comparative effectiveness research, our findings corroborate the need to further examine quality and quantity of service provision in PAC settings and how that may impact DTC.[79]

This study has several limitations, several of which are detailed in Chapter 3: although the definition of social capital used in this study is broad, it is not exhaustive, and other definitions may be more impactful on health outcomes; the social capital index used to create the silhouette index is a county-based measure assigned to all beneficiaries who live in the same county, which may be an incorrect assumption; and the crosswalk method used to create the silhouette index may not be correct in all cases. As mentioned above, there were only 22 HRRs in Texas, which may limit the effect of the silhouette index on DTC. Additionally, Texas may be a unique state in regards to social capital as the region has generally low social capital,[57] a wide range of county-level social capital indices (as described in Chapter 4), and generally negative silhouette indices, indicating high dissimilarity or disparity of social capital among counties within HRRs. Finally, Medicare data from this study was claims-based, and variables that may describe PAC services more comprehensively, such as quality or quantity of care, were not available[79] and were not included in analyses.

Despite these limitations, this study contributes to the literature on social capital research as it is the first to examine disparities in county-level social capital within Texas. Although there was a lack of a significant association between the silhouette index, this does not mean that no association exists between social capital disparities and DTC after PAC services for lower limb fracture and joint replacement. Additional research should include additional states or compare disparities among regions with *a priori* higher and lower levels of social capital.

Table 5.1. Univariate descriptions of variables at the patient- and HRR-level for the lower limb fracture and joint replacement groups.

	Lower Limb Fracture (N = 8983)		Joint Replacement (N = 17540)	
	(n or mean)	(% or SD)	(n or mean)	(% or SD)
PATIENT-LEVEL (n and %)				
PAC Type				
SNF	5034	56.039	9476	54.025
IRF	3949	43.961	8064	45.975
Age				
66–69	365	4.063	2013	11.477
70–74	864	9.618	3479	19.835
75–79	1324	14.739	4210	24.002
80–84	1995	22.209	3706	21.129
85+	4435	49.371	4132	23.558
Sex				
Male	2131	23.723	4812	27.434
Female	6852	76.277	12728	72.566
Race				
NH White	7341	81.721	14699	83.803
NH Black	250	2.783	743	4.236
Hispanic	1199	13.347	1753	9.994
Other	193	2.149	345	1.967
Hospital LOS				
0–3	1759	19.581	10291	58.672
4–7	6023	67.049	6303	35.935
8–11	933	10.386	700	3.991
12+	268	2.983	246	1.403
Medicaid Eligibility				
No	7511	83.613	15659	89.276
Yes	1472	16.387	1881	10.724
ICU/CCU Stay				
No	7144	79.528	15710	89.567
Yes	1839	20.472	1830	10.433
Hospitalized in the Last Year				
No	6396	71.201	13827	78.831
Yes	2587	28.799	3713	21.169
Hospital Bed Count				
0–99	809	9.006	3318	18.917
100–199	1308	14.561	2288	13.044
200–299	1671	18.602	2793	15.924
300–399	1059	11.789	1625	9.265
400–499	1246	13.871	2304	13.136
500+	2890	32.172	5212	29.715
Hospital Control Status				
Profit	4694	52.254	9111	51.944
Non-profit	3149	35.055	1950	11.117
Government	1140	12.691	6479	36.938
Hospital Teaching Status				

	No	5681	63.242	10820	61.688
	Yes	3302	36.758	6720	38.312
PAC LOS, quartiles					
	1	2248	25.025	4386	25.006
	2	2245	24.992	4387	25.011
	3	2247	25.014	4385	25
	4	2243	24.969	4382	24.983
Specified Heart Arrhythmias		2299	25.593	3039	17.326
Diabetes Without Complication		1909	21.251	3788	21.596
Congestive Heart Failure		1853	20.628	1996	11.38
Chronic Obstructive Pulmonary Disease		1616	17.99	2197	12.526
Acute Renal Failure		1429	15.908	1515	8.637
Coagulation Defects and Other Specified Hematological Disorders		872	9.707	1046	5.964
Vascular Disease		866	9.64	1066	6.078
Protein-Calorie Malnutrition		771	8.583	658	3.751
Hip Fracture/Dislocation		636	7.08	369	2.104
Cardio-Respiratory Failure and Shock		505	5.622	544	3.101
Diabetes with Chronic Complications		415	4.62	511	2.913
Rheumatoid Arthritis and Inflammatory Connective Tissue Disease		401	4.464	989	5.639
Septicemia, Sepsis, Systemic Inflammatory Response Syndrome/Shock		297	3.306	363	2.07
Parkinson's and Huntington's Diseases		258	2.872	372	2.121
Other Significant Endocrine and Metabolic Disorders		257	2.861	-	-
Morbid Obesity		-	-	1059	6.038
30-day Successful DTC					
	No	4066	45.263	3767	21.477
	Yes	4917	54.737	13773	78.523
HRR-LEVEL (mean and SD)					
Average Age, yrs		75.264	0.481	75.272	0.476
Female, %		0.562	0.006	0.562	0.006
Minority, %		0.236	0.141	0.230	0.137
Medicaid Eligibility, %		0.156	0.073	0.154	0.069
Part A & B, n		314964.693	230701.249	310048.195	227916.874
Average HCC Score		0.993	0.067	0.992	0.065

Counts and frequencies are presented for the discrete patient-level variables; means and standard deviations are presented for the continuous HRR-level variables; the silhouette index is not listed as it identical in the two diagnosis groups; PAC = post-acute care; LOS = length of stay, ICU/CCU = intensive care unit/coronary care unit; HCC = hierarchical condition category

Table 5.2. Bivariate relationships between each variable and DTC.

	Lower Limb Fracture (N = 8983)					Joint Replacement (N = 17540)				
	DTC: No	**%**	**DTC: Yes**	**%**	***P***	**DTC: No**	**%**	**DTC: Yes**	**%**	***P***
PATIENT-LEVEL										
PAC Type					<0.001					<0.001
SNF	2503	0.497	2531	0.503		2239	0.236	7237	0.764	
IRF	1563	0.396	2386	0.604		1528	0.189	6536	0.811	
Age					<0.001					<0.001
66–69	111	0.304	254	0.696		204	0.101	1809	0.899	
70–74	258	0.299	606	0.701		447	0.128	3032	0.872	
75–79	459	0.347	865	0.653		679	0.161	3531	0.839	
80–84	857	0.430	1138	0.570		838	0.226	2868	0.774	
85+	2381	0.537	2054	0.463		1599	0.387	2533	0.613	
Sex					<0.001					
Male	1048	0.492	1083	0.508		1142	0.237	3670	0.763	<0.001
Female	3018	0.440	3834	0.56		2625	0.206	10103	0.794	
Race					0.012					0.031
NH White	3371	0.459	3970	0.541		3206	0.218	11493	0.782	
NH Black	119	0.476	131	0.524		156	0.210	587	0.790	
Hispanic	501	0.418	698	0.582		348	0.199	1405	0.801	
Other	75	0.389	118	0.611		57	0.165	288	0.835	
Hospital LOS					<0.001					<0.001
0–3	642	0.365	1117	0.635		1387	0.135	8904	0.865	
4–7	2693	0.447	3330	0.553		1874	0.297	4429	0.703	
8–11	542	0.581	391	0.419		343	0.490	357.000	0.510	
12+	189	0.705	79	0.295		163	0.663	83.000	0.337	
Medicaid Eligibility					0.083					<0.001
No	3369	0.449	4142	0.551		3252	0.208	12407	0.792	
Yes	697	0.474	775	0.526		515	0.274	1366	0.726	
ICU/CCU Stay					<0.001					<0.001
No	3049	0.427	4095	0.573		3041	0.194	12669	0.806	
Yes	1017	0.553	822	0.447		726	0.397	1104	0.603	
Hospitalized in the Last Year					<0.001					<0.001
No	2742	0.429	3654	0.571		2642	0.191	11185	0.809	
Yes	1324	0.512	1263	0.488		1125	0.303	2588	0.697	
Hospital Bed Count					0.462					<0.001
0–99	349	0.431	460	0.569		528	0.159	2790	0.841	
100–199	603	0.461	705	0.539		524	0.229	1764	0.771	

