ASSESSMENT OF VARIABILITY IN HOSPITAL READMISSIONS AMONG MEDICARE BENEFICIARIES IN THE UNITED STATES

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By

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List of Abbreviations

- ACA ------------------- Affordable Care Act
- ACO ------------------- Accountable Care Organization
- ADI ------------------- Area Deprivation Index
- AHA ------------------- American Hospital Association
- AHRF ------------------- Area Health Resources Files
- AMI ------------------- Acute Myocardial Infarction
- BPCI ------------------- Bundled Payments for Care Improvement
- BRFSS ------------------- Behavioral Risk Factor Surveillance System
- CCM ------------------- Cumulative Complexity Model
- CCTP ------------------- Community-based Care Transitions Program
- CDC ------------------- Centers for Disease Control and Prevention
- CHF ------------------- Congestive heart failure
- CMS ------------------- Centers for Medicare and Medicaid Services
- COB ------------------- The Congressional Budget Office
- COTH ------------------- Council of Teaching Hospitals
- DSHSI ------------------- Disproportionate Hospital Share Index
- DRG ------------------- Diagnosis Related Group
- DUA ------------------- Data Use Agreement
- ED ------------------- Emergency department
- EHR ------------------- Electronic Health Records
- EMR ------------------- Electronic Medical Records
- ER ------------------- Emergency room
- FFS ------------------- Fee-For-Service
- FIPS ------------------- Federal Information Processing Standard
- GLLMM ------------------- Generalized Linear Mixed Model
- HCAHPS ------------------- Hospital Consumer Assessment of Healthcare Providers and Systems
- HF ------------------- Heart failure
- HLM ------------------- Hierarchical linear model
- HQA ------------------- Hospital Quality Alliance
- ICD-9-CM - ---------- International Classification of Diseases, Ninth Revision, Clinical Modification
- IDS ------------------- Integrated Delivery Systems
- IOM ------------------- Institute of Medicine
- IVR ------------------- Interactive voice response
• LDS -------------------Limited Data Set
• MedPAC - ------------Medicare Payment Advisory Commission
• NQF -----------------National Quality Forum
• PCA ------------------Principle components analysis
• PCMH ----------------Patient-Centered Medical Homes
• PN -------------------Pneumonia
• SAF ------------------Standard Analytic Files
• SES ------------------Socioeconomic status
• SNFs -----------------Skilled Nursing Facilities
• SSA ------------------Social Security Administration
• SSI ------------------Supplemental Security Income
• US ------------------United States
• VA -------------------Veteran Administration
• VBP ------------------Value-Based Purchasing
Chapter 1

Introduction and Statement of the Problem

Problem Background

A hospital readmission is an event that occurs when a patient who has been discharged from an acute care hospital is hospitalized again within a specified time interval. The Centers for Medicare and Medicaid Services (CMS) specifies this period as 30-days. Fundamentally, hospital readmissions in the Medicare program are hardly a new problem having been studied for over 30 years. They are common and costly but some are preventable. A research study by Jencks et al. indicated that around 20 percent of hospitalized Medicare patients are re-hospitalized within 30 days and 56 percent within a year with considerable variation between states – lowest in Idaho (13 percent) and highest in Washington DC (23 percent) (Jencks, Williams, & Coleman, 2009). Current efforts to reduce readmission rates are fundamentally driven by a steady rise in health care costs and a need to reduce hospital errors and optimize overall quality of care.

Among all adults in the U.S., 30-day all-cause hospital readmissions are associated with approximately $41.3 billion in hospital costs (Anika, Marguerite, H. Joanna, & Claudia, 2014). Moreover, frequent unplanned readmissions cost Medicare over $26 billion dollars annually of which $17 billion is spent on preventable or unplanned readmissions (Jencks, Williams, & Coleman, 2009). A report to Congress in 2007 by Medicare Payment Advisory Commission
(MedPAC) - an independent federal body that advises the U.S. Congress - indicated that 13.3 percent of Medicare readmissions at 30 days may indeed be avoidable (Medicare Payment Advisory Commission, 2007). In addition, a systematic review by van Walraven et al. found that 27.1 (range 5 to 79) percent of readmissions can be avoided (van Walraven, Bennett, Jennings, Austin, & Forster, 2011).

CMS has targeted heart failure (HF), acute myocardial infarction (AMI), and pneumonia (PN) because these conditions are costly to treat and are highly prevalent among Medicare beneficiaries. Moreover, a notable number of AMI, HF and PN readmissions may be prevented through rigorous improvements in quality of care including intensified post-discharge care coordination and patient follow-ups (Jencks et al., 2009; Vest, Gamm, Oxford, Gonzalez, & Slawson, 2010). Most importantly, AMI, HF and PN risk standardized 30-day readmission rates vary considerably among hospitals in the United States (U.S.). Between July 2011 and June 2014, hospital-level 30-day RSRRs following HF (Figure 1), AMI and PN ranged from 15.8 to 31.7, 13.3 to 20.8, and 13.2 to 22.9 percent respectively (figures for AMI and PN not shown).

Additionally, HF had the highest absolute difference (15.9 percentage points) in RSRRs across all hospitals (Table 1). Various factors at different levels - patient, hospital or community - may be contributing to this variability. The objective of this research study is to assess the amount of variability in AMI, HF and PN hospital-level readmission rates that is attributable to the county of hospital location including some of the factors implicated in that variability.
Even though these differences have been noted for some time, health policy researchers still know very little regarding precise sources of inter-hospital variability in specific medical conditions including AMI, HF and PN. Broadly, it has been suggested that variability in hospital-level readmission rates may be due to hospital structural differences (such as size, location and safety-net status) coupled with differences in admission rates (Epstein, Jha, & Orav, 2011; Joynt & Jha, 2013a). Others have suggested that patients’ socioeconomic position and neighborhoods of hospital location are responsible for some of the observed differences in readmission rates between hospitals (Calvillo-King et al., 2013; Herrin et al., 2015; Kind et al., 2014; Nagasako et al., 2014; van Walraven, Wong, & Forster, 2013). It is important to note that regardless of lack of consensus on underlying sources of variability, currently CMS views variability in RSRRs as
a reflection of quality of care performance differences among hospitals. Thus, CMS policies on
30-day hospital readmissions are profoundly geared at incentivizing hospitals to do more in
improving quality of patient care.

Table 1: Distributions of hospital 30-day RSRRs for HF, AMI and PN July 2011-June 2014

<table>
<thead>
<tr>
<th></th>
<th>Distribution of HF RSRRs (%)</th>
<th>Distribution of AMI RSRRs (%)</th>
<th>Distribution of PN RSRRs (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>31.7</td>
<td>20.8</td>
<td>22.9</td>
</tr>
<tr>
<td>90%</td>
<td>24.1</td>
<td>18.4</td>
<td>18.4</td>
</tr>
<tr>
<td>75%</td>
<td>23.0</td>
<td>17.7</td>
<td>17.6</td>
</tr>
<tr>
<td>Median (50%)</td>
<td>21.9</td>
<td>17.0</td>
<td>16.9</td>
</tr>
<tr>
<td>25%</td>
<td>21.0</td>
<td>16.3</td>
<td>16.2</td>
</tr>
<tr>
<td>10%</td>
<td>20.2</td>
<td>15.7</td>
<td>15.7</td>
</tr>
<tr>
<td>Minimum</td>
<td>15.8</td>
<td>13.3</td>
<td>13.2</td>
</tr>
<tr>
<td>Absolute difference</td>
<td>15.9</td>
<td>7.5</td>
<td>9.7</td>
</tr>
</tbody>
</table>

Source: Yale New Haven Health Services Corporation (YNHHS) Center for Outcomes Research and Evaluation (CORE) in a report to CMS September 2015.

Even though presently little is known regarding the actual sources of inter-hospital variability in RSRRs in specific medical conditions, evidence is gradually accumulating and a few studies have attempted to address this gap. First, Herrin et al., deploying a pooled hospital-level RSRR for HF, AMI and PN, found that the county in which hospitals were located explained 58 percent of the variation in readmission rates across hospitals (Herrin et al., 2015). Their study utilized data from the publicly reported hospital-level readmission rates posted on the Hospital Compare website. It is important to note that data used in Herrin et al. study were from July 1, 2007, to June 30, 2010 – a period predating ACA. As compared to post-ACA period, this time frame was characterized by high but stable RSRRs across all disease conditions (Figure 2) (Wasfy et al., 2016; Zuckerman, Sheingold, Orav, Ruhter, & Epstein, 2016). Although Herrin et al. study provides valuable insights regarding patterns and factors associated with readmissions in HF, AMI and PN combined, it is plausible that county or neighborhood factors
that influence readmissions in HF (a chronic condition) are different from those that influence AMI or PN (acute conditions) (Graham, Wilker, Howell, Davis, & Marcantonio, 2015).

Figure 2: Change in Readmission Rates for Targeted Conditions and Nontargeted Conditions within 30 Days after Discharge

Another study by Singh et al., restricted to only 272 hospitals in Texas, found that of the total risk of readmission, only 0.84 percent of variability could be attributed to the hospital. Additional analyses to partition this variability revealed that as compared to hospital characteristics and provider type, patient characteristics contributed the largest variability (56.2 percent) in readmission rates (Singh, Lin, Kuo, Nattinger, & Goodwin, 2014). One important limitation of this study is that the final study cohort (514,064 admissions) included all patients with a medical diagnosis-related group (DRG). As such, the study provides little insight on how specific medical conditions may be influenced by hospital-level or patient-level factors included
in the study. Despite, Singh et al. study findings are indirectly supported by another study by Barnett et al. that demonstrated a decrease in between-hospital variation in readmission rates after adjustment for additional patient characteristics beyond age, sex and disease comorbidities (Barnett, Hsu, & McWilliams, 2015).

Figure 3: Sources of variation in 30-day risk of readmission among hospitals with at least 1,500 Medicare admissions in Texas.


A study by Fonarow et al. found considerable variation in risk-adjusted 30-day readmission rates among fee-for-service Medicare beneficiaries diagnosed with acute ischemic stroke (Fonarow et al., 2011). The goal of this study was to determine the extent to which readmissions (and mortality) vary among hospitals and their association with various hospital characteristics after adjusting for patient characteristics. Their hospital-level results showed substantial variation across hospitals in both mortality and readmission at various time points – 30-day, 90-day, and 1-year before and after adjustments for various patient- and hospital-level factors. Hospital characteristics accounted for less than 4 percent of the variation in both
outcomes. However, generalizability of their findings is weakened by failure to investigate or account for community or patients’ socioeconomic factors.

Meanwhile, in 2012 a study by Yeh et al. investigated all-cause RSRRs for all non-federal hospitals (n = 24) performing percutaneous coronary intervention (PCI) in Massachusetts (Yeh et al., 2012). Data for this study were collected between 2005 and 2008. Hospital-level RSRRs ranged from 9.5 percent to 17.9 percent. Clinical and angiographic variables included in the study accounted for 10.4 percent of the variation among hospitals. Although the authors observed wide variation in hospital-level 30-day all-cause RSRRs after PCI, much of that variation could not be explained by factors such as insurance type, race, PCI characteristics and procedure complications. No community or social factors were adjusted for in this study either.

The present study builds on these prior findings. Undoubtedly, findings and conclusions on what truly drives variability in 30-day hospital readmission rates in Medicare patients differ among researchers. Methodological and sample differences notwithstanding, findings from above previous studies provide an important base for health policy researchers to conduct more exhaustive research that uncovers precise reasons why readmission rates differ widely between hospitals. Certainly, one area that has received insufficient attention is the influence of neighborhood or community factors on hospital readmissions. Assessing the role of neighborhood factors on 30-day readmission rates is important considering that a number of social research studies have demonstrated explicitly that place or neighborhood of residence has a strong influence on health outcomes (Arbaje et al., 2008; Gilstrap & Joynt, 2014; Joynt & Jha, 2011).