200–299	767	0.459	904	0.541		663	0.237	2130	0.763	
300–399	498	0.470	561	0.530		355	0.218	1270	0.782	
400–499	545	0.437	701	0.563		495	0.215	1809	0.785	
500+	1304	0.451	1586	0.549		1202	0.231	4010	0.769	
Hospital Control Status					0.587					0.032
Profit	2105	0.448	2589	0.552		2023	0.222	7088	0.778	
Non-profit	1431	0.454	1718	0.546		1325	0.205	5154	0.795	
Government	530	0.465	610	0.535		419	0.215	1531	0.785	
Hospital Teaching Status					0.874					0.286
No	2575	0.453	3106	0.547		2352	0.217	8468	0.783	
Yes	1491	0.452	1811	0.548		1415	0.211	5305	0.789	
PAC LOS, quartiles					<0.001					<0.001
1	1126	0.501	1122	0.499		1007	0.230	3379	0.770	
2	950	0.423	1295	0.577		657	0.150	3730	0.850	
3	1027	0.457	1220	0.543		967	0.221	3418	0.779	
4	963	0.429	1280	0.571		1136	0.259	3246	0.741	
Specified Heart Arrhythmias					<0.001					<0.001
No	2808	0.420	3876	0.580		2747	0.189	11754	0.811	
Yes	1258	0.547	1041	0.453		1020	0.336	2019	0.664	
Diabetes Without Complication					0.471					0.624
No	3188	0.451	3886	0.549		2942	0.214	10810	0.786	
Yes	878	0.460	1031	0.540		825	0.218	2963	0.782	
Congestive Heart Failure					<0.001					<0.001
No	3008	0.422	4122	0.578		2998	0.193	12546	0.807	
Yes	1058	0.571	795	0.429		769	0.385	1227	0.615	
Chronic Obstructive Pulmonary Disease					<0.001					<0.001
No	3252	0.441	4115	0.559		3097	0.202	12246	0.798	
Yes	814	0.504	802	0.496		670	0.305	1527	0.695	
Acute Renal Failure					<0.001					<0.001
No	3269	0.433	4285	0.567		3464	0.210	13030	0.790	
Yes	797	0.558	632	0.442		303	0.290	743	0.710	
Coagulation Defects and Other Specified Hematological Disorders					0.002					<0.001
No	3629	0.447	4482	0.553		3464	0.21	13030	0.79	
Yes	437	0.501	435	0.499		303	0.29	743	0.71	
Vascular Disease					<0.001					<0.001

No	3607	0.444	4510	0.556		3420	0.208	13054	0.792	
Yes	459	0.530	407	0.470		347	0.326	719	0.674	
Protein-Calorie Malnutrition					<0.001					<0.001
No	3640	0.443	4572	0.557		3450	0.204	13432	0.796	
Yes	426	0.553	345	0.447		317	0.482	341	0.518	
Hip Fracture/ Dislocation					0.451					<0.001
No	3769	0.452	4578	0.548		3631	0.211	13540	0.789	
Yes	297	0.467	339	0.533		136	0.369	233	0.631	
Cardio-Respiratory Failure and Shock					<0.001					<0.001
No	3772	0.445	4706	0.555		3530	0.208	13466	0.792	
Yes	294	0.582	211	0.418		237	0.436	307	0.564	
Diabetes with Chronic Complications					0.015					<0.001
No	3854	0.450	4714	0.550		3618	0.212	13411	0.788	
Yes	212	0.511	203	0.489		149	0.292	362	0.708	
Rheumatoid Arthritis and Inflammatory Connective Tissue Disease					0.035					0.008
No	3905	0.455	4677	0.545		3588	0.217	12963	0.783	
Yes	161	0.401	240	0.599		179	0.181	810	0.819	
Septicemia, Sepsis, Systemic Inflammatory Response Syndrome/ Shock					0.037					<0.001
No	3914	0.451	4772	0.549		3637	0.212	13540	0.788	
Yes	152	0.512	145	0.488		130	0.358	233	0.642	
Parkinson's and Huntington's Diseases					0.0934					<0.001
No	3936	0.451	4789	0.549		3629	0.211	13539	0.789	
Yes	130	0.504	128	0.496		138	0.371	234	0.629	
Other Significant Endocrine and Metabolic Disorders					0.396					-
No	3943	0.452	4783	0.548		-	-	-	-	
Yes	123	0.479	134	0.521		-	-	-	-	
Morbid Obesity					-					<0.001
No	-	-	-	-		3583	0.217	12898	0.783	
Yes	-	-	-	-		184	0.174	875	0.826	
HRR-LEVEL										

SI	−0.469	-	−0.470	-	0.915	−0.470	-	−0.462	-	0.059
Average Age, yrs	75.260	-	75.267	-	0.516	75.243	-	75.279	-	<0.001
Female, %	0.562	-	0.561	-	0.070	0.562	-	0.562	-	0.790
Minority, %	0.234	-	0.238	-	0.121	0.227	-	0.231	-	0.047
Medicaid Eligibility, %	0.155	-	0.157	-	0.295	0.151	-	0.155	-	0.002
Part A & B, n	317307.700	-	313027.200	-	0.382	325957.900	-	305696.800	-	<0.001
Average HCC Score	0.993	-	0.994	-	0.470	0.990	-	0.992	-	0.135

Counts, frequencies, and *P* values from chi-squared tests are presented for the discrete patient-level variables; means and *P* values from two-sample *t*-tests are presented for the continuous HRR-level covariates; PAC = post-acute care; LOS = length of stay, ICU/CCU = intensive care unit/coronary care unit; SI = silhouette index; HCC = hierarchical condition category

Table 5.3. Final single-level logistic regression models for lower limb fracture and joint replacement regressing DTC on the silhouette index and patient-level covariates.

		Lower Limb Fracture (N = 8983)				Joint Replacement (N = 17540)			
		OR	**95%**	**CI**	***P***	**OR**	**95%**	**CI**	***P***
HRR-LEVEL									
SI		0.915	0.786	1.064	0.332	1.172	1.018	1.349	0.063
PATIENT-LEVEL									
PAC Type									
	SNF	Ref.				Ref.			
	IRF	1.804	1.641	1.984	<0.001	1.386	1.285	1.496	<0.001
Age									
	66–69	Ref.				Ref.			
	70–74	1.056	0.839	1.328	0.698	0.786	0.676	0.915	0.009
	75–79	0.867	0.698	1.076	0.276	0.624	0.541	0.721	<0.001
	80–84	0.575	0.467	0.708	<0.001	0.434	0.376	0.501	<0.001
	85+	0.371	0.303	0.454	<0.001	0.226	0.196	0.260	<0.001
Sex									
	Male	Ref.				Ref.			
	Female	1.129	1.034	1.233	0.023	1.072	0.996	1.154	0.120
Race									
	NH White	-	-	-	-	-	-	-	-
	NH Black	-	-	-	-	-	-	-	-
	Hispanic	-	-	-	-	-	-	-	-
	Other	-	-	-	-	-	-	-	-
Hospital LOS									
	0–3	Ref.				Ref.			
	4–7	0.813	0.739	0.896	<0.001	0.535	0.497	0.576	<0.001
	8–11	0.588	0.507	0.682	<0.001	0.324	0.278	0.378	<0.001
	12+	0.379	0.295	0.488	<0.001	0.203	0.157	0.263	<0.001
Medicaid Eligibility									
	No	-	-	-	-	Ref.			
	Yes	-	-	-	-	0.686	0.619	0.759	<0.001
ICU/CCU Stay									
	No	Ref.				Ref.			
	Yes	0.799	0.726	0.879	<0.001	0.826	0.746	0.915	0.002
Hospitalized in the Last Year									
	No	Ref.				Ref.			
	Yes	0.892	0.817	0.974	0.032	0.790	0.728	0.857	<0.001
Hospital Bed Count									
	0–99	-	-	-	-	Ref.			
	100–199	-	-	-	-	0.880	0.777	0.998	0.093
	200–299	-	-	-	-	0.823	0.732	0.926	0.007
	300–399	-	-	-	-	0.946	0.823	1.086	0.508
	400–499	-	-	-	-	0.797	0.693	0.916	0.007
	500+	-	-	-	-	0.820	0.729	0.922	0.005

Hospital Control Status								
Profit	-	-	-	-	Ref.			
Non-profit	-	-	-	-	1.084	1.007	1.166	0.071
Government	-	-	-	-	0.929	0.830	1.041	0.285
Hospital Teaching Status								
No	-	-	-	-	Ref.			
Yes	-	-	-	-	1.145	1.054	1.244	0.007
PAC LOS, quartiles								
1	Ref.				Ref.			
2	1.294	1.163	1.440	<0.001	1.931	1.750	2.131	<0.001
3	1.644	1.476	1.832	<0.001	1.661	1.514	1.823	<0.001
4	2.458	2.179	2.772	<0.001	1.982	1.791	2.193	<0.001
Specified Heart Arrhythmias	0.839	0.766	0.919	0.001	0.830	0.762	0.904	<0.001
Diabetes Without Complication	0.890	0.812	0.975	0.036	0.851	0.785	0.923	0.001
Congestive Heart Failure	0.789	0.714	0.871	<0.001	0.802	0.726	0.886	<0.001
Chronic Obstructive Pulmonary Disease	0.863	0.782	0.953	0.014	0.789	0.718	0.867	<0.001
Acute Renal Failure	0.805	0.725	0.895	0.001	0.755	0.678	0.841	<0.001
Coagulation Defects and Other Specified Hematological Disorders	-	-	-	-	-	-	-	-
Vascular Disease	0.858	0.756	0.974	0.046	0.856	0.754	0.972	0.044
Protein-Calorie Malnutrition	0.814	0.712	0.931	0.011	0.580	0.499	0.673	<0.001
Hip Fracture/Dislocation	-	-	-	-	-	-	-	-
Cardio-Respiratory Failure and Shock	-	-	-	-	-	-	-	-
Diabetes with Chronic Complications	0.803	0.669	0.963	0.047	0.785	0.652	0.943	0.030
Rheumatoid Arthritis and Inflammatory Connective Tissue Disease	-	-	-	-	-	-	-	-
Septicemia, Sepsis, Systemic Inflammatory Response Syndrome/Shock	-	-	-	-	-	-	-	-
Parkinson's and Huntington's Diseases	0.779	0.625	0.971	0.063	0.483	0.397	0.588	<0.001
Other Significant Endocrine and Metabolic Disorders	-	-	-	-	-	-	-	-
Morbid Obesity	-	-	-	-	-	-	-	-

OR = adjusted odds ratio; CI = confidence interval; SI = silhouette index; PAC = post-acute care; LOS = length of stay, ICU/CCU = intensive care unit/coronary care unit; HCC = hierarchical condition category

Chapter 6: Conclusion

Social capital is a risk factor manifesting in the community context, that must be further explored to better understand its effect on health outcomes. Knowledge of this complex concept and its effects on health is necessary to improve policy towards the aim of reaching equity in the US healthcare system. However, the social capital construct is very complex and challenging from a research perspective due to three dimensions of the construct that must be taken into account in its analysis: 1) the definition of the construct, 2) the amount available to each individual, and 3) the geographic level of analysis. These three dimensions form the sides of a Rubik's cube (Figure 6.1). In a perfect world, the dimensions are easy to visualize and interpret (Figure 6.1A). However, in the real world, these concepts are difficult to disentangle and examine (Figure 6.1B). This dissertation examines only a few blocks of the complex Rubik's cube of social capital research. This was done by 1) operationally defining social capital as the Rupasingha et al. social capital index, 2) assessing all the county-level social capital in the US (Chapter 3) and Texas (Chapters 4 and 5), and 3) analyzing the effects of social capital at the level of the county (Chapter 3) and the HRR (Chapters 4 and 5).

Post-acute care is also a difficult part of the healthcare continuum to study, as it is not particularly clear what drives variation in spending, use, and quality in PAC. Post-acute care is famously known for its substantial contribution to variation in total Medicare spending, where a whopping 73% of the total variation occurs in PAC settings.[33] Therefore, PAC is a prime target for research, and in particular how social risk factors may impact PAC outcomes such as DTC.

Each chapter of this dissertation analyzed social capital in a slightly different way, but the results overall were similar and our findings were cohesive. Chapter 3 examined the influence of social capital on DTC among all beneficiaries in the US. This chapter attempted a multilevel analysis and showed that the grouping structure of the data with patients nested within counties only accounted for < 1.5% of the variation in DTC. Given the low amount of explained variance, we believe a multilevel approach was not necessary. Therefore, we used traditional single-level regression techniques and did not include county as a variable in the models. There was also a directional difference in the effect of social capital on DTC by diagnosis group. For those who received PAC services for lower limb fracture, each one-unit increase in social capital was associated with 3.2% lower odds of DTC; for those with joint replacement, each one-unit increase in social capital was associated with 3.0% higher odds of DTC. We also found higher odds of DTC for both groups when patients received care in IRFs compared to SNFs, but we interpret this finding cautiously due to patient access issues to IRFs and SNFs.

Chapter 4 was an ecological study that calculated the silhouette index, a proxy of social capital disparity among counties in HRRs in Texas. Additionally, in this chapter we regressed the percent of DTC in each HRR on the silhouette index and other HRR-level covariates to see if social capital disparity among HRRs was significantly associated with the percent of DTC at the HRR level. This chapter showed that there was substantial disparity among counties in Texas HRRs; only Harlingen, Texas had high SI indicating homogeneity and lack of disparity among its constituent counties. All but three Texas HRRs had negative silhouette indices, indicating poor clustering and disparate values of social capital among the counties within these HRRs. Although there were only 22 observations in the model studied in this chapter, leading us to tentatively interpret the findings, the SI was not significantly associated with the percent of DTC at the HRR level.

Finally, Chapter 5 examined if disparities in the silhouette index were significantly associated with DTC. The analysis in this chapter was similar to that which was performed in Chapter 3, except it included only beneficiaries who lived in Texas HRRs, and the geographic level of analysis was at a more macro level—the HRR. Just as in Chapter 3, the grouping structure of patients within HRRs did not account for significant variation in the binary outcome, DTC. Additionally, the silhouette index was not significantly associated with DTC. Finally, similar to the findings in Chapter 3, the odds of DTC were significantly greater if the patient received care in an IRF compared to a SNF. These findings across these three chapters show that associations and findings may change based on the definition of social capital (social capital vs disparities in social capital), the amount of social capital available (all amounts across the US or lower amounts available in Texas), and at different levels of geographic analysis (from the county to the HRR level).

In light of these results, and to continue the analogy of the social capital Rubik's cube, additional research should focus on additional blocks that compose the cube. For example, examining different definitions analyzed at different geographic levels will contribute to a more comprehensive understanding of how social capital affects health and post-acute care rehabilitation. For example, defining social capital at a more micro level such as at the level of the neighborhood[26-28] may show more distinct associations with PAC outcomes; county-level social capital may be too broad of a boundary to understand differences that occur at a more granular level. To put this into context, Galveston county in Texas spans both Galveston Island and parts of mainland Texas, two areas that have distinctly different characteristics and communities. By grouping these two areas together as is done at the county-level, more granular relationships between social capital in these areas and PAC outcomes may be lost. Therefore, social capital could be grouped at a smaller level such as in neighborhoods to better understand what may contribute to social capital and explore its relationship with PAC outcomes.