In general, variability in Medicare readmissions may be emblematic of larger quality and cost issues facing the U.S. healthcare system. In October 2012, the Affordable Care Act (ACA)
established the Hospital Readmission Reduction Program (HRRP) effectively requiring CMS to reduce payments to inpatient prospective payment system (IPPS) hospitals with excess risk-adjusted 30-day readmission rates. Excess readmission rate is a ratio of a hospital’s performance compared with the national average for a set of patients with similar conditions and it is based upon 3 years of prior discharge data for hospitals with 25 or more cases of a specific measured condition (Fontanarosa & McNutt, 2013). Accordingly, the National Quality Forum (NQF), an agency created by Congress to develop health care quality measures, endorsed the use of hospital risk-standardized readmission rates as a quality performance metric (Mulvey et al., 2009). Yet, HRRP policy has continued to face considerable criticism from those who question the validity of the hospital as the focal point in reducing readmissions and the limited nature of current measure itself (Joynt & Jha, 2013b; McIlvennan et al., 2015). Current HRRP policy adjusts and sets expected readmission rates based only on patients’ age, sex, discharge diagnosis, and recent diagnosis (12 months before admission) but not for race, ethnicity, or socioeconomic status (National Quality Forum, 2014).

Medicare has indicated that the main reason for this partial risk adjustment is to avoid rewarding hospitals providing care to lower socioeconomic patients when that care is of lower quality (Fiscella, Burstin, & Nerenz, 2014; National Quality Forum, 2014). However, a key question for this current research is not whether the current risk-adjustment approach is appropriate or not but whether variations in readmission rates across hospitals are reflective of quality of care differences or other unaccounted for factors such as neighborhood poverty rates. Therefore, the main goal of this study is to assess the amount of variability in hospital readmissions attributable to the neighborhood or county where hospitals are located and further
assessment of county-level factors implicated in that variability among Medicare patients with a primary discharge diagnosis of AMI, HF and PN.

**Knowledge Gaps**

First, although it is known that county-level factors explain a substantial portion of inter-hospital variability in pooled 30-day all-cause RSRRs for AMI, HF and PN, it is unknown how county-level variables explain variability in RSRRs for each specific condition and whether the influence of county factors varies across medical conditions. Second, it is known how certain community factors such as access to primary care influence variability in pooled 30-day all-cause RSRRs for AMI, HF and PN. However, these relationships have not been investigated separately for each specific medical condition. Third, although much research has been conducted in regard to SES and RSRRs, little is known on how behavioral factors such as county-level smoking rates influence RSRRs for specific disease conditions when adjusted for other county-level factors. Fourth, NQF has endorsed AMI, HF and PN hospital risk-standardized 30-day readmissions rates (adjusted only for age, gender and comorbidities) as publicly reportable quality measures that are directly linked to hospital financial reimbursement. However, uncertainty remains on whether CMS should consider further adjustment for certain community factors. Fifth, although comprehensive assessment of the relationship between community-level factors and AMI, HF and PN readmission rates has been previously assessed using pre-ACA datasets (Herrin et al., 2015), it is unknown whether different findings would be obtained when utilizing post-ACA nationwide Medicare data (years 2011 to 2013). Following the passage of ACA in 2010, risk standardized readmissions rates for AMI, HF and PN declined
sharply (figure 2). CMS has attributed this sudden drop to quality improvement changes implemented by hospitals in anticipation of financial penalties.

**New Contributions to the Literature**

First, to my knowledge, this is the first study to assess hospital-level variability in 30-day risk adjusted readmission rates separately for each of the three most common medical conditions among Medicare patients – AMI, HF and PN. This is important considering that unlike AMI or PN, HF is considered a chronic condition that is greatly influenced by contextual factors such as access to care and social living conditions (Graham et al., 2015). Second, this is the first study to assess the influence of certain county-level factors including poverty and PCP rates on variability in AMI, HF and PN RSRRs. Third, this is the first study to assess the influence of community cigarette smoking rates – a behavioral risk factor known to strongly impact clinical outcomes at individual level – on AMI, HF and PN RSRRs. Fourth, this study provides important insights regarding additional county-level variables that CMS should probably consider adjusting for in future risk adjustment models. Fifth, this is the first study to comprehensively assess variability in hospital-level readmission rates in the Medicare program utilizing post-ACA nationally representative Medicare dataset. Specifically, in comparison to Herrin et al. study that was conducted using pre-ACA datasets, this current research seeks to utilize post-ACA datasets (Year 2011-Year 2013) to assess how much of variability in readmission rates is attributable to the county of hospital location following implementation of ACA.

Overall and compared to previous research studies that were either restricted to a single state or a single hospital, this current study utilizes relatively recent nationwide Medicare dataset linked to a large sample of hospitals. Noteworthy, the Medicare dataset in use for this study is the same primary data used by CMS for public reporting of hospital-level RSRRs although from
different years. Among other information, these CMS data files contain patients’ demographic information and diagnostic codes for Medicare-eligible beneficiaries seen as inpatients across all Medicare hospitals in the U.S.

**Importance and Significance of the study**

First, RSRRs are now a measure of quality. As such, hospital performance on these measures is directly linked to reimbursement. Hospitals with above national average RSRRs are being financially penalized for certain disease conditions including AMI, HF and PN. However, there is much uncertainty on whether these measures are a true signal of hospital quality or whether other hospital or community-level variables are involved. Researchers have tried to address this concern by assessing the role of patient- and hospital-level factors (Singh et al., 2014; Yeh et al., 2012). However, only 1 study has comprehensively assessed the role of community factors in explaining variability in readmission rates among Medicare patients (Herrin et al., 2015). Additional research studies are required to better understand and ascertain the source of variability in specific disease conditions. This understanding is crucial in implementing cost-effective and strategically focused interventions in community settings. Moreover, knowing the source of variability in specific disease conditions is important in assessing whether all-cause 30-day RSRR is a true measure of hospital quality of care.

Second and closely connected to quality is cost. With the passage of ACA in 2010, much emphasize has now been placed on cost reduction and quality improvement in acute care settings. Insufficient understanding of source of variability in readmission rates may result in some hospitals – specifically safety-net hospitals that primarily serve low socioeconomic patients – being financially penalized for simply serving this demographic. Consequently, hospitals serving the poor may be forced to scale down services or shut down altogether due to financial
constraints. Researchers have warned of exacerbation of healthcare disparities if care to low SES patients is rationed (Bhalla & Kalkut, 2010; Fiscella & Williams, 2004; Jha, 2015; Tsai, Orav, & Joynt, 2014; Wakeam et al., 2014; Wan, Ortiz, Du, & Golden, 2015). As such, it is important that additional research studies support extant findings that community and other downstream factors play a significant role in determining hospital readmission rates and thus should probably be considered in penalty calculation and reimbursement decisions.

Third, hospital readmissions have been studied for a long time and much is known regarding risk factors and prevention strategies. However, very little is known regarding inter-hospital variability and available findings vary among researchers. Accordingly, lack of consensus necessitates additional studies to clarify and support extant findings. This current study will add to the literature by providing some clarity and fresh perspective on how county-level factors influence RSRR variability in AMI, HF and PN among Medicare patients. The study will also provide insight on whether to risk-adjust readmission rates for certain county and demographic variables.

Fourth, this study is important in guiding current and future preventions efforts. The ACA and specifically HRRP policy is sharply focused on patient-centered care that is also thoroughly integrated with population health. As such, it is important to know where exactly to intervene or direct prevention resources including funding and personnel.
Primary Problem
- Variability in hospital-level all-cause AMI, HF and PN RSRRs among hospitals in the U.S.
  - Currently, RSRRs adjusted only for age, gender and comorbidities.

Secondary Problems
- Poorly performing hospitals are being penalized.
- Possible exacerbation of healthcare disparities.
- Uncertainty on whether to adjust for community-level factors

Approach
Ascertain variability in RSRR

Expected Contribution
- Ascertainment of the amount of variability explained at the county-level for each specific condition - AMI, HF and PN.
- Assess and suggest which context variables should probably be considered in future risk adjustment efforts.
Importance of this Topic to Patients, Providers, Payers, and Policy makers

In addition to its overall contribution to the literature, this study has potential direct benefits to patients, providers, payers and policy makers. Indeed, improved understanding of factors contributing to 30-day hospital readmissions is crucial in strategizing prevention efforts in specific groups and across the continuum of care.

(a) Patients

Frequent hospital admissions and readmissions can be a source of much discomfort and stress to patients. Granted, patients draw much value from care that is efficient, effective, and of high quality. As such, patients would rather not frequent hospitals unless for planned continued treatment or follow-up. In addition, considering the costs involved – copays, deductibles, and co-insurance - and the potential for hospital acquired infections and other malpractices, many patients would rather not be hospitalized. The Institute of Medicine (IOM) report *To Err is Human* revealed the extent of harm extant in U.S. hospitals and how it is directly correlated to inpatient quality of care (Institute of Medicine Committee on Quality of Health Care in America, 2000). Moreover, research studies show that hospital readmissions are associated with functional decline and other complications unrelated to the principal reason for admission (Creditor, 1993; Graf, 2006; Greysen, Stijacic Cenzer, Auerbach, & Covinsky, 2015).

Frequent re-hospitalizations have also been linked to what has come to be known as “post-hospital syndrome” (Krumholz, 2013). This is a period of transient vulnerability and a time of generalized risk among recently hospitalized patients. Focusing on hospitalization itself - by for instance minimizing testing or blood draws – may be an important step in minimizing worries and concerns associated with an inpatient hospital stay and also in accelerating the healing
process once the patient is discharged from the hospital (Detsky & Krumholz, 2014; Krumholz, 2013). Additionally, hospital readmissions have been associated with increased anxiety, uncertainty and in some cases severe depression both for the patients and their families (Tsai, Orav, & Jha, 2015b). In some other cases, early hospital readmission has been associated with increased one-year mortality among community-dwelling Medicare patients (Lum, Studenski, Degenholtz, & Hardy, 2012). Thus, better understanding of factors contributing to readmissions is crucial in uncovering strategic intervention points for reducing unnecessary hospital admissions and readmissions particularly among comorbid elderly Medicare patients.

(b) Providers

Hospitals have become the focal point of readmission reduction programs. A major reason for this is because hospitals can, by doing nothing on readmissions, easily take advantage of the current volume-based fee-for-service reimbursement model and benefit financially from avoidable readmissions. Indeed, this practice was relatively common before year 2012 when hospitals had little to no incentive in addressing readmissions. However, an analysis by MedPAC in 2007 indicated that hospitals may not gain much financially from readmitted patients (Medicare Payment Advisory Commission, 2007). Nonetheless, now more than ever before, hospitals are required to pay closer attention to what happens to their patients once discharged from the hospital. Care coordination and follow-up with primary care physicians has gradually evolved to be the primary responsibility of the discharging hospital. Presently, the kind of care hospitals provide to Medicare patients is highly scrutinized and hospitals with higher-than-expected risk-standardized 30-day readmission rates are bound to lose financially. Consequently, it is important for hospital administrators to clearly understand why frequent and unnecessary
readmissions occur at their institutions and how to prevent them. Some hospitals however continue to view CMS instituted penalties as excessive punishment considering that year-to-year improvements are no sufficient to warrant lighter or no financial penalty.

Equally important, this topic is imperative to providers because lower readmission rates provide hospitals with leverage when negotiating better payment rates from health insurance plans and other payers (Silow-Carroll, Edwards, & Lashbrook, 2011). Additionally, now that the readmission metrics are being reported publicly, hospitals with excessive readmission rates face unprecedented public relations problem that could gradually impact their overall financial standing. Improved understanding of factors contributing to readmissions is important in guiding hospital leadership decisions - especially on how best to leverage available resources (financial and personnel) to prevent unnecessary hospitalizations.

(c) Payers

Hospital readmissions contribute to significant avoidable health care expenses (Jencks et al., 2009). Both private and public payers are therefore looking for ways to reign on financial waste and other inefficiencies. Medicare, in particular, is interested in implementing innovative strategies that can simultaneously improve quality of care and lower overall cost of care. Lowering avoidable readmissions is therefore a promising path to achieving these two important goals in the Medicare program. Thus, better understanding of factors contributing to readmissions is essential in guiding payers as they seek to develop reimbursement plans that can both reward and financially incentivize providers to improve care coordination, curtail unnecessary readmissions and healthcare lower costs.
(d) Policymakers and political leaders

This topic is also important and timely to policymakers and political leaders alike as they seek practical alternatives to lower increasing health care costs while concurrently improving quality of care. Although, the issue of Medicare hospital readmissions has been a major national priority issue over the last few years, there is still no clear understanding of what exactly drives avoidable hospital readmissions in specific care settings and why hospital readmission rates for AMI, HF and PN differ substantially across hospitals. Considering the complexity of causes of readmission and the possibility of unfairly penalizing hospitals serving low SES patients, this issue has received attention in Congress. In March 2015, Rep. Renacci (R-Ohio), Rep. Engel (D-N.Y.), Sen. Portman (R-Ohio), and Sen. Manchin (D-W.Va.) introduced in Congress the Establishing Beneficiary Equity in the Hospital Readmissions Program Act of 2015 (Rep. Renacci, James B. [R-OH-16], 2015). This bill requires CMS to account for patients’ socioeconomic status when determining the expected number of readmissions for each hospital. A similar bill - H.R.5273 - Helping Hospitals Improve Patient Care Act of 2016 - was passed in the house (Rep. Tiberi, Patrick J. [R-OH-12], 2015). Accordingly, an improved understanding of factors responsible for frequent hospital readmissions directly benefits health policymaking process particularly in better understanding of factors to include or exclude in risk-adjustment models.

Conceptual Framework

Conceptually, and based on extant literature, it can be predicted that certain county characteristics would explain a notable portion of inter-hospital variability in readmission rates
as compared to hospital, patient-level medical characteristics or health care system factors. These county characteristics or explanatory variables can conceptually be grouped into five categories:
(a) Access to primary care factors such as per capita number of primary care physicians (PCPs);
(b) Demographic factors such as percentage resident population 65 years and over and percentage black only resident population;
(c) Socioeconomic factors such as median household income and percentage estimate of all ages in poverty;
(d) Access to skilled nursing home care factors such as per capita number of skilled nursing facilities and percentage population aged 65 or older in nursing homes;
(e) Neighborhood health behaviors such as percentage of residents who smoke cigarettes.
Figure 5: Conceptual framework on sources of variability in hospital readmissions rates.

- **Patient-level Factors**
  - Demographics – age, gender, race
  - Severity of sickness
  - SES - education, employment, income

- **Hospital-level Factors**
  - Quality of care – discharge planning
  - Structural - size, teaching status etc.

- **Community-level Factors**
  - SES - Poverty rates
  - Access to care – PCPs and SNFs
  - Behavioral factors such as smoking rates
  - Demographics

- **OTHER – Health System factors**
  - Spending patterns
  - Utilization patterns

**Primary Problem**
Variability in hospital-level AMI, HF, and PN RSRPs.
Research Questions and Specific Aims

Research Question # 1: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI and PN in the U.S., how much of hospital-level variability in 30-day RSRRs is attributable to the county of hospital location for each specific diagnosis?  
H1: Among fee-for-service Medicare beneficiaries diagnosed with HF, AMI, and PN, a notable portion of hospital-level variability in readmission rates may be explained by county of hospital location beyond that which is explained by patient, hospital or health care system characteristics.

Research Question # 2: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI and PN in the U.S., which county-level factors drive variability in hospital-level 30-day RSRRs for each specific diagnosis?  
H1: Among fee-for-service Medicare beneficiaries diagnosed with HF, AMI, and PN, variability in hospital-level readmission rates may be influenced by the following county-level factors; median household income, per capita number of primary care physicians, percentage resident population 65 years and over, percentage black resident population, percentage estimate of all ages in poverty, per capita number of skilled nursing facilities, percentage population aged 65 or older in nursing homes, and percentage of adults who are current smokers.

Research Question # 3: Among fee-for-service Medicare beneficiaries diagnosed with HF, AMI and PN in the U.S., how do hospital structural characteristics influence the relationship between hospital-level 30-day RSRRs and county-level factors?  
H1: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN, hospital characteristics would have minimal effect on the relationship between hospital-level readmission rates and county-level factors.
Specific Aims

Specific Aim # 1: To assess the amount of variability in hospital-level readmission rates that would be explained by county of hospital location among fee-for service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN in the U.S.

H1: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN, a notable portion of hospital-level variability in 30-day RSRRs may be explained by county of hospital location.

Specific Aim # 2: To assess the contribution of certain county-level factors in explaining the variability in hospital-level 30-day RSRRs among fee-for service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN in the U.S. These factors include median household income, per capita number of primary care physicians, percentage resident population 65 years and over, percentage black resident population, percentage estimate of all ages in poverty, per capita number of skilled nursing facilities, percentage population aged 65 or older in nursing homes, and percentage of adults who are current smokers.

Hypothesis for Each Explanatory (County) Variable

**H1a:** Hospitals located in low median household income counties are more likely to have higher readmission rates when compared to hospitals located in high median household income counties.

**H1b:** Hospitals located in counties with fewer per capita number of primary care physicians are more likely to have higher readmission rates when compared to hospitals located in counties with higher per capita number of primary care physicians.
**H1c:** Hospitals located in counties with higher percentage black resident population are more likely to have higher readmission rates when compared to hospitals located in counties with less percentage black resident population.

**H1d:** Hospitals located in counties with high percentage resident population 65 years and over are more likely to have higher readmission rates when compared to hospitals located in counties with low percentage resident population 65 years and over.

**H1e:** Hospitals located in counties with high percentage estimate of all ages in poverty are more likely to have higher readmission rates when compared to hospitals located in counties with low percentage estimate of all ages in poverty.

**H1f:** Hospitals located in counties with fewer numbers of skilled nursing facilities are more likely to have higher readmission rates when compared to hospitals located in counties with higher per capita number of skilled nursing facilities.

**H1g:** Hospitals located in counties with higher percentage population aged 65 or older in nursing homes are more likely to have higher readmission rates when compared to hospitals located in counties with fewer percentage population aged 65 or older in nursing homes.

**H1h:** Hospitals located in counties with higher percentage of adults who are current smokers are more likely to have higher readmission rates when compared to hospitals located in counties with fewer adults who are current smokers.

**Specific Aim # 3:** To examine how hospital characteristics influence the relationship between county characteristics and readmission rates among fee-for service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and pneumonia in the U.S.
H1: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN, hospital characteristics would have an effect on the relationship between hospital-level readmission rates and county-level factors.
Chapter 2

Literature Review

Thirty-day Readmission Rates in Medicare

Over the last decade, the U.S. healthcare system has witnessed considerable improvement in common quality measures such as length of stay (LOS), in-hospital mortality, and total hospital admissions but not so with 30-day readmissions (Bueno et al., 2010). It has been reported that hospital readmissions may account for up to half of all hospital admissions in the U.S. – a majority of which are concentrated in older adults (Weinberger, Oddone, & Henderson, 1996). Although many re-hospitalizations in the Medicare program are necessary and indeed part of treatment plan, the federal government – being the single largest healthcare payer in the U.S. - has the authority to question and investigate inordinate hospital readmissions.

Depending on diagnosis, overall 30-day readmission rates range between 8 and 25 percent in both private and public hospitals (Baker, Einstadter, Husak, & Cebul, 2004; Jencks et al., 2009; Jha, Orav, & Epstein, 2009). A study by Joynt et al. has indicated that public hospitals with limited financial and clinical resources are more likely to have higher readmission rates (Joynt & Jha, 2011). Meanwhile, HF remains the leading cause of early readmissions among Medicare beneficiaries with 1 in 4 HF patients being re-hospitalized within 30 days of initial hospital discharge (Krumholz et al., 2009). Notably though, HF, AMI, and PN account for just
about 15 percent of hospitalizations in the Medicare program (Dharmarajan, Hsieh, Lin, Bueno, Ross, Horwitz, Barreto-Filho, Kim, Bernheim et al., 2013). A study by Smith et al. found that 23.3 percent of patients seen at nine VA medical centers were readmitted (Smith et al., 2000). For surgical cases, 1 in 7 patients hospitalized for a major surgical procedure is readmitted to the hospital within 30 days after discharge (Tsai, Joynt, Orav, Gawande, & Jha, 2013). However, this rate may vary considerably depending on surgical specialty, provider, and patient case-mix.

Of note, the definition of readmission is not standard across research fields. Accordingly, this may partly explain why there continues to be considerable national and regional variation in reported readmission rates across both hospitals and medical conditions (M. Hasan, 2001; Vest et al., 2010; Weissman, 2001). CMS’s definition of readmission includes re-hospitalization to any hospital, not just the hospital of index hospitalization for any cause or rather “all-causes” (Medicare Payment Advisory Commission, 2007). Per CMS, “all-cause” means that re-hospitalization within 30 days, regardless of the reason, is considered a readmission. Precisely, Medicare considers the cause of readmission and cause of index admission as distinct and unrelated - unless deemed planned based on certain International Classification of Diseases (ICD) codes. For instance, a patient discharged after heart failure treatment and readmitted 2 weeks later after falling and breaking his leg would be included in hospital’s heart failure readmission rate. Even though limited data evidence supports the use of all-cause readmissions as a performance measure, CMS continues to utilize this all-cause definition to determine the national average readmission rates and hospital specific readmission rates. CMS has justified this position by arguing that hospitals ought to be more engaged with patient care and wellbeing following hospital discharge. By actively doing so, many triggers of re-hospitalization can be identified and mitigated.
Moreover, although very little has been published on the association between the cause of initial or index admission and readmission, Jencks et al. found minimal association between the two; only 37 percent of heart failure and 29 percent of pneumonia patients were readmitted for the same condition (Jencks et al., 2009). Yet, regardless of the index admission diagnosis, rehospitalizations in the Medicare cohort are mostly because of heart failure, pneumonia, infections, mental illness, trauma, and gastrointestinal conditions suggesting a greater need to better understand readmission factors linked to these medical conditions (Krumholz, 2013). On the other hand, accumulating body of research has shown that a vast majority of rehospitalizations among Medicare patients occur in the same hospital of index hospitalization while readmission to other hospitals - different from the hospital of index hospitalization - has been shown to occur only in about 10 to 15 percent of cases (Greenblatt et al., 2010; Halfon et al., 2002).

Most importantly, health care spending continues to rise among Medicare patients threatening the very existence of the Medicare program itself. Indeed, the Social Security and Medicare Boards of Trustees estimate that the Medicare Hospital Insurance Fund will be depleted by 2030 (Mantel, 2015). Overtreatment of Medicare patients including frequent admission and readmissions has been cited as part of the reason for skyrocketing costs in Medicare (D. M. Blumenthal et al., 2015; Mantel, 2015). When patients are readmitted for avoidable reasons, they automatically become candidates for further clinical tests and expensive treatments – dramatically increasing costs of care. However, some reports indicate that healthcare spending growth has slowed down and much of that improvement can be attributed to the recently enacted ACA policies such as HRRP (D. Blumenthal, Stremikis, & Cutler, 2013). Even so, current healthcare spending in the U.S. remains very high in comparison to realized
clinical benefits. As such, continued cost control efforts are warranted. A recent Kaiser Family Foundation report indicates that in 2017 Medicare is expected to save $528 million dollars through Medicare penalties assessed on hospitals with high readmission rates (Boccuti & Casillas, 2016). Better understanding of neighborhood factors that contribute to frequent re-hospitalizations in the Medicare program is indispensable in designing interventions that can substantially reduce unnecessary readmissions, lower overall health care costs and improve quality of care for Medicare beneficiaries.

Following the NQF endorsement of RSRRs as hospital quality measures, the CMS is now reporting these rates publicly and this reporting has indeed been associated with improved measures of inpatient care and related quality outcomes (Werner & Bradlow, 2010). In year 2015, hospitals with high readmissions are bound to lose up to 3 percent of their base Medicare reimbursement. As such, hospitals are currently highly engaged in strategies to cut costs and reduce unnecessary readmissions by both improving care transitions and working together with primary care providers. Indeed, restraining cost growth is a key piece of ACA (Orszag & Emanuel, 2010). Seminal work by Anderson et al. in a random sample of Medicare beneficiaries indicated that Medicare inpatient expenditures are concentrated on a small percentage of repeatedly admitted patients with multiple chronic conditions (G. F. Anderson & Steinberg, 1984). Notably, a 2012 and 2013 Medicare report showed considerable county and state variation in prevalence of multiple chronic conditions among Medicare beneficiaries. In 2013, over two-thirds of Medicare beneficiaries had two or more chronic conditions while 1 in 7 (14 percent) had 6 or more (Lochner, Goodman, Posner, & Parekh, 2013; Lochner & Shoff, 2015). Meanwhile, wide variations in patterns and practice of medicine in the U.S. reveals unwarranted
variation in per capita Medicare spending even after adjustment for patients’ demographic factors, illness severity or type, and price of care (Wennberg, 2002).