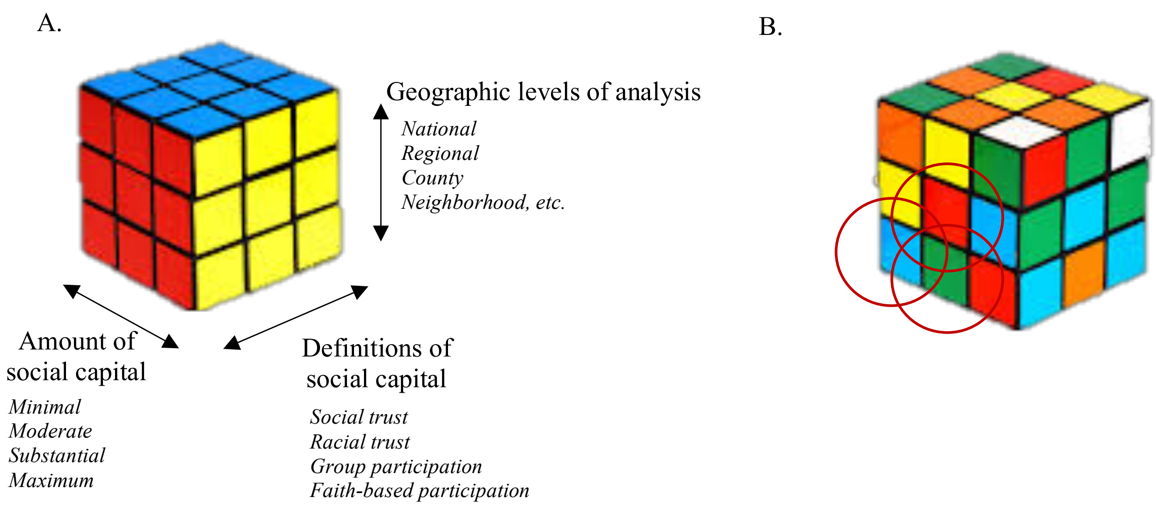
After completing the analyses in this dissertation, we understand that successful DTC at 30 days may not have been the most informative outcome with which to explain geographic variation in PAC outcomes, or there may be better predictors of it that were not represented here. For example, the ICCs in Chapters 3 and 5 were all negligible and close to 0. Mathematically, higher ICCs are obtained when a variable has a larger difference between the frequency of success and the frequency of failure as well as substantial variation. In our studies, only a little over half of all beneficiaries in the US who received PAC services for lower limb fracture were discharged successfully (56.0%, Chapter 3). Additionally, the variance in the percent of successful discharges in each Texas HRR was very small (LLFx: 0.17%, JR: 0.10%, from analyses in Chapter 4). Therefore, the effect of geography may be different if another PAC outcome were to be examined with greater success and more variability.

It is also possible that in order to better understand the association between social capital and PAC outcomes, different outcomes that are more temporally proximal to PAC should be analyzed. The current outcome, successful DTC at 30 days, is distal to PAC discharge and may not be the best outcome to analyze due to extraneous and confounding factors that may develop or occur during the 30 days and affect success. As extreme examples, life events or factors such as death of a family member or sale of a house may impact 30-day DTC: these are not captured by Medicare claims or other linkable datasets which make them difficult to quantify and adjust for. Therefore, more proximal outcomes such as discharge destination at discharge from the PAC facility may help to more clearly explain the relationship between social capital and PAC outcomes. Since “discharge home” includes four Patient Status Discharge codes (i.e., 01, 06, 81, 86), analyses could examine each discharge home status separately to understand if the relationship with social capital is the same or different for each status. Analyses could also identify the affected joint for each diagnosis group, e.g., hip JR, knee, JR, ankle, JR, etc. to understand if the affected joint plays a significant role in the association between social capital and PAC outcomes. Additionally, future studies from cohorts using ICD-10 codes could potentially provide more detail on severity of diagnosis which may also effect this relationship.

Variables concerning PAC quality and quantity were not explored in this dissertation and may affect the relationship between social capital and PAC outcomes. In these analyses, some acute hospital characteristics were included (e.g., teaching and profit status, bed count); however, for PAC only, the PAC type was identified (i.e., SNF or IRF). However, we know all SNFs and all IRFs are not identical in terms of quality of care, and this could be explored and accounted for. For example, a mandatory reporting measure for IRFs and SNFs is new or worsening pressure ulcers, a measure which may shed light on the quality of care provided in PAC facilities. Incorporating this or similar measures of PAC quality or quantity (e.g., the number of beds or staff) in analyses may provide more detail on the relationship between social capital and PAC outcomes. Additionally, this dissertation does not incorporate what individuals *think* about their PAC. Therefore, future research may include patient perspectives of care from surveys that exist at the hospital level (i.e., Hospital Consumer Assessment of Healthcare Providers and Systems, HCAHPS) or which may be developed for PAC.

Finally, the notion of social capital encompasses many concepts inherent to many variables that are commonly found in the health literature (e.g., age, education, income and income inequality, homeownership, marriage and family, and ethnic divisions).[21] This creates another layer of complexity in the study of social capital and health—overlapping concepts in regression models lead to inflated standard errors and decreases in the number of significant estimates. Therefore, this dissertation aimed to remove variables that were collinear with the focal social capital variable, while at the same time being mindful of the danger in this process. Although removal of a collinear variable removes part of the variable that overlapped with social capital, it also removes from consideration aspects of the variable that are unique to social capital or distinct from it, which may significantly affect health outcomes. Only by expanding the literature base on the effect of social capital on health can we begin to determine which aspects of social capital are shared with the standard demographic variables typically recorded and which aspects are particularly unique to this social risk factor. This dissertation reveals a few more blocks of the social capital Rubik's cube by assessing the effects of social capital on successful community discharge after post-acute care among Medicare beneficiaries.

Figure 6.1 The Rubik's cube analogy of the complexity of social capital research. A) The three dimensions of social capital complexity: definitions, levels of analysis, and amount available. B) the limited findings of this dissertation in comparison to the overall complexity of social capital.



Appendix A Additional Tables

Table A3.1. Adjusted odds ratios (OR) and 95% confidence intervals (CI) from single-level logistic regression modeling the odds of successful community discharge at 30 days when social capital is coded as a binary variable.

		Lower Limb Fracture				Joint Replacement			
Variables		**OR**	**95%**	**CI**	***P***	**OR**	**95%**	**CI**	***P***
COUNTY-LEVEL									
Social Capital									
	1	Ref.				Ref.			
	2	0.948	0.927	0.970	<0.001	1.024	1.004	1.044	0.047
Median Household Income, quartiles									
	1	Ref.							
	2	0.960	0.931	0.990	0.031	1.013	0.986	1.040	0.435
	3	0.980	0.949	1.013	0.313	1.029	1.000	1.059	0.096
	4	1.023	0.989	1.059	0.271	1.036	1.005	1.067	0.052
Percent Female, quartiles									
	1	Ref.							
	2	0.980	0.951	1.010	0.271	0.953	0.928	0.978	0.002
	3	0.959	0.931	0.989	0.023	0.926	0.902	0.951	<0.001
	4	0.942	0.911	0.973	0.002	0.935	0.908	0.962	<0.001
Percent Rural, quartiles									
	1	Ref.							
	2	0.925	0.897	0.953	<0.001	0.979	0.953	1.006	0.190
	3	0.896	0.868	0.925	<0.001	0.962	0.935	0.990	0.024
	4	0.941	0.908	0.976	0.006	0.992	0.960	1.025	0.683
PATIENT-LEVEL									
Sex									
	Male	Ref.							
	Female	1.095	1.068	1.122	<0.001	1.076	1.054	1.098	<0.001
Age, years									
	66–69	Ref.							
	70–74	0.817	0.758	0.880	<0.001	0.863	0.826	0.900	<0.001
	75–79	0.629	0.587	0.674	<0.001	0.666	0.639	0.694	<0.001
	80–84	0.440	0.412	0.471	<0.001	0.474	0.455	0.494	<0.001
	85+	0.268	0.251	0.286	<0.001	0.249	0.239	0.259	<0.001
Race									
	Non-Hispanic White	Ref.							
	Non-Hispanic Black	1.073	1.008	1.143	0.065	0.918	0.879	0.960	0.001
	Hispanic	1.375	1.297	1.458	<0.001	1.213	1.148	1.282	<0.001