Granted, not all readmissions are “bad” readmissions. Indeed, some re-hospitalizations are central to patient recovery but many more can be avoided. Even though the true number of avoidable readmissions in the Medicare program remains uncertain, the policy relevance of this issue and the eminent cost savings cannot be underestimated. Indeed, the Congressional Budget Office (COB) has estimated that readmission penalties currently being instituted on hospitals will save Medicare approximately $7 billion in 10 years (Hansen et al., 2013). Part of these savings will be deployed in Medicare’s Partnership for Patients campaigns to reduce hospital readmissions (McCarthy, Johnson, & Audet, 2013). Some policy experts and researchers have suggested that readmissions occurring a few days after discharge are more likely to be related to inpatient quality of care (such as discharge processes) and are therefore more likely to be avoided if hospitals optimized their quality of care. (van Walraven et al., 2011). To assess whether a readmission can be avoided or not, a majority of past research studies have relied heavily on medical chart reviews and prognostic models coupled with multivariable risk-adjustment – methods that undoubtedly are prone to statistical errors and misinterpretation (Frankl, Breeling, & Goldman, 1991; O. Hasan et al., 2010; Padhukasahasram, Reddy, Li, & Lanfear, 2015; Shulan, Gao, & Moore, 2013; van Walraven et al., 2011).

**Hospital Readmissions Reduction Program (HRRP)**

CMS, through HRRP, is now holding hospitals accountable for the quality of inpatient care that they provide to Medicare patients. Accountability is happening in two fronts - public reporting of hospital-specific excess versus expected readmission rates and reduced
reimbursements. Hospital compare website now publicly provides comparative information regarding performance of U.S. hospitals on various quality measures including 30-day hospital readmissions. So far, public reporting has been associated with improved measures of inpatient care and quality outcomes (Werner & Bradlow, 2010). However, prior research by Jha et al. had shown modest to no association between publicly reported process of care measures and readmission rates (Jha et al., 2009). Notwithstanding, HRRP is an important policy change with major implications on patients, payers and providers. Whether this policy and others will indeed succeed in holding hospitals accountable and in lowering avoidable readmissions is at the moment difficult to gauge.

In December 2014, CMS released a report flaunting the achievements of ACA policies such as HRRP in lowering Medicare readmission rates and reducing costs (Centers for Medicare & Medicaid Services, 2015). Precisely, the all-cause 30-day hospital readmission rate among Medicare fee-for-service beneficiaries fell to 17.8 percent in 2013 after holding steady at 19.0 percent from 2007 to 2011 (Gerhardt et al., 2013; Jha, 2015). However, this positive early evidence has encountered criticism from those who perceive it as biased toward safety-net and major teaching hospitals that primarily provide health care services to poor and much sicker Medicare patients (Barnett et al., 2015). In addition, selected research findings indicate that these institutions are more likely to be financially penalized (Joynt & Jha, 2013a). If these reports are indeed true, this suggests that under the current HRRP policy formulation, hospitals are not necessarily being penalized for substandard care but on the type of patients they serve – evidently something beyond hospital control.

But assuming important improvements are made to HRRP to incorporate other patient characteristics including patient’s SES, how will the success of HRRP policy be ascertained?
Marsh et al. developed a framework incorporating three elements of a successful policy – success in the policy making process, political success, and programmatic success (Marsh & McConnell, 2010). Applying this concept to re-hospitalizations, all-cause readmissions among Medicare patients have decreased significantly - from 18.5 to 17.5 percent between 2012 and 2013. Therefore, based on Marsh’s framework, this undoubtedly signifies an important programmatic success and thus reasonable to conclude that HRRP triggered this decrease. But on the other hand, serious questions are bound to arise on whether hospitals by themselves - without unprecedented government intervention - can institute sustainable programs to lower unplanned re-hospitalizations. In other words, the introduction of HRRP-based readmission financial penalties forced hospitals to rethink their quality of care and to follow through with their patients following hospital discharge. It is doubtful that hospitals would have achieved similar results without CMS intervention.

However, on a different note, attributing decrease in readmissions solely to HRRP may be devious at best especially considering new evidence suggesting that coding and reclassification may be playing a role in observed improvements. As a way to prevent excessive readmissions and avoid fines, some hospitals are indeed beginning to game the system by reclassifying patients returning to the hospital within 30 days as “observation status” instead of outright readmission by placing them in clinical decision units (Feng, Wright, & Mor, 2012; Himmelstein & Woolhandler, 2015; Jha, 2013; Joynt & Jha, 2013b; McIlvennan et al., 2015). Observation status is a subjectivity-prone determination made by an attending physician when a patient fails to meet the routine criteria for inpatient admission. Of note, any services received by a patient under observation status are billed as outpatient services and patients’ out-of-pocket costs are higher when compared to inpatient stays. Thus, while this strategy seems financially
rewarding and virtuous for hospital reputation, it may be harmful to patients – both in terms care quality and costs.

One potential benefit emerging from HRRP, however, is robust support for hospitals with high risk-adjusted readmission rates (McCarthy et al., 2013). In other words, a marginal role of HRRP is to offer quality improvement support and guidance to hospitals that are trying to implement various programs to lower preventable readmissions. Prior to HRRP, this kind of support was not available to hospitals. Rather, hospitals implemented prevention programs based on their own internal policies and best practices. Medicare has indicated that ACA and national health reform will continue to present new opportunities geared at maximizing quality and reducing unnecessary costs. Besides, hospitals are likely to respond to HHRP policy in various ways; develop robust programs to improve quality of care, expand service lines or market share, curtail discretionary readmissions, avoid high-risk patients, place patients under observation status instead of admission (as discussed above), or differ readmission until after 30 days (Joynt & Jha, 2013b; McCarthy et al., 2013; Nuckols, 2015; Vaduganathan, Bonow, & Gheorghiade, 2013). It is important to note that if specific hospital entities perceive the cost of improvement as being greater than the cost of the penalty, they will be more likely to opt for the latter – a critical weakness of current HRRP policy.

**Reasons for Hospital Readmission in Medicare**

There are many known reasons why patients return to the hospital following an acute care hospital stay. Admittedly, even though the issue of early hospital readmission may seem trivial and therefore easily amenable to simple interventions, the chief reasons driving unnecessary hospital readmissions among Medicare patients are poorly understood. However, poor quality of
hospital care has received considerable attention and scrutiny. Accordingly, hospitals have become the locus of accountability in addressing avoidable readmissions. Albeit hospital environments and quality of inpatient care play a crucial role in preventing unnecessary re-hospitalizations, it is worth noting that hospital operating environments are also highly influenced by the surrounding policy environment, local health markets, membership in integrated care systems and local leadership – factors that may also influence early unplanned readmissions (Silow-Carroll et al., 2011).

Another widely mentioned reason driving re-hospitalizations in Medicare relates to care fragmentation and poor communication between care providers. In many cases, patients’ leave the hospital with minimal or no plan of post-discharge care, dramatically increasing their odds of being readmitted (Radhakrishnan, Jones, Weems, Knight, & Rice, 2015; Tsai, Orav, & Jha, 2015a). Other patients’ leave the hospital with minimal understanding of their illness or their responsibilities post-discharge. In other cases, there is utter lack of continuity of care – partly because care accountability is ambiguous once the patient has left the hospital door (Goodman, Fisher, & Chang, 2013). In some instances, poor accountability has been linked to poor financial incentives for caregivers in community settings including primary care physicians and home-health nurses (Epstein, 2009; Jones et al., 2015; Marks, Loehr, & McCarthy, 2013). Therefore, integrating inpatient and outpatient care and providing the necessary financial support to community providers may be a critical step in reducing early unplanned readmissions. Indeed, strong relationships between hospitals and primary care providers, nursing homes, home health care agencies, and other community-level care providers including hospice and palliative care providers have been shown to significantly reduce early unplanned hospital readmissions (Schoenfeld et al., 2016; Silow-Carroll et al., 2011).
Yet in other instances, patients stay in the hospital is characterized by utter lack of understanding of their illness or prognosis. As such, patients tend to experience fear and uncertainty regarding appropriate medications and care regimens, diet management, and what post-discharge activities to engage in. Research studies show that without patient-centered education and patient engagement, while still in the hospital, patients tend to be re-hospitalized more (Hansen, Young, Hinami, Leung, & Williams, 2011; Jack et al., 2009; O'Day, 1996; G. Williams, Akroyd, & Burke, 2010). Another reason associated with early unplanned re-hospitalizations include deterioration in health status either due to natural causes, treatment complications, or comorbidities that arise following a successful hospital stay.

There are also many important factors driving readmissions that are downstream of patient immediate hospital care-path. Factors such as availability and access to outpatient care and social support are beyond hospitals’ control but undoubtedly capable of strongly influencing readmissions (Hu, Gonsahn, & Nerenz, 2014; Joynt, Orav, & Jha, 2011; Kangovi & Grande, 2011; Rennke et al., 2013). For instance, patients who live in disadvantaged neighborhoods with no access to primary care are indeed more likely to use acute care hospitals as their sole site of care (Naylor, 2000). Accordingly, these patients are more likely to be re-hospitalized (Hu et al., 2014). Finding ways to intervene in community settings and especially with high-risk Medicare patients may be crucial in improving outcomes and preventing unnecessary readmissions.

Hospital leaders continue to lobby Congress and Medicare to consider patient’s socioeconomic factors and other community-level factors when determining hospital quality performance and related readmission penalties.

Importantly, although patient-level factors such as diagnosis, severity of illness, age, race and quality of inpatient care have been strongly linked to likelihood of getting readmitted,
preventing unnecessary hospital readmissions is a health system issue that must be viewed and addressed along the full continuum of care. In other words, preventable readmissions are not only a hospital quality of care issue but also a place or locality issue that for research completeness must also assess the influence of community and neighborhood factors. Yet, as noted previously, much of extant research on hospital readmissions among Medicare patients has been primarily focused on patient-level medical characteristics.

Meanwhile, although various policy initiatives have been and continue to be undertaken, up until now, the U.S. health care system has failed to marshal a sustainable plan to prevent Medicare patients from making unnecessary return trips to hospitals across the country. In other words, a sustainable solution to this important healthcare policy issue remains elusive (American Hospital Association, 2011). However, the HRRP policy initiative appears promising in curtailing unnecessary readmissions and especially early readmissions that are linked to quality of inpatient hospital care. Of note, following HRRP implementation, readmission rates have reduced sharply and CMS has been quick to label this as a significant policy success. Prior to HRRP hospitals and other care providers had no urgency or incentive to energetically address re-hospitalizations considering that reimbursements were primarily based on the quantity of services provided (fee-for-service) and not necessarily the quality of care or value received by patients.

Previously Developed Conceptual Models on Causes of Hospital Readmissions

Several conceptual and risk prediction models have been developed in the past to explain why both preventable and unpreventable readmissions occur among Medicare patients (Kansagara et al., 2011). Kangovi et al. developed a model suggesting that readmission rates are
largely determined by access to care, social determinants of health, and regulatory policies such as financial penalties (Kangovi & Grande, 2011). Calvillo-King et al., on the other hand, developed a conceptual model that expounds on how social factors contribute to poor outcomes in pneumonia and HF patients (Calvillo-King et al., 2013). They stratified social factors into 3 levels. Level 1 included socio-demographic factors such as age, gender and race while level 2 included socioeconomic factors such as education, employment, income, insurance, and marital status. Level 3 factors encompassed social environmental factors (social support and housing), behavioral factors (diet, substance use, smoking), socio-cognitive factors (health literacy), and neighborhood factors (urban or rural, access to care, poverty index).

Another model, the Donabedian quality of care framework conceptualizes that medical care quality outcomes such as 30-day hospital readmissions are a function of care settings structure (physical and organizational aspects) coupled with care processes (activities that rely on structure in order to improve patient’s health (Donabedian, 1988; McDonald, Sundaram, & Bravata, 2007; Mitchell, 2015). Donabedian’s framework deliberately excludes patient and socioeconomic factors that are downstream of the care delivery system choosing instead to focus on provider ability to optimize patient outcomes (Donabedian, 1988).

Yet another model, the Cumulative Complexity Model (CCM) conceptualizes that clinical outcomes such as readmission rates are influenced by the balance of patient’s workload and capacity to perform certain tasks and responsibilities once discharged from the hospital (Shippee, Shah, May, Mair, & Montori, 2012). Tasks and responsibilities may include self-care, engagement with care plan, and making and honoring clinical appointments. Capacity refers to the ability to meet responsibilities as influenced by social and financial resources, literacy or
cognitive function (Chokshi & Chang, 2014). As such, the CCM model predicts that patients with workload that exceeds capacity are more likely to be readmitted.

Besides, Amarasingham, et al. constructed and validated an electronic predictive model that identified hospitalized HF patients at greatest risk of hospital readmission or death (Amarasingham et al., 2010). Based on their findings, clinical factors are limited in their ability to accurately predict the odds of readmission. Instead, their model posits that synergistic effect derived by examining social, behavioral, and utilization factors can accurately stratify risk of readmission among HF patients. Lastly, Arbaje et al. conceptualized that early unplanned readmissions are chiefly due to patient socioeconomic (SES) factors (including education, income, and Medicaid participation) and post-discharge environment (such as dwelling type and access to usual source of care) (Arbaje et al., 2008). These conceptual models suggest that variations in hospital readmission rates may be due to various forces - both within and outside of acute care hospital setting and therefore beyond hospital control.

**Hospital Readmission as a Quality Metric for Inpatient Care**

Whether variability in 30-day hospital readmission rates is as a result of poor quality of care during the index hospitalization or whether it is due to other community-level factors is controversial. Nonetheless, the premise behind intense focus on reducing readmission rates revolves around costs reduction and overall improvement in quality of care. These two elements – costs and quality - form part of the triple aim movement that is vigorously focused on optimizing healthcare performance by improving the experience of care, the health of populations, and reducing per capita costs of care (Berwick, Nolan, & Whittington, 2008). But even with such intense assessment, the utility and validity of readmission rate as a performance
measure remains controversial. The measure has generated varying opinions from researchers with some arguing that readmission rate is a utilization measure as opposed to a quality measure (Ashton & Wray, 1996; Benbassat & Taragin, 2000; Jha, 2015; Kangovi & Grande, 2011; Luthi, Burnand, McClellan, Pitts, & Flanders, 2004; Press et al., 2013; Weissman et al., 1999).

In a widely-cited study, Jecks et al. demonstrated that readmissions among Medicare patients are frequently related to provision of substandard care during the index hospitalization (Jencks et al., 2009). Yet, not all re-hospitalizations reflect suboptimal hospital quality of care. Indeed, a notable portion of re-hospitalizations may be part of planned care including treatment and mandatory continued supervision. Given the potential impact on thousands of hospitals and millions of patients, health policy experts have warned that accountability measures such as readmission rates should capture quality of care with minimal or no bias while retaining a strong evidence base and unquestionable validity (Axon & Williams, 2011; Chassin, Loeb, Schmaltz, & Wachter, 2010; Conway, Mostashari, & Clancy, 2013). Milne et al. argues that readmission rates are not a direct measure of care quality but rather a proxy of adverse health outcomes (M. Hasan, 2001; Milne & Clarke, 1990).

Others have argued that if readmission was a true quality measure in medical conditions, it would be noticeably correlated with other well-known quality metrics such as mortality, volume, or process of care compliance. A study by Aston et al in 1995, demonstrated increased risk for unplanned readmission among patients experiencing lower quality inpatient care (Ashton, Kuykendall, Johnson, Wray, & Wu, 1995). In recent years, no such clear correlation has been shown in medical conditions such as pneumonia or heart failure (Dimick & Ghaferi, 2015). In surgical conditions, however, strong evidence is emerging that indeed quality of hospital care is associated with 30-day readmissions (Morris, Deierhoi, Richman, Altom, &
A meta-analysis by Aston et al. supports these findings even though the authors included studies encompassing both medical and surgical conditions (Ashton, Del Junco, Souchek, Wray, & Mansyur, 1997).

Moreover, the crude nature of readmission metrics is demonstrable in its inability to distinguish between high quality and poor quality care (Epstein, 2009). Benbassat et al. found that a majority of hospital readmissions are caused by unmodifiable factors and concluded that readmission rate is not a useful proxy measure of care quality (Benbassat & Taragin, 2000). A prospective observational research study conducted by Shimizu et al. at Harbor-UCLA Medical Center (HUMC), a public safety-net, teaching hospital in Los Angeles County, attributed 31 percent of scheduled but avoidable readmissions to resource constraints including inadequate access to non-emergent expensive procedures such as endoscopy (Shimizu et al., 2014). Whether readmission rate is a true representative of quality of care or not is uncertain. More research on this issue is indeed required for better understanding of why RSRRs vary considerably across hospitals in the U.S.

Validity of 30 days in Assessing Readmission Rates

On a related subject, a section of health care policy stakeholders have questioned the validity of 30 days in assessing hospital readmission rates of which they consider an arbitrary proxy of healthcare quality (Jha, 2015). This is important considering that much of what is known regarding AMI, HF and PN variability in RSRRs among hospitals has been assessed at 30 days. Thirty days may be a time when readmission rates are more likely to be influenced by quality of hospital care and patient follow-up after discharge. However, it is not clear whether a shorter or longer period would widen or narrow the observed variability range in AMI, HF and
PN. Vaduganathan et al. has suggested that the 30-day timeframe is devoid of clear clinical or therapeutic evidence base and therefore should not be used to assess clinical outcomes (Vaduganathan et al., 2013). Others have suggested use of a shorter window such as 7 days since this is the period of greatest vulnerability and may serve to indicate true suboptimal inpatient quality of care and care coordination (Bhalla & Kalkut, 2010). However, across medical specialties, 30 days is frequently used to gauge response to treatment and to refine prognostic trajectory. For instance, in cancer treatment oncologists frequently wait until 4 weeks before stating that a patient is in remission status. But research shows that relatively very few readmissions occur within 30 days. A large multicenter clinical trial in 2010 indicated that in heart failure, 58 percent of readmissions in fact occur after 60 days and only 23 percent occur within 30 days (O'Connor et al., 2010). Therefore, readmission prevention strategies that rely on the 30-day window may clearly underestimate the true readmission burden and may have minimal to no impact on vast readmissions that occur after 30 days. Accordingly, whether 30 days is an appropriate timeframe to benchmark Medicare reimbursements remains a contentious issue.

Nonetheless, urgent, unplanned hospital readmissions occurring few days after discharge are more likely to be classified as preventable and majority of researchers seem to agree on this fact. However, such readmissions are relatively uncommon when compared to those occurring weeks and months after discharge and deemed unavoidable (Clarke, 1990; van Walraven et al., 2011). Interestingly, in a multicenter prospective cohort study, van Walraven et al. found no association between urgent readmissions and avoidable readmissions (van Walraven et al., 2011). Dharmarajan et al. found no relationship between patient demographic characteristics (age, gender, race), diagnosis, and time of readmission (Dharmarajan et al., 2013). Stated
differently, readmissions in the Medicare program are frequent throughout the 30-day window regardless of diagnosis or demographic characteristics. Yet, Graham et al. found causal factors for readmission differ substantially between early and late readmissions (Graham et al., 2015). Early readmissions were associated with factors such as acute illness burden, inpatient care quality, and discharge process while late readmissions were more likely associated with downstream social economic and behavioral factors. Even so, Medicare continues to view readmission within 30 days of discharge as an indicator of poor patient care including care during the index hospitalization and ineffective care coordination following hospital discharge.

Readmission Financial Penalties and Rewards as Instituted by PPACA

For federal fiscal year 2013, 2217 hospitals were penalized for excessive readmissions to an amount totaling $280 million (Gilman et al., 2015). Of note, this amount is a small fraction of close to $600 billion that Medicare spent in 2012 (Fontanarosa & McNutt, 2013). In 2014, 61 percent of hospitals were assessed a reimbursement penalty. Penalties averaged between 0.24 percent with approximately 10 percent of hospitals facing full penalty of 1 (Rau, 2015). Of the 3 high prevalent disease conditions currently included in the HRRP program – HF has been identified as the single most important driver of readmission penalties independent of case volume or hospital characteristics (Vidic, Chibnall, & Hauptman, 2015).

Even so, Medicare continues to evaluate various care delivery and payment models in various community settings (Epstein, Joynt, Jha, & Orav, 2014). The goal of these demonstration projects is to create incentives to reward providers for quality rather than volume. The models are also geared at incentivizing providers to work together along the continuum of care. Early results from all these structural changes are encouraging with Medicare reporting significant
declines in readmission rates among its members (Gerhardt et al., 2013). However, it is worth noting that although various Medicare demonstration programs have succeeded in improving care quality, cost containment under these programs remains elusive (Ayanian, 2009). As such, and as discussed earlier, it is premature to strongly make any direct attribution of achieved quality improvements to just ACA or HRRP. More research studies, in different healthcare regions, are indeed needed to fully validate the role of ACA policy changes in these improvements.

On the other hand, there are legitimate concerns that penalties may worsen disparities in quality of care or widen the quality gap if poorly performing hospitals are also resource-poor (Bhalla & Kalkut, 2010; Gani, Lucas, Kim, Schneider, & Pawlik, 2015; Joynt & Jha, 2011). An analysis of Medicare data by Joynt et al. found that safety-net hospitals – that deliver care to patients regardless of their ability to pay – are more likely to be penalized (Joynt & Jha, 2013a). Gilman et al. found that, under Medicare’s Value-Based Purchasing (VBP) and HRRP, safety-net hospitals were more likely to incur larger financial penalties than other hospitals (Gilman et al., 2015). With ongoing expansion of Medicaid in many states, this problem could worsen. In addition, some hospitals especially those caring for medically complex patients and particularly dual eligible beneficiaries may be doubly penalized for both high complication rates and higher readmission rates (Bennett & Probst, 2015; Merkow et al., 2015).

After all, policy experts agree that financial penalties alone are not likely to succeed in driving down hospital readmissions (McCarthy et al., 2013). Instead, a holistic approach that emphasizes multi-payer and multi-provider collaboration, population health, and strengthening of community providers especially primary care providers is vital (T. A. Peterson, Bernstein, & Spahlinger, 2016). The Center for Medicare and Medicaid Innovation is experimenting with
broad novel payment models and some including Accountable Care Organizations (ACOs) have thus far had demonstrable positive impact on quality of care and cost savings for the Medicare Trust Fund (Pham, Cohen, & Conway, 2014).

**Hospital Readmissions and Mortality**

Although hospital-level mortality rate is an outcome of principal interest to patients, providers and payers, very little is known on how mortality is indeed associated with variability in hospital readmissions. An important policy question is whether hospitals providing high quality inpatient care and therefore affording to keep their patients alive for discharge are more likely to have higher readmission rates. In an examination of CMS Hospital Compare public database, Gorodeski et al. found that higher readmissions were associated with decreased risk-adjusted 30-day mortality among heart failure patients (Gorodeski, Starling, & Blackstone, 2010). As such, hospitals that provide greater intensity of inpatient quality care may have fewer patients dying during their inpatient stay. Consequently, more of these patients are potential candidates for readmission once discharged from the hospital and consequently placing the hospital in a position of unjustly being penalized. This is a yet another noteworthy weakness of the current HRRP readmission policy and an issue that demands further research.

Noteworthy, findings by Gorodeski et al. are inconsistent with a study by Krumholz et al. that found modest inverse association between heart failure mortality and readmission and no association at all for patients admitted with an acute myocardial infarction or pneumonia (Krumholz et al., 2013). As such, these two measures can be viewed as addressing distinct elements in patient care process and hospitals can indeed perform well in both measures. Other researchers have suggested existence of an inverse relationship between readmission and
mortality (Ong et al., 2009). Considering potential competing risk factors at play in the readmission measure, policy experts have suggested rewarding hospitals with low mortality rates by including mortality rates in readmission penalty formula (Joynt & Jha, 2013b). It is not clear whether adjusting for hospital mortality rates would have an impact on variability in RSRRs.