	Other	1.460	1.363	1.565	<0.001	1.306	1.225	1.393	<0.001
Dual Eligibility									
	No	Ref.							
	Yes	0.567	0.550	0.586	<0.001	0.567	0.550	0.584	<0.001
Acute LOS, days									
	0–3	Ref.							
	4–7	0.800	0.779	0.822	<0.001	0.495	0.485	0.505	<0.001
	8–11	0.546	0.523	0.570	<0.001	0.304	0.292	0.317	<0.001
	12+	0.431	0.403	0.461	<0.001	0.224	0.209	0.239	<0.001
Acute Hospital Control Status									
	For-Profit	Ref.							
	Not-For-Profit	0.957	0.929	0.985	0.013	0.947	0.923	0.972	<0.001
	Government	0.996	0.964	1.029	0.848	0.963	0.936	0.992	0.036
Acute Hospital Teaching Status									
	No	Ref.							
	Yes	-	-	-	-	1.039	1.018	1.061	0.002
Acute Hospital Bed Count									
	0–99	-	-	-	-	Ref.			
	100–199	-	-	-	-	0.936	0.904	0.969	0.002
	200–299	-	-	-	-	0.921	0.890	0.954	<0.001
	300–399	-	-	-	-	0.939	0.906	0.974	0.004
	400–499	-	-	-	-	0.931	0.893	0.969	0.004
	500+	-	-	-	-	0.923	0.890	0.957	<0.001
ICU/CCU Stay									
	No	Ref.							
	Yes	0.875	0.851	0.899	<0.001	0.819	0.796	0.842	<0.001
Hospitalized in the Last Year									
	No	Ref.							
	Yes	0.848	0.827	0.869	<0.001	0.802	0.783	0.820	<0.001
Specified Heart Arrhythmias		0.884	0.862	0.906	<0.001	0.860	0.840	0.881	<0.001
Congestive Heart Failure		0.812	0.790	0.835	<0.001	0.774	0.754	0.796	<0.001
Diabetes Without Complication		0.864	0.841	0.887	<0.001	0.902	0.881	0.923	<0.001
Chronic Obstructive Pulmonary Disease		0.935	0.909	0.962	<0.001	0.809	0.788	0.830	<0.001
Acute Renal Failure		0.789	0.765	0.813	<0.001	0.792	0.768	0.816	<0.001

Hip Fracture/ Dislocation	0.951	0.913	0.990	0.038	0.754	0.713	0.797	<0.001
Protein-Calorie Malnutrition	0.744	0.713	0.777	<0.001	0.597	0.568	0.627	<0.001
Cardio-Respiratory Failure and Shock	0.889	0.849	0.930	<0.001	-	-	-	-
Diabetes with Chronic Complications	0.719	0.681	0.759	<0.001	0.783	0.745	0.824	<0.001
Parkinson's and Huntington's Diseases	0.707	0.666	0.751	<0.001	0.497	0.470	0.525	<0.001
Other Significant Endocrine and Metabolic Disorders	0.898	0.844	0.956	0.004	0.843	0.795	0.894	<0.001
Vascular Disease	-	-	-	-	0.887	0.857	0.918	<0.001
Morbid Obesity	-	-	-	-	0.895	0.858	0.935	<0.001
Coagulation Defects and Other Specified Hematological Disorders	-	-	-	-	0.935	0.902	0.970	0.003
PAC Type								
SNF	Ref.							
IRF	1.746	1.696	1.798	<0.001	1.139	1.111	1.168	<0.001
PAC LOS, quartiles								
1	Ref.							
2	1.918	1.862	1.976	<0.001	2.187	2.129	2.245	<0.001
3	3.247	3.143	3.354	<0.001	2.478	2.413	2.545	<0.001
4	2.911	2.818	3.007	<0.001	2.199	2.142	2.259	<0.001

Odds ratios are adjusted for all other covariates; DTC = discharge to community; LOS = length of stay; ICU/CCU = intensive care unit/coronary care unit; PAC = post-acute care; PCP = primary care physician

Table A3.2. Adjusted odds ratios (OR) and 95% confidence intervals (CI) from single-level logistic regression modeling the odds of successful community discharge at 30 days when social capital is coded in quartiles.

		Lower Limb Fracture				Joint Replacement			
Variables		**OR**	**95%**	**CI**	***P***	**OR**	**95%**	**CI**	***P***
COUNTY-LEVEL									
Social Capital									
	1	Ref.				Ref.			
	2	1.017	0.984	1.050	0.402	1.048	1.020	1.078	0.005
	3	0.957	0.926	0.989	0.026	1.038	1.010	1.068	0.028
	4	0.958	0.926	0.990	0.033	1.069	1.038	1.100	<0.001
Median Household Income, quartiles									
	1	Ref.							
	2	0.959	0.930	0.989	0.027	1.007	0.981	1.035	0.651
	3	0.980	0.948	1.012	0.297	1.025	0.996	1.054	0.157
	4	1.021	0.986	1.057	0.327	1.028	0.998	1.059	0.131
Percent Female, quartiles									
	1	Ref.							
	2	0.981	0.952	1.011	0.297	0.957	0.932	0.983	0.006
	3	0.958	0.929	0.987	0.020	0.924	0.900	0.949	<0.001
	4	0.938	0.907	0.970	0.002	0.927	0.900	0.955	<0.001
Percent Rural, quartiles									
	1	Ref.							
	2	0.925	0.897	0.953	<0.001	0.971	0.944	0.998	0.072
	3	0.896	0.868	0.925	<0.001	0.950	0.923	0.978	0.004
	4	0.941	0.908	0.976	0.006	0.977	0.944	1.010	0.240
PATIENT-LEVEL									
Sex									
	Male	Ref.							
	Female	1.095	1.067	1.122	<0.001	1.076	1.054	1.098	<0.001
Age, years									
	66–69	Ref.							
	70–74	0.817	0.758	0.880	<0.001	0.863	0.826	0.900	<0.001
	75–79	0.629	0.587	0.674	<0.001	0.666	0.639	0.694	<0.001
	80–84	0.440	0.412	0.471	<0.001	0.474	0.455	0.494	<0.001
	85+	0.268	0.251	0.286	<0.001	0.249	0.239	0.259	<0.001
Race									

Non-Hispanic White	Ref.							
Non-Hispanic Black	1.074	1.008	1.143	0.065	0.918	0.879	0.959	0.001
Hispanic	1.378	1.299	1.462	<0.001	1.220	1.154	1.289	<0.001
Other	1.462	1.364	1.566	<0.001	1.309	1.228	1.397	<0.001
Dual Eligibility								
No	Ref.							
Yes	0.568	0.550	0.586	<0.001	0.567	0.550	0.585	<0.001
Acute LOS, days								
0–3	Ref.							
4–7	0.800	0.779	0.822	<0.001	0.495	0.485	0.505	<0.001
8–11	0.546	0.523	0.570	<0.001	0.304	0.292	0.317	<0.001
12+	0.431	0.403	0.461	<0.001	0.223	0.209	0.239	<0.001
Acute Hospital Control Status								
For-Profit	Ref.							
Not-For-Profit	0.958	0.930	0.986	0.015	0.951	0.927	0.976	0.001
Government	0.996	0.964	1.030	0.852	0.965	0.937	0.993	0.044
Acute Hospital Teaching Status								
No	Ref.							
Yes	-	-	-	-	1.039	1.018	1.061	0.002
Acute Hospital Bed Count								
0–99	-	-	-	-	Ref.			
100–199	-	-	-	-	0.937	0.905	0.970	0.002
200–299	-	-	-	-	0.923	0.892	0.956	<0.001
300–399	-	-	-	-	0.942	0.909	0.977	0.007
400–499	-	-	-	-	0.934	0.897	0.973	0.006
500+	-	-	-	-	0.925	0.893	0.959	<0.001
ICU/CCU Stay								
No	Ref.							
Yes	0.875	0.851	0.899	<0.001	0.819	0.797	0.843	<0.001
Hospitalized in the Last Year								
No	Ref.							
Yes	0.848	0.827	0.870	<0.001				
Specified Heart Arrhythmias	0.884	0.862	0.906	<0.001	0.860	0.840	0.881	<0.001

Congestive Heart Failure	0.812	0.790	0.835	<0.001	0.774	0.753	0.796	<0.001
Diabetes Without Complication	0.864	0.841	0.887	<0.001	0.902	0.881	0.923	<0.001
Chronic Obstructive Pulmonary Disease	0.935	0.909	0.962	<0.001	0.809	0.788	0.830	<0.001
Acute Renal Failure	0.788	0.765	0.812	<0.001	0.792	0.768	0.816	<0.001
Hip Fracture/ Dislocation	0.951	0.913	0.989	0.037	0.753	0.712	0.796	<0.001
Protein-Calorie Malnutrition	0.744	0.713	0.777	<0.001	0.597	0.569	0.627	<0.001
Cardio-Respiratory Failure and Shock	0.889	0.849	0.930	<0.001	-	-	-	-
Diabetes with Chronic Complications	0.719	0.681	0.759	<0.001	0.783	0.744	0.824	<0.001
Parkinson's and Huntington's Diseases	0.707	0.666	0.751	<0.001	0.496	0.470	0.525	<0.001
Other Significant Endocrine and Metabolic Disorders	0.898	0.844	0.955	0.004	0.842	0.794	0.893	<0.001
Vascular Disease	-	-	-	-	0.887	0.857	0.918	<0.001
Morbid Obesity	-	-	-	-	0.895	0.858	0.934	<0.001
Coagulation Defects and Other Specified Hematological Disorders	-	-	-	-	0.935	0.902	0.970	0.003
PAC Type								
SNF	Ref.							
IRF	1.748	1.698	1.801	<0.001	1.144	1.116	1.173	<0.001
PAC LOS, quartiles								
1	Ref.							
2	1.918	1.862	1.977	<0.001	2.188	2.131	2.247	<0.001
3	3.246	3.143	3.354	<0.001	2.480	2.415	2.547	<0.001
4	2.911	2.818	3.008	<0.001	2.202	2.144	2.262	<0.001

Odds ratios are adjusted for all other covariates; DTC = discharge to community; LOS = length of stay; ICU/CCU = intensive care unit/coronary care unit; PAC = post-acute care; PCP = primary care physician

Table A3.3. C statistics with social capital coded as a continuous variable, a binary variable, and a variable in quartiles. The variables included in the model are from the final chosen model as presented in Table 3.3.

Social Capital Coding	C Statistic	
	LLFx	JR
Continuous	0.6835	0.7399
Binary	0.6835	0.7399
Quartiles	0.6835	0.7399

Table A4.1. Non-Texas counties that corresponded to Texas HRRs.

FIPS County Code	County Name	County State	HRR Number	HRR Name	HRR State
20129	Morton	KS	383	Amarillo	TX
40013	Bryan	OK	391	Dallas	TX
40033	Cotton	OK	420	Wichita Falls	TX
40067	Jefferson	OK	391	Dallas	TX
40007	Beaver	OK	383	Amarillo	TX
40025	Cimarron	OK	383	Amarillo	TX
40139	Texas	OK	383	Amarillo	TX
40005	Atoka	OK	391	Dallas	TX
40023	Choctaw	OK	391	Dallas	TX
40089	McCurtain	OK	391	Dallas	TX
35021	Harding	NM	383	Amarillo	TX
35051	Sierra	NM	393	El Paso	TX
35013	Dona Ana	NM	393	El Paso	TX
35029	Luna	NM	393	El Paso	TX
35009	Curry	NM	400	Lubbock	TX
35041	Roosevelt	NM	400	Lubbock	TX
35015	Eddy	NM	400	Lubbock	TX
35025	Lea	NM	400	Lubbock	TX
35035	Otero	NM	393	El Paso	TX
35037	Quay	NM	383	Amarillo	TX
35047	San Miguel	NM	383	Amarillo	TX

Table A4.2. Top ten counties with highest social capital indices in Texas HRRs.

County FIPS	County Name	County State	HRR Number	HRR City	HRR State	Social Capital Index
48345	Motley	TX	400	Lubbock	TX	7.156
48155	Foard	TX	420	Wichita Falls	TX	3.214
48243	Jeff Davis	TX	406	Odessa	TX	2.923
35021	Harding	NM	383	Amarillo	TX	2.737
48125	Dickens	TX	400	Lubbock	TX	2.620
48447	Throckmorton	TX	420	Wichita Falls	TX	2.406
40025	Cimarron	OK	383	Amarillo	TX	2.289
20129	Morton	KS	383	Amarillo	TX	2.198
48385	Real	TX	412	San Antonio	TX	2.162

Table A4.3. Bottom ten counties with lowest social capital indices in Texas HRRs.

County FIPS	County Name	County State	HRR Number	HRR City	HRR State	Social Capital Index
48427	Starr	TX	402	McAllen	TX	–2.952
48323	Maverick	TX	412	San Antonio	TX	–2.875
48507	Zavala	TX	412	San Antonio	TX	–2.801
48479	Webb	TX	412	San Antonio	TX	–2.649
48247	Jim Hogg	TX	412	San Antonio	TX	–2.581
48215	Hidalgo	TX	402	McAllen	TX	–2.501
48061	Cameron	TX	396	Harlingen	TX	–2.412
48141	El Paso	TX	393	El Paso	TX	–2.390
48489	Willacy	TX	396	Harlingen	TX	–2.310
48163	Frio	TX	412	San Antonio	TX	–2.221

Table A4.4. The silhouette index for each HRR in Texas from any county (n = 267) with a Texas HRR based on the HRR to county assignment of the fewest number of patients in the eligible HRR.

HRR City	HRR State	HRR Number	Number of Counties in HRR Cluster	Silhouette Index
Harlingen	TX	396	3	0.761
McAllen	TX	402	1	0.000
Beaumont	TX	386	8	–0.127
Amarillo	TX	383	29	–0.191
Dallas	TX	391	24	–0.212
Tyler	TX	416	9	–0.234
Victoria	TX	417	5	–0.263
Corpus Christi	TX	390	10	–0.287
Fort Worth	TX	394	9	–0.294
Longview	TX	399	5	–0.325
Bryan	TX	388	5	–0.366
Temple	TX	413	8	–0.375
Abilene	TX	382	16	–0.385
Austin	TX	385	7	–0.433
San Angelo	TX	411	13	–0.477
Houston	TX	397	26	–0.491
Wichita Falls	TX	420	11	–0.510
Odessa	TX	406	11	–0.575
Lubbock	TX	400	30	–0.605
El Paso	TX	393	8	–0.694
San Antonio	TX	412	26	–0.709
Waco	TX	418	3	–0.756

HRR = Hospital Referral Region

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Curriculum Vitae

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BIOGRAPHICAL:

Birth:	Houston, Texas, United States
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EDUCATION:

08/16 – exp. 8/19	Doctor of Philosophy Candidate Division of Rehabilitation Sciences Preventive Medicine and Community Health Graduate School of Biomedical Sciences The University of Texas Medical Branch Galveston, TX Advisor: Timothy Reistetter, PhD, OTR, FAOTA Dissertation Title: The influence of social capital on community discharge in post-acute care among Medicare beneficiaries
08/14 – 05/16	Master of Science Exercise and Health Sciences University of Houston–Clear Lake Houston, TX Advisor: William E. Amonette, PhD
08/10 – 05/11	Near-Native Russian Proficiency National Security Education Program St. Petersburg State University St. Petersburg, Russia
08/06 – 05/10	Bachelor of Arts Russian Language and Literature Scripps College Claremont, CA
06/08 – 08/08	Level 5 Russian Proficiency

Kathryn Davis School of Russian
Middlebury College Language Schools
Middlebury, VT

CERTIFICATIONS:

07/16 – present DEXA Operator
Hologic Training, Shriners Hospitals for Children–Galveston
Galveston, TX

04/16 – present Certified Strength and Conditioning Specialist (CSCS)
National Strength and Conditioning Association
Houston, TX

08/14 – present Certified Personal Trainer (ACSM–CPT)
American College of Sports Medicine
Houston, TX