**Emergency Department Visits and Readmission Rates**

Policies that incentivize lowering readmissions may inadvertently lead to unintended consequences such as increased use of Emergency Departments (EDs). Vashi et al. found that among adults, ED visits accounted for 39.8 percent of post-discharge hospital-based acute care visits (Vashi et al., 2013). A study by Stern et al. determined that lower socioeconomic patients were more likely to be admitted or readmitted to the hospital through ED (Stern, Weissman, & Epstein, 1991). It is unknown whether hospitals with higher ED usage also have higher readmission rates among recently discharged Medicare patients. The use of EDs following hospital discharge is viewed by many policy experts as an important marker of inpatient quality of care and therefore an important healthcare outcome.

It is not certain how ED utilization could be driving observed 30-day RSRR differences among hospitals. It is also unclear how many ED visits, following hospital discharge, result in readmission. There is therefore an emerging need to better evaluate and understand how ED utilization following an acute stay discharge is correlated with 30-day hospital readmissions in the Medicare program and how this impacts inter-hospital variability.

As previously noted, there is evidence that hospitals are finding ways to avoid readmissions by treating their recently discharged patients in ED instead of admitting them directly (Himmelstein & Woolhandler, 2015). Of note, Medicare does not track and therefore
cannot differentiate between providers who are gaming the system from those who are truly redesigning and improving their processes of care to improve patient care and lower readmission rates.

**Risk Factors for Hospital Readmission in Medicare**

There are many known risk-factors for unnecessary or early hospital readmission in the Medicare program. This section summarizes findings from extant literature while the next section reviews what is currently being done to mitigate these risk factors and lower readmission rates. To systematically do so, these factors are examined along the full continuum of care – patients’ medical characteristics, hospital or provider characteristics, post-discharge factors, health system aspects and neighborhood level risk factors.

**Patient Demographic and Medical Characteristics**

Patient-level factors - including race, ethnicity, insurance status, comorbidity, complications and length of stay – have been strongly linked to increased readmission rates among Medicare patients (Gani et al., 2015; Weber & Kennedy, 2015). Precisely, African-American patients have been shown to experience higher readmission rates when compared to other races (Girotti, Shih, Revels, & Dimick, 2014; Hernandez et al., 2010; Joynt et al., 2011). In addition, African-American patients who seek care in minority-serving hospitals are more likely to be readmitted within 30 days (Joynt et al., 2011; Tsai et al., 2014). Disparities in health care may be associated with hospital readmission such that minority black patients are more likely to be re-hospitalized either because of bias or racism. Gu el al. found that vulnerable Medicare patients are mostly concentrated in communities with poor access to care (Gu et al., 2014).
Baicker et al. found that minorities are more likely to live in areas with lower quality hospitals and few primary care physicians (Baicker, Chandra, Skinner, & Wennberg, 2004; Baicker, Chandra, & Skinner, 2005). To validate this observation, Hasnain-Wynia et al. found that quality of care for minority patients is disproportionally lower compared to other patients and minority patients are more likely to experience lower quality of clinical care partly due to where they seek care. (Hasnain-Wynia et al., 2007). Thus, where Medicare patients are admitted is a strong predictor of odds of getting readmitted - regardless of race or socioeconomic status.

Moreover, patient functional status has been strongly linked to hospital readmission. A study by Greysen et al. found a strong positive correlation between patients’ degree of functional impairment and hospital readmission (Greysen et al., 2015). Importantly, the number of prior hospitalizations is associated with patient’s functional status, burden of illness, and illness severity making it an important predictor of hospital readmission (Donze, Aujesky, Williams, & Schnipper, 2013). Research also shows that elderly heart failure patients with complex comorbidities coupled with weak social support are at greatest risk of readmission (Rathore et al., 2003). Many other patient-level medical characteristics not currently adjusted for by CMS such as depression have been shown to strongly predict readmission risk (Barnett et al., 2015; Jiang et al., 2001).

Within the Veteran Administration (VA) system, Smith et al. found that older unemployed Caucasian patients were at an increased risk of being readmitted non-electively (Smith et al., 2000). Smith and colleagues also found that among elderly patients in nine VA centers, patients with more hospitalizations and emergency room visits, lower mental health function, and abnormal blood urea nitrogen were at an increased risk of readmission (Smith et al., 2000). Although their findings may be somehow biased considering that VA health system
primarily attends to older and highly vulnerable patients, these findings provide important perceptions to understanding chief clinical and patient-centered drivers of hospital readmissions. Dual-eligible beneficiaries have also been shown to have higher unadjusted 30-day readmission rate - at 21.5 percent - when compared to their Medicare-only counterparts (Bennett & Probst, 2015).

Researchers have also found that drivers of readmissions are different between medical and surgical patients. Readmissions among medical patients are mostly due to poor social support, limited access to primary care, medical complexity and illness severity. On the other hand, surgical readmissions occur primarily because of postoperative complications especially surgical site infections (Kassin et al., 2012; Merkow et al., 2015). Although the reasons why some patients develop worse complications than others are varied, complications arising post-discharge place patients at greater risk of hospital readmission (Morris et al., 2014; Tevis, Kohlnhofer, Weber, & Kennedy, 2014). Moreover, patients that experience an adverse safety event - such as hemorrhage - during their index hospitalization are more likely to be readmitted (Bernard & Encinosa, 2004). Disease severity has also been associated with risk for readmissions such that as disease severity increases, the odds of getting re-hospitalized also increase – particularly for patients diagnosed with CHF and COPD (Smith et al., 2000).

**Provider or Hospital Characteristics**

Few studies have examined structural and performance provider characteristics as drivers of hospital readmissions especially at the light of wide variations being witnessed across care settings. Indeed, research studies show that some of the variation in hospital readmission rates can be explained by hospital attributes or characteristics (Joynt et al., 2011; Krumholz et al.,
2009). However, majority of studies examining provider attributes are characterized by small sample sizes and are mostly limited to just a few providers.

Recent evidence has demonstrated an association between hospital measures of quality, capacity, and intensity of medical care. For instance, hospitals with greater capacity of care as measured by an increased tendency to admit patients also have higher 30-day readmission rates (J. R. Brown et al., 2014). Importantly, hospitals that admit or serve a higher proportion of black patients have higher readmission rates even after adjusting for structural characteristics such as teaching status, size, and ownership (Joynt et al., 2011). These findings are consistent with mortality metrics such that hospitals serving a high proportion of black patients tend to have higher death rates (Skinner, Chandra, Staiger, Lee, &McClellan, 2005).

Other hospital structural aspects have been implicated in early unplanned readmissions. Reduced staffing on weekends in most hospitals has been investigated as an indirect predictor of readmission. Cloyd et al. found that patients discharged on a weekend were not at an increased of readmission (Cloyd, Chen, Ma, &Rhoads, 2015a; Cloyd, Chen, Ma, &Rhoads, 2015b). This study is consistent with findings from McAlister et al. who, in Canadian hospitals, found no correlation between day of hospital discharge and readmission in patients diagnosed with AMI, HF, and pneumonia (McAlister, Youngson, Padwal, & Majumdar, 2015).

Variation in rates of readmission across U.S. hospitals may be related to other markers of the quality of care such as hospital volume but the evidence is mixed. Horwitz et al. and retrospective cross-sectional study showed that standardized readmission rates were lowest in low volume hospitals (Horwitz et al., 2015). Merkow et al. study on underlying reasons associated with hospital readmission after surgery concluded that higher surgical volume was associated with a higher risk of hospital readmission (Merkow et al., 2015). These findings
contrast what researchers have found and known for a while - that superior outcomes are directly correlated with higher volume of procedures especially among patients undergoing surgical operations (Gooiker et al., 2010). Hospitals performing many surgical procedures can streamline and standardize their care processes by eliminating waste and other inefficiencies that are linked to poor outcomes. As such, these high performing hospitals – as measured by surgical volume and mortality rates – tend to have lower readmission rates than their low-performing counterparts regardless of time to readmission (Dharmarajan, Hsieh, Lin, Bueno, Ross, Horwitz, Barreto-Filho, Kim, Suter et al., 2013; Tsai et al., 2013). As discussed earlier, the reason why high performing hospitals have low readmissions rates could be related to another marker of quality – mortality. It is possible that best performing high volume hospitals tend to keep more of their patients alive, inadvertently creating a greater opportunity for these patients to be readmitted.

Evidence regarding how hospital size and locality influences 30-day readmission is varied. Some researchers have found that larger hospitals are more likely to have higher 30-day readmission. Others have found the contrary; smaller hospitals are more likely to have higher 30-day readmission for AMI even after adjusting for patient-level factors (J. R. Brown et al., 2014). However, larger hospitals, as compared to smaller hospitals, are more likely to have greater resources that can support readmission prevention initiatives. These resources may include financial capital and human resource expertise. Evidence regarding how hospital locality - urban or rural – is associated with re-hospitalization is also mixed. Some studies show significant differences with rural hospitals registering fewer risk-standardized readmission rates (Bennett, Probst, Vyawaharkar, & Glover, 2012).

Hospital length of stay - a marker of hospital efficiency - has been associated with early readmissions but varies across hospitals (Baker et al., 2004; Kaboli et al., 2012). Smith et al.
found that patients with more emergency room visits and more hospital admissions coupled with extended length of stay in the prior 6 months to admission are more likely to be readmitted (Smith et al., 2000). Previous work by Anderson et al. showed that when patients are discharged too soon due to high utilization of post-operative beds, their chances of readmission increase by 0.35 percent (D. Anderson, Golden, Jank, & Wasil, 2012). However, very little is known on how an extra day of stay after surgery changes the prognostic trajectory of patients and potentially prevent them from returning to the hospital. Other evidence indicates that greater intensity of care as measured by more hospital days in the last 6 months of life including lengthy LOS and the number of physicians seen within a certain stay is associated with higher 30-day readmission rates for AMI (J. R. Brown et al., 2014).

Even so, robust evidence on how length of stay influences hospital readmissions especially among Medicare patients is lacking. Health policy experts have suggested that increase in readmissions and reduction in LOS may be unintended consequence of CMS Diagnosis Related Group (DRG) policy that essentially pays hospitals fixed amount for inpatient hospital care (Fontanarosa & McNutt, 2013). Bueno et al. found a decrease in length of stay among Medicare fee-for-service heart failure patients hospitalized between 1993 and 2006 and this decrease in length of stay was accompanied with an increase in 30-day readmissions within the same temporal period (Bueno et al., 2010). A Veterans Affairs hospitals observational study from 1997 to 2010 found a modest tradeoff between hospital LOS and readmission rates - as LOS decreased, hospital readmissions did not significantly increase (Kaboli et al., 2012). Among surgical patients, Merkow et al. found that drivers of early and late readmissions were similar irrespective of length of stay (Merkow et al., 2015).
Hospitals have increasingly adopted hospitalist programs (physicians providing round-the-clock care and monitoring to patients admitted in the hospital) to optimize efficiency and reduce LOS. But besides increased focus on improving efficiency in hospitals, Medicare Fee-For-Service policy has also been partly blamed for observed temporal reduction in LOS. In the last decade, FFS has incentivized providers to discharge patients quickly - shortening length of stay. FFS payment model is the predominant physician payment method in the United States and is characterized by unbundled services that are paid for separately (Berenson & Rich, 2010). Payments are issued retrospectively and are based purely on quantity of services provided and not necessarily quality of care. Under FFS hospitals have minimal concern of being penalized for any short-term or long-term adverse patient outcomes such as unnecessary readmissions or increased mortality (Moore, McGinn, & Halm, 2007). FFS continues to provide hospital insurance (Part A) and supplementary medical insurance (Part B) to millions of qualified seniors above the age of 65. However, the Obama administration has been working to reform FFS policy by requiring all FFS payments be tied to quality or value by year 2018 (Burwell, 2015). Alternative value-based payment models being suggested include bundled payments, capitated payments and other shared payment arrangements such as Patient-Centered Medical Homes (PCMH), and Accountable Care Organizations (ACOs) (Jha, 2015). Currently, only about 20 percent of Medicare payments are being made through these alternative arrangements.