08/14 – present CPR/AED/First Aid
American Heart Association
Galveston, TX

PROFESSIONAL AND TEACHING EXPERIENCE

04/19 – present Graduate
Scholars in Education Program, 2017–2019 Cohort
The University of Texas Medical Branch

01/18 – 05/18 Teaching Assistant
Biostatistics for PhD Biomedical Science Students
The University of Texas Medical Branch

08/16 – present Graduate Assistant
Division of Rehabilitation Sciences
The University of Texas Medical Branch

08/16 – 05/18 Graduate Assistant
Department of Surgery
Shriners Hospitals for Children–Galveston

06/16 – 08/16 Exercise Physiologist
Department of Surgery
Shriners Hospitals for Children–Galveston

01/16 – 05/16 Wellness Intern
Department of Surgery
Shriners Hospitals for Children–Galveston

08/15 – 12/15	Undergraduate Supplemental Instructor, Biomechanics Department of Health and Human Performance University of Houston–Clear Lake
06/15 – 12/15	Undergraduate and Graduate Tutor, Exercise and Health Sciences Department of Health and Human Performance University of Houston–Clear Lake
10/15 – 12/15	Fitness Coach YES! Fitness and Sports Performance
10/11 – 06/14	Instructor and Lecturer New Planet School of Foreign Languages St. Petersburg, Russia

RESEARCH ACTIVITIES:

A. Areas of Research

1. Public Health and Rehabilitation Research: Major goals of my research are to (1) understand the role of social risk factors such as social capital on rehabilitation health outcomes and use of post-acute care services; and 2) identify how exercise can be used as part of a comprehensive rehabilitation program in chronically ill patients. My efforts focus on (1) examining the influence of Medicare beneficiaries' structural, collective social capital on successful community discharge, and (2) identifying the mechanisms affected by structured exercise programs affect to improve physical function and quality of life outcomes short term and over time.
2. Education Research: My main interests are: (1) curriculum design for introductory statistical computer programming courses for non-programmers, and (2) teaching methods of statistical computer programming software to non-programmers.

B. Pre-doctoral Grant

Current: T32 Predoctoral Fellowship, Agency for Healthcare Research and Quality
Grant # T32HS26133
Amount: $656,685
MPI: Yong-Fang Kuo and Kenneth Ottenbacher
Period of Support: 07/01/18–06/30/19
Role: Predoctoral Trainee
Effort: 100%

C. Other:

03/18 – present Research Collaborator of Timothy Reistetter, PhD, The University of Texas Medical Branch, Galveston, TX

09/17 – present	Principal Investigator: "Assessing Research Students' and Instructors' Understanding and Attitudes in R." UTMB Scholars in Education project, The University of Texas Medical Branch, Galveston, TX
08/16 – present	Research Collaborator of Oscar E. Suman, PhD, Shriners Hospitals for Children–Galveston, Galveston, TX
08/15 – 07/16	Principal Investigator: "Kinematic and kinetic characterization of jumping and landing tasks." Human Performance Laboratory, University of Houston–Clear Lake, Houston, TX
01/15 – 07/16	Research Assistant: "Biomechanical characterization of common clinical assessments in patients with multiple sclerosis compared to apparently healthy matched controls." Human Performance Laboratory, University of Houston–Clear Lake, Houston, TX
03/15 – 03/16	Research Assistant, CES Performance for Houston Dash Women's Professional Soccer Team, Houston, TX

COMMITTEE RESPONSIBILITIES:

A. UTMB:

09/18 – present	Member, GSBS Recruitment Committee
08/18 – present	Vice Chair, Committee for Career Development
10/18 – 05/19	Member, Internal Relations Subcommittee, Student Government Association
07/18 – 05/19	Senator from the Graduate School of Biomedical Sciences, Student Government Association
07/18 – 10/18	Member, Intramural/Fieldhouse Subcommittee, Student Government Association
08/17 – 07/18	Secretary, Committee for Career Development

B. Graduate School of Biomedical Sciences:

07/18 – 06/19	President, Graduate Student Organization
08/17 – 06/19	GSBS Executive Committee, Representative from Graduate Student Organization
06/17 – 06/18	Treasurer, Graduate Student Organization

C. Department of Preventive Medicine and Community Health:

08/18 – present	Secretary/Treasurer, Preventive Medicine and Community Health Graduate Student Organization

TEACHING/MENTORING RESPONSIBILITIES:

A. Teaching:

Graduate School of Biomedical Sciences (GSBS):

01/18 – 05/18	Teaching Assistant for Introduction to Biostatistics Course for PhD-level Basic Biomedical Sciences Curriculum; led three-hour per week laboratory applications component using the R programming language and environment for approximately 30 students

B. Mentoring:

School of Medicine (SOM):

08/17 – 03/18	Richy Charls, SOM, third-year student
06/17 – 08/17	Joan Tran, SOM, second-year student
06/17 – 08/17	Martha Chapa, SOM, second-year student
06/17 – 08/17	Rachel Laird, SOM, second-year student
06/17 – 08/17	Kevin Sanchez, SOM, second-year student
06/16 – 12/16	Blake Moore, SOM, first-year student

C. Teaching Responsibilities at Other Universities:

Supplemental Instructor: Undergraduate Biomechanics, University of Houston–Clear Lake (60 hours): 2015

Tutor: Graduate and Undergraduate Exercise and Health Sciences, University of Houston–Clear Lake (60 hours): 2015

Instructor: English and Mathematics, New Planet School of Foreign Languages (30 hours/week): 2011 – 2014

MEMBERSHIP IN PROFESSIONAL AND SCIENTIFIC SOCIETIES:

Member, Academy Health (2019 – present)
Member, American Association for the Advancement of Science (2018 – present)
Member, American Congress of Rehabilitative Medicine (2018 – present)
Member, American Burn Association (2017 – present)
Member, National Strength and Conditioning Association (2015 – present)
Member, American College of Sports Medicine (2014 – present)
Member, Texas Chapter, American College of Sports Medicine (2014 – present)

HONORS:

02/19 Delta Omega Honor Society Inductee, Delta Nu Chapter, The University of Texas Medical Branch, Galveston, TX

12/18 The Charles F. Otis Clinical Research Award, The University of Texas Medical Branch, Galveston, TX

12/18 Michael Gilles Purgason Memorial Scholarship, The University of Texas Medical Branch, Galveston, TX

08/18 Best Early Career Poster in Geriatric Rehabilitation, American Congress of Rehabilitation Medicine (ACRM) Annual Conference

08/18 Ambassador, American Congress of Rehabilitation Medicine (ACRM)

07/18 Pre-Doctoral Fellowship, T32, Agency of Healthcare Research and Quality (AHRQ)

05/18 Nomination and Awardee, American Association for the Advancement of Science (AAAS) and *Science* Program for Excellence in Science

12/17 Edith and Robert Zinn Presidential Scholarship, The University of Texas Medical Branch, Galveston, Texas
10/17 Excellence in Research Award, Rehabilitation Category, Forum on Aging, The University of Texas Medical Branch, Galveston, Texas
08/17 Inductee, Scholars in Education Program, The University of Texas Medical Branch, Galveston, Texas
03/17 Second Place Tie, Best Poster, American Burns Association Annual Conference, Boston, Massachusetts
12/16 Stephen C. Silverthorne Memorial Scholarship, The University of Texas Medical Branch, Galveston, Texas
10/16 First Place Tie, Best Rehabilitation Sciences Poster, Forum on Aging, The University of Texas Medical Branch, Galveston, Texas
06/16 First-Annual President's Cup Southeast U.S. Representative, American College of Sports Medicine Annual Conference, Boston, Massachusetts
02/16 First Place Poster Presentation, Texas American College of Sports Medicine Annual Conference, College Station, Texas
02/16 Honor and Stipend to Present at President's Cup at American College of Sport Medicine Annual Conference
05/16 Outstanding Graduate Student of the Year, University of Houston–Clear Lake, Houston, Texas
05/16 Phi Kappa Phi Honor Society Inductee, University of Houston–Clear Lake, Houston, Texas
05/15 Omicron Delta Kappa Honor Society Inductee, University of Houston–Clear Lake, Houston, Texas
12/14 Honor Society, Exercise and Health Sciences Inductee, University of Houston–Clear Lake, Houston, Texas
05/10 Phi Beta Kappa Honor Society Inductee, Theta of California Chapter, Scripps College, Claremont, California
05/10 Dean's List, Scripps College, Claremont, California (05/06 – 05/10)
05/09 Ament Scholar Award, Outstanding Scholarship in the Humanities, Scripps College, Claremont, California
06/08 Kathryn Davis Fellowship for Peace, Middlebury College, Middlebury, Vermont

ADDITIONAL INFORMATION:

A. Ad-hoc Reviewer:

Archives of Physical Medicine and Rehabilitation (2017 – present)
Journal of Burn Care Research (2017 – present)
Center for Large Data Research in Rehabilitation Pilot Grants (2019 – present)

B. Professional Development:

04/19 Debunking Learning Truths, Teaching Skills Workshop, The University of Texas Medical Branch
04/19 How to Increase the Validity of Your Tests through Test Blueprinting, Teaching Skills Workshop, The University of Texas Medical Branch
03/19 Writing Multiple Choice Questions, Teaching Skills Workshop, The University of Texas Medical Branch

03/19 Why Should Teachers Bother Writing Instructional Objectives
12/18 Health Professions Learner Mistreatment is a Problem Nationally and at UTMB, Teaching Skills Workshop, The University of Texas Medical Branch
10/18 Educator's Portfolio, Teaching Skills Workshop, The University of Texas Medical Branch
08/18 Increasing Reading Compliance Among Learners, Education Workshop, The University of Texas Medical Branch
07/18 Ensuring Student Buy-In for Pre-Learning in Flipped or Team-Based Learning Classes, Education Workshop, The University of Texas Medical Branch
09/17 Adverse Childhood Experiences Screening: Resilience, The University of Texas Medical Branch
07/17 Methods to Madness Teaching Workshop, The University of Texas Medical Branch
06/17 Can We Talk? Addressing Poor Behavior Workshop, The University of Texas Medical Branch
05/17 So You Want to Be a Teacher, Teaching Workshop, The University of Texas Medical Branch

C. Professional Skills:

Advanced problem-solving and critical-thinking skills; experience with Medicare Data; R programming; SAS programming; ArcGIS; SPSS; Exercise prescription/training for healthy and special populations; DEXA Operation; Isokinetic dynamometry, VO_2, body composition, electromyography, and lactate testing; force platform use; functional assessment administration: timed up-and-go, Berg balance, sit-to-stand; 3-D kinematics and motion capture with Vicon Nexus software; basic C++ programming; DartPower software; DartFish software; SkillSpector software

D. Other:

Volunteering:

04/19	Lead Crawfish Boil Volunteer, The University of Texas Medical Branch
03/19	United to Serve Site Liaison, Galveston Railroad Museum
08/18 – present	Tour Guide, The University of Texas Medical Branch, Galveston, TX
03/18 – present	Food and meal preparation and delivery; Moody Methodist Church, Galveston, TX
05/17 – present	Poster Judge, Doctor of Physical Therapy Poster Session; The University of Texas Medical Branch, Galveston, TX
03/16 – present	SMART Literacy Garden Adult Volunteer, Morgan Elementary School, Galveston, TX
08/16 – present	Middle School Science Fair Judge, Austin Middle School, Galveston, TX

08/16 – present	Galveston County Science Fair Judge, Galveston County, TX
02/15 – 09/16	Council Member, Upward Sports League, Clear Lake United Methodist Church, Houston, TX
08/16 – 09/16	High School Lacrosse Coach, Gulf Coast Girls Lacrosse Association, Seabrook, TX
09/06 – 09/16	Youth Group Volunteer, Sunday School Teacher, Clear Lake United Methodist Church, Houston, TX

PUBLICATIONS:

A. Articles in Peer-Reviewed Journals:

1. Bores, J.M., Glover, S.Q., Gutierrez, I., Andersen, C., Herndon, D.N., Lee, J.O., Suman, O.E. Use of Isokinetic Dynamometry to Assess Muscle Function in Burned Patients is Reliable and Practical for Progressive Resistance Exercise Prescription. ***J Burn Care Res.*** doi: 10.1093/jbcr/irz003. [Epub ahead of print], 2019.

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1. Foncerrada, G., Capek, D.D., Wurzer, P., Herndon, D.H., Mlcak, R.P., Porter, C., Suman, O.E. Functional exercise capacity in children with electrical burns. ***J Burn Care Res.*** 38(3): e647-52, 2017.
2. Foncerrada, G., Clayton, R.P., Mlcak, R.P., Enkhbaatar, P., Herndon, D.N., Suman, O.E. Safety of Nebulized Epinephrine in Smoke Inhalation Injury. ***J Burn Care Res.*** 38(6): 396-402, 2017.

B. Other:

Proceedings and Symposia

1. Bores, J.M., Karmarkar, A., Downer, B. Patient Characteristics Associated with Functional Status Change in Stroke. ***Archives of Physical Medicine and Rehabilitation***. 99(10):e57-e58, 2018.

2. Bores, J.M., Glover, S.Q., Gutierrez, I., Andersen, C., Lee, J.O., Herndon, D.N., Suman, O.E. Use of isokinetic dynamometry to assess muscle function in burn patients is reliable and practical for progressive resistance exercise prescription. ***J Burn Car Res.*** 39(S1): S139, 2018.

3. Bores, J.M., Glover, S.Q., Gutierrez, I.G., Stevens, P., Andersen, C.R., Herndon, D.N., Suman, O.E. Subjective vs objective assessment of physical activity in burn patients. ***J Burn Care Res.*** 39(S1): S139, 2018.

4. Bhavnani SK., Lin Y.L., Chennuri L.R., Bores J.M., Chen C.H., Kuo Y.F. Identification, Replication, Visualization, and Interpretation of Patient Subgroups: Implications for Precision Medicine, and Predictive Modeling. ***Proceedings of AMIA Summit on Translational Bioinformatics*** (in press).

5. Bores, J.M., Rontoyanni, V.G., Gutierrez, I., Herndon, D.N., Porter, C., Suman, O.E. Characterization of nutritional intake and distribution of pediatric burn patients. ***Med Sci Sports Exercise*** 49(5S): 905-906, 2017.

6. Bores, J.M., Foncerrada, G., Anderson, C.R., Herndon, D.N., Suman, O.E., Mlcak, R.P. Effects of propranolol on lung spirometry in severely burned children with inhalation injury. ***J Burn Care Res***, 2017.

7. Rivas, E., Bores, J.M., Herndon, D.N., Kinsky, M., Suman, O.E. Burn injury reduces cardiac output and stroke volume during submaximal aerobic exercise in children. ***Med Sci Sports Exercise*** 49(5S): 322, 2017.

8. Bores, J.M., Vernon, C., Ridings, D., Champion, J., Amonette, W.E. Isokinetic knee strength is associated with knee flexion range of motion kinematics in the vertical jump. ***J of Strength Cond Res*** 30(1): S16-S17, 2016.

9. Bores, J.M., Vernon, C., Ridings, D., Champion, J., and Amonette, W.E. Isokinetic knee strength is associated with knee landing kinematics during double-leg vertical and depth jumps. ***Int J of Exer Sci*** Conference Proceedings 2(8): Article 45, 2016.

INVITED LECTURES – ON-CAMPUS:

“Navigating the PhD.” For the graduate course Introduction to Rehabilitation Sciences, The University of Texas Medical Branch, November 19, 2018, Galveston, Texas.

INVITED LECTURES – OFF-CAMPUS:

Texas:

“Life as a PhD.” For the undergraduate class Introduction to Exercise Science, University of Houston–Clear Lake, March 29, 2019, Houston, Texas.

International Lectures:

“Interview Techniques.” Seminar Instructor, St. Petersburg Graduate School of Management, May 5–6, 2013. St. Petersburg, Russia.