**Discharge, Post-discharge Transition, and Care Coordination**

For elderly patient’s the period of greatest vulnerability is during transitions from hospital to home or to another care setting such as a nursing home. As such, the completeness of discharge instructions is an important determinant of readmission (Li, Young, & Williams, 2014;
Mitchell, 2015). When patients leave the hospital with unresolved medical issues, their likelihood of getting readmitted increases significantly – more so in instances where post-discharge follow-up is inexistent or inadequate (Hernandez et al., 2010). In a study conducted by Moore et al., at Mount Sinai Medical Center, patients were frequently discharged with medical issues that required outpatient workups, but these workups were rarely completed mostly due to unavailable, incomplete or poor quality discharge summaries (Moore et al., 2007). Yet, the authors also found positive association between the availability of complete discharge summaries to PCPs and completion rates of recommended outpatient workups. Consistent with other studies (van Walraven, Seth, Austin, & Laupacis, 2002); this indicates that the availability of high quality and complete discharge summaries to PCPs is crucial in preventing unnecessary readmissions.

On the other hand, care fragmentation where patients are attended by several care providers and medical specialists for each care episode has exacerbated care transition problems – particularly for comorbid medically complex Medicare patients (Li & Williams, 2015; M. V. Williams, 2013). Care fragmentation coupled with inadequate care coordination can lead to medication errors, duplication of care, increased costs, wrong treatment or even more serious patient harms including death. Moreover, and as stated earlier, Wennberg et al. found that during the last 6 months of life, 16.9 to 58.5 percent of Medicare patients were seen by 10 or more physicians (Wennberg et al., 2004). The chief reason for this is that older patients have multiple chronic conditions that can only be satisfactorily managed by clinicians of varying specialties.

Once the patient has been discharged, there are many challenges to care coordination. Chief among them is provider lack of communication and information transfer between the hospital-based and primary care doctors (Kripalani et al., 2007). It is manifest in the literature
that hospital internists and primary care doctors do not always communicate or share patient information before and after patient discharge. Jones et al. investigated this issue and found that lack of time, lack of personal relationships, lack of information feedback loops and lack of clarity on who is responsible for or accountable for the patients care post-discharge were some of the reasons why providers failed to communicate (Jones et al., 2015). In a separate study, direct communication between PCPs and hospitalists occurred only 23 percent of the time and discharge information was available to PCPs only half of the time (Bell et al., 2009). This is important considering that 70 percent of US hospitals now have attending hospitalists who for most part make patient-related decisions without necessarily involving primary care physicians (Mor & Besdine, 2011). Other studies have found that PCPs are unaware of their patient hospitalization let alone discharge (Arora et al., 2010).

Also, related to care-coordination and a major risk factor for readmission is lack of post-discharge follow-up once the patient has been discharged (Hernandez et al., 2010). When hospitals fail to offer post-discharge support – especially due to inherent short-term costs or lack of time – patients’ risk of readmission is dramatically heightened. Jencks et al. found that half of all readmitted patients in the Medicare program had no ambulatory visit before hospital readmission (Jencks et al., 2009). Communication with patients following discharge ensures that any questions that patients’ have about their treatment plan are addressed promptly and that their primary care physician is engaged with their care. Follow-up should be available to all patients and not just those at greatest risk of readmission. However, early patient follow-up by itself may not adequate in preventing unnecessary hospital readmission. Merkow at al. found that among surgical patients, early and timed follow-up after surgical discharge had minimal impact on readmission rates by itself (Merkow et al., 2015).
Community level factors

Although researchers have yet to come to full understanding of what community factors account for observed variability in readmission rates across hospitals in the U.S., a growing body of work suggest that community factors may play a significant role. Research studies show that social, behavioral, environmental and other measures of social disadvantage influence readmissions in a variety of important ways including medical insurance status, social support and substance use (Andersen, 1995; Calvillo-King et al., 2013). A study by Hu et al. found that patients living in high-poverty neighborhoods were 24 percent more likely to be readmitted even after adjusting for demographic characteristics and clinical conditions (Hu et al., 2014). Other studies show that hospital readmissions are strongly related to patients’ socioeconomic status and severity of illness (Joynt et al., 2011; Rathore et al., 2003; Weissman, Stern, & Epstein, 1994).

Besides, community factors may explain a substantial amount of variation in hospital readmission rates and the county where a hospital is located has been cited as a major predictor of hospital readmission (Herrin et al., 2015). Moreover, hospitals located in neighborhoods with high proportion of residents who never married, high numbers of Medicare beneficiaries per 100,000 residents, low employment, heightened social isolation, and poor access to primary care are more likely to have excessive readmission rates (Herrin et al., 2015; Jasti, Mortensen, Obrosky, Kapoor, & Fine, 2008). The mechanisms involved in the relationship between neighborhood factors and hospital readmission in Medicare have not been adequately explored. Due to multiple related factors at the neighborhood level, it is quite challenging to disentangle various relationships and establish significant and independent causal chains (Diez Roux, 2004; Diez Roux, 2007; Diez Roux & Mair, 2010; Diez Roux, 2016; Pickett & Pearl, 2001). Additionally,
community or neighborhood factors are for most part beyond hospital purview and hospitals are not incentivized enough or lack the necessary resources to reach out to the communities where patients live. Indeed, many hospital leaders perceive this downstream role as beyond their responsibility. Better understanding of the role of neighborhood factors in explaining variability in readmission rates is essential in strengthening current evidence base and informing prevention efforts.

**Healthcare System Factors**

System factors include availability of healthcare services, regional or local health care related policies, and inherent medical practice patterns (Calvillo-King et al., 2013). Although research is scant to substantiate this theory, regions with greater access to primary care coupled with regimented care coordination programs are more likely to have fewer early hospital readmissions. Evidence of whether the number of primary care physicians in a community is correlated with hospital readmission rates is inconsistent. Weinberger et al., in a multicenter randomized controlled trial at nine Veterans Affairs Medical Centers, found that a strategy designed to increase access to primary care increased rather than reduced readmissions (Weinberger et al., 1996). The authors postulated that these results may have been due to newly detected disease conditions coupled with improved communication between patients and their primary care physicians.

Lack of access to appropriate medication has been shown to be an important risk factor for readmission. Regions with few or no accessible pharmacies are likely to have higher readmission rates. Besides, when uninsured or underinsured patients leave the hospital without proper guidance of where to obtain their medications whether at free health clinics or local drug
assistance programs, their chances of returning to the hospital increase dramatically (R. E. Burke, Guo, Prochazka, & Misky, 2014; Jones et al., 2015; Kivekas, Luukkonen, Mykkanen, & Saranto, 2014). Under such circumstances patients are also less likely to comply with their medication plan and therefore heightening their odds of being readmitted.

Another health system related risk factor is hospital capacity to admit patients. Recent studies reveal enormous variation in readmission rates across the U.S. The State of Idaho, for instance, has very low readmission rates at 13.3 percent while Maryland has very high rates at 22 percent compared to national average based on 2009 data (Jencks et al., 2009). Again, it is not clear why such huge variations exist at state level but anecdotal evidence suggests that higher readmission rates in some states could be correlated to the number of available hospital beds (Epstein et al., 2011; Herrin et al., 2015). This may be evidence that discretionary medical use is indeed common and could help explain large differences in predisposition to hospitalize being observed across the country. Variation in readmission rates could also be explained by the clinical criteria that providers in specific geographic regions use to admit or readmit patients (Nuckols, 2015). Equally important, excessive liberal use of hospital services by local physicians could mean more admissions and subsequently more readmissions. In fact, research studies indicate that regions with higher hospitalization rates have higher readmission rates suggesting that to significantly lower readmissions hospital use must somehow be minimized (Epstein et al., 2011). State capacity and local market dynamics may therefore influence how hospitals operate in an increasingly competitive healthcare environment and this in turn may influence when and how many patients are readmitted.

Moreover, where patients go after an acute hospital stay may be a function of local healthcare system. Hospitals located in areas with many easily accessible skilled nursing
facilities are less likely to have more of their patients discharged home. A research study by Merkow et al. showed that non-home discharge is associated with higher risk of hospital readmission among general patients undergoing surgery in the United States (Merkow et al., 2015). Bueno et al. found significant temporal changes in Medicare heart failure patient’s disposition following hospital discharge between 1993 and 2006 (Bueno et al., 2010). According to their study, rates of patients discharge to skilled nursing facilities increased through this period. The number of skilled nursing facilities in a neighborhood may therefore explain some of the inter-hospital variation in readmission rates among Medicare patients.

Lastly, while competition for patients is innately not a bad thing, in some regions this practice has harnessed “silos of care” whereby providers operate completely independent of others with very little or no information sharing (Jones et al., 2015). Undoubtedly, failure of providers to communicate or work together within a continuum of care disrupts care coordination and exacerbates the risk of patient re-hospitalization.

Current Initiatives to Lower Medicare Hospital Readmissions Rates

To date, there is paucity of evidence on how best to lower unnecessary re-hospitalizations in the Medicare program (Bradley et al., 2013). Due to complex interplay of personal, medical, and socioeconomic factors, thus far, no single intervention has been effective in reducing unnecessary readmissions (McCarthy et al., 2013). Research studies are showing that hospitals implementing multiple concurrent strategies are more likely to succeed in curtailing avoidable readmissions (Bradley et al., 2013; Dharmarajan et al., 2013). Nonetheless, providers and payers have and continue to institute various innovative and resource-intense strategies (Hagland,
This section reviews some of the strategies being deployed by hospitals, health systems and the federal government at national, state, and local levels to lower readmissions.

**Hospitals and Healthcare Providers**

**Identifying patients at a higher risk of readmission**

Majority of current hospital interventions are aimed at identifying high-risk patients early enough in their index admission period and tailoring practical interventions to deter unplanned readmissions (R. E. Burke & Coleman, 2013). Research studies show that hospitals that target high-risk patients with customized interventions - particularly the elderly, heart failure patients, patients with comorbidities, patients with complicated social needs and those with minimal financial resources - achieve better clinical outcomes overall (Silow-Carroll et al., 2011; Strunin, Stone, & Jack, 2007). Research studies have also shown that Medicare beneficiaries with multiple chronic conditions are at an increased risk of early hospital readmissions. In 2013, over two-thirds of Medicare beneficiaries had 2 or more chronic conditions while 1 in 7 (14 percent) had 6 or more (Lochner et al., 2013; Lochner & Shoff, 2015). Accordingly, hospitals are starting to identify these high-risk patients within hours of admission and then building a community plan of care depending on each patient’s medical complexity and access to post-discharge care.

**Improving inpatient clinical processes of care and patient safety**

Research studies have demonstrated strong a relationship between hospital care processes and clinical outcomes (Ashton & Wray, 1996; Chassin et al., 2010; Daley, 2010; E. D. Peterson et al., 2006; Werner & Bradlow, 2010). As a result, top-performing hospitals on Hospital Quality Alliance (HQA) process-of-care measures are seeking to achieve clinical excellence in outcomes
by continuously investing in quality improvement programs that reduce avoidable readmissions long-term (Silow-Carroll et al., 2011). They incorporate strategies such as use of evidence-based procedures and protocols, standard work with minimal or no variation, and deployment of electronic data collection via robust clinical information systems. Indeed, evidence-based care processes are viewed as surrogate markers of hospital’s quality and safety culture and consequently better outcomes for patients (E. D. Peterson et al., 2006). However, it is worth noting that the traditional business model of designing hospital-specific interventions to address inordinate readmissions may not suffice in an era where collaborative provider shared cost-savings are instead being encouraged.

**Improving discharge process and care transitions**

Comprehensive discharge planning coupled with home follow-up has been associated with reduced hospital readmissions, lengthened time between discharge and readmission, and lower costs (Brooke et al., 2014; Naylor et al., 1999). Although the evidence base is weak, recent studies show that higher Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores for discharge planning and care transition are associated with lower 30-day readmission rates (J. R. Brown et al., 2014; Jha et al., 2009; Naylor et al., 1999). As such, hospitals are initiating care management and discharge plan as soon as the patient is admitted (J. R. Brown et al., 2014). A reengineered hospital discharge program involving a clinical pharmacist and a nurse discharge advocate was found to have a significant effect in reducing hospital utilization 30 days following discharge (Jack et al., 2009). Hospitals are also adopting transitional care programs specifically aimed at improving post-discharge care coordination (Naylor, Aiken, Kurtzman, Olds, & Hirschman, 2011; Nguyen, Kruger, Greysen, Lyndon, &
Goldman, 2014). A Kaiser Permanente Southern California hospital care transition bundle consisting of risk stratification, standardized discharge summary, medication reconciliation, a post-discharge phone call, and a timely follow-up with a primary care doctor reduced readmission rates at a single medical center to less than 10 percent (Tuso et al., 2013). Top-performing hospitals are also deploying risk-assessment software to evaluate patients’ readiness for discharge and to establish appropriate level of post-discharge care. Other transitional care interventions attempted include supporting patients and caregivers in playing a more active role during care transitions including obtaining essential information regarding their condition and communicating regularly with the care team (Coleman et al., 2004; Coleman, Parry, Chalmers, & Min, 2006; Voss et al., 2011). However, no single intervention bundle has been shown to consistently reduce readmissions across settings of care (Hansen et al., 2011; Li et al., 2014; Li & Williams, 2015).

**Educating patients’ and their families**

Patient-centered education – that includes family members and caregivers – has been shown in multiple studies to be an important strategy in preventing unnecessary re-hospitalizations (Coleman et al., 2006; Hansen et al., 2011). When patients and their families are fully engaged with their care and understand their responsibilities post-discharge, clinical outcomes are better and fewer patients end up returning to the hospital. Indeed, education interventions that support patient capacity for self-care have been shown to be very effective but difficult to implement and sustain (Leppin et al., 2014).
Improving access

Improving access to care is essential in preventing early unplanned hospital readmissions. For instance, research studies show that top-performing hospitals are ensuring that patients with no medical insurance or those that are underinsured can receive care through free clinics. For instance, Memorial Hermann Memorial City Medical Center in Houston, Texas - a top-performer in patients’ re-hospitalizations - works closely with local home health agencies and home health liaisons to provide post-discharge care to all their patients including the uninsured (Silow-Carroll et al., 2011). However, improving access to primary care can increase readmission rates especially among socioeconomically vulnerable patients (Weinberger et al., 1996). Other providers are starting to offer same-day appointments and other nontraditional hospital hours as a strategy to reduce emergency department use and avoid hospital readmissions (Kiran & O'Brien, 2015).

Improving post-discharge continuity of outpatient care

Hospitals are deploying various strategies such as telephone calls and telemonitoring to ensure frequent communication with patients following an acute care stay (Bikdeli et al., 2014; Chaudhry et al., 2010; Heeke, Wood, & Schuck, 2014). Telemonitoring devices allow for remote patient assessment and swift intervention when evidence of clinical deterioration is present. Regular communication via phone calls ensures that anyone involved or likely to be involved in patient’s care along the care continuum understands and can follow the treatment plan. Other hospitals are using an Interactive voice response (IVR) system to monitor cardiac patients after discharge (Piette, 2000). Another post-discharge continuity of care strategy that has shown promise in restraining early readmissions is hiring of social workers that can work directly with
patients - educating and training them on treatment plan and disease management (Coleman et al., 2006).

**Care coordination and alignment across settings**

Provider collaboration along the continuum of care – health systems, hospitals, physicians, allied health professionals, and community providers – has been associated with lower costs and better patient outcomes (Uddin, Hossain, & Kelaher, 2012). ‘Systems collaboration’ tends to emphasize primary prevention, health promotion, sharing of best practices, and continuous flow of information among community providers. Shared electronic health records (EHR) that allow mutual access is necessary in facilitating communication between hospitalists, specialists, and primary care providers (Ahmad, Metlay, Barg, Henderson, & Werner, 2013). White et al. found that a culture of care continuity that involved strengthening outpatient-inpatient caregiver communication reduced hospital readmissions (White, Carney, Flynn, Marino, & Fields, 2014). As such, hospitals are continuously seeking ways to partner and better engage primary care in care transition and coordination activities. (Balaban & Williams, 2010; Bradley et al., 2013; Lindquist, Yamahiro, Garrett, Zei, & Feinglass, 2013). However, for collaboration to yield results, hospital initiatives must clearly be aligned with those of community providers - including skilled nursing facilities and community-based organizations - to provide a continuum of care for patients and reduce unnecessary readmissions. In the coming years, communication and collaboration will be essential especially in safety net hospitals where demand for services is set to increase due to ongoing Medicaid expansion.
**Hospital membership in Integrated Delivery Systems (IDS)**

Hospitals that are part of integrated delivery systems such as accountable care organizations (ACOs) and medical homes are showing potential in lowering unnecessary hospitalizations, reducing costs and optimizing care quality (Berenson, 2010; Edwards et al., 2014; Pham et al., 2014; Schwartz, Chernew, Landon, & McWilliams, 2015). ACOs are groups of providers (hospitals or doctors) that come together voluntarily to coordinate patient care.

**Targeting emergency room “frequent flyers”**

Hospitals are targeting ED frequent fliers with customized disease management interventions including ensuring that they have a medical home or their primary care physician is actively engaged with their care (Singh, Lin, Nattinger, Kuo, & Goodwin, 2015; Storrow et al., 2014). Targeting more general health system effects and larger care delivery context has been shown to reduce overall hospital admission rates – including intensity of hospital ED use among Medicare beneficiaries (J. R. Brown et al., 2014).

**Use of health information technology (HIT)**

Hospitals are increasingly using electronic medical records (EMRs) to standardize ordering, storage and retrieval of patients’ clinical data. EMRs are essential in real time tracking of outcomes including readmission rates and efficient sharing of patient data with other providers along the continuum of care (Adler-Milstein, Bates, & Jha, 2013; Cipriano et al., 2013; Jha et al., 2011; Lee, Kuo, & Goodwin, 2013).
Aligning Physician compensation to outcomes

Some researchers have suggested the need to tie physician compensation to clinical outcomes such as readmission (D. Anderson et al., 2012). Although this proposal seems logical and plausible in curtailing unnecessary readmissions, physicians are vehemently opposed citing a plethora of variables beyond their control that can drive hospital readmissions. Arrangements that provide shared incentives for hospitals and physicians to optimize quality of inpatient care are necessary in any effort to reduce avoidable readmissions (Epstein, 2009).

Legislative Efforts and National Quality Improvement Programs

Following the enactment of the ACA in 2010, Medicare initiated several demonstration programs geared strategically at increasing care coordination among providers and lowering hospital readmissions (R. S. Brown, Peikes, Peterson, Schore, & Razafindrakoto, 2012; Li et al., 2014). Many of these programs involve the use of financial incentives - penalties and rewards and pay-for-performance programs – with an aim of encouraging providers to work together in providing the best possible care to their patients.

Hospital Readmissions Reduction Program (HRRP)

Section 3025 of the ACA added section 1886(q) to the Social Security Act establishing the HRRP. Subsequently, HRRP became operative on October 1, 2012 – the first day of fiscal year 2013 - and now requires CMS to reduce payments to hospitals with excess readmissions (Gilman et al., 2015; Gu et al., 2014; Lu, Huang, & Johnson, 2016; McIlvennan et al., 2015; Zuckerman, Sheingold, & Epstein, 2016). As discussed earlier, although HRRP has shown promise in restraining re-hospitalizations, it has also come under intense criticism for
unintentionally penalizing hospitals based on their patient population. Indeed, there are growing concerns that penalties could lead to further deterioration of quality of care among hospitals serving poor Medicare patients.

**Community-based Care Transitions Program (CCTP)**

CCTP was created by Section 3026 of the Affordable Care Act to test models for improving care transitions from the hospital to other settings including home and skilled nursing homes. The goals of the CCTP are to improve transitions of beneficiaries from the inpatient hospital setting to other care settings, to improve quality of care, to reduce readmissions for high-risk beneficiaries, and to document measurable savings to the Medicare program (Kocher & Adashi, 2011). A review by Naylor et al. found CCTP to be highly effective in reducing unnecessary hospital readmissions among Medicare patients (Naylor et al., 2011). The CCTP is part of the Partnership for Patients, a nationwide public-private partnership that aims to drastically reduce preventable errors in hospitals and reduce hospital readmission rates.

**Accountable Care Organizations (ACOs)**

As discussed in the previous section, ACOs are a type of integrated delivery system where care providers work together to optimize patient care. Providers who achieve measurable value and quality for their patients through ACOs share in the financial gains. Presently, 600 ACOs are in operation in different parts of the country (Berwick, Feeley, & Loehrer, 2015).
Bundled Payments for Care Improvement (BPCI)

The Bundled Payments for Care Improvement (BPCI) initiative was developed by the Center for Medicare and Medicaid Innovation Center. BPCI initiative is comprised of four broadly defined models of care, which link payments for the multiple services beneficiaries receive during an episode of care. Financial and performance accountability that is tied to quality is a key element of BPCI. Bundled payments are characterized by one payment for all services associated with a given episode of care (Jha, 2015). Research studies show that bundled payments can align incentives for providers allowing them to work together in providing the best care possible to Medicare patients.

Aligning Financial Incentives in Primary Care

To allow proper reimbursement of physicians providing care to patients transitioning from hospital settings, CMS has implemented two new Current Procedural Terminology Transitional Care Management codes (Medicare, 2013). This new policy strengthens primary care and incentivizes primary care to work tirelessly in meeting patients’ post-discharge medical needs.

Ongoing Policy and Leadership Issues

Risk adjustment for Patients Socioeconomic Status

One of the major concerns expressed by MedPAC is the fact that hospitals serving a higher proportion of poor Medicare patients are either being disproportionately penalized or are more likely to be penalized. As such, the National Quality Forum has proposed an alternative risk
adjustment model that would account for patients’ socioeconomic status (Fiscella et al., 2014). However, Medicare has resisted this approach arguing that such an approach would hide disparities and de-incentivize hospitals caring for poor Medicare patients from continuously seeking ways to improve quality of care. Policy experts have also suggested that unadjusted measures may be optimal if the main goal is to motivate quality improvement in hospitals regardless of patient demographics (Jha & Zaslavsky, 2014).

Another proposed simple alternative strategy involves refining the current HRRP policy without instituting radical changes via a statutory mandate (Medicare Payment Advisory Commission, 2015). This alternative would require all hospitals to report their all-condition risk adjusted readmission rate not including SES adjustment. Readmission penalties would then be recalculated by accounting for each hospital’s share of low-income Medicare patients or those on Supplemental Security Income (SSI) - in a way, leveling the playing field. Hospital-specific penalty rate would then be determined by comparing with pre-determined peer group benchmark rate. With this approach, therefore, it is expected that hospitals with higher proportion of poor Medicare patients would either be penalized less or not at all. More importantly, this approach requires minimal statutory language changes and therefore can quickly be implemented.

Another suggested alternative approach is what the authors refer to as a “warranty” payment (Berenson, Paulus, & Kalman, 2012). Such as a payment arrangement would be characterized by a single-episode price for all services provided (including readmissions) within a specific period. Under this approach, hospitals would measure their readmission performance against their own historical trend and thus eliminating the need for risk-adjustment innate in the current HRRP approach. Subsequently, CMS would reimburse each hospital based on predetermined hospital-specific baseline rate plus extra payment based on historical improvement in readmission rates.
Other researchers and policy experts have suggested introduction of weighted HRRP penalties (Joynt & Jha, 2013b). Under such a scheme, readmission timing is crucial. Readmissions occurring within a few hours or days after discharge could receive heavier weight. The premise of such an arrangement is that readmissions occurring very soon after discharge may reflect true poor inpatient quality of care, inadequate care coordination, or poor overall post-discharge planning. On the other hand, readmissions occurring 3 to 4 weeks after discharge may primarily be due to disease severity and not necessarily the quality of care provided during the hospital stay. Weighted HRRP arrangement would prevent hospitals serving poor, sicker and medically complex patients from being unnecessarily penalized simply because of the demographic characteristics of the patients they serve.

Several studies have also called into question the extent to which differences in readmission rates reflect inpatient quality of care. Multiple patient characteristics, not currently included in risk adjustment, have been found to significantly predict the risk of readmission. Patients admitted in hospitals with higher readmission rates, disproportionately, tend to have higher prevalence of social and clinical predictors of readmissions (Barnett et al., 2015). In other words, patient characteristics are not distributed evenly across hospitals. Such findings further weaken the validity of the current CMS penalty-determination criteria. Equally important, the current HRRP policy imposes major financial burden on hospitals caring for patients at greater risk of readmission. These hospitals will therefore be required to deploy greater amount of resources in readmission-prevention strategies.
**Hospital Leadership and 30-day Readmissions**

Even as the realities of ACA and health reform settle in, it will be interesting to see what new roles healthcare leaders embrace in driving further changes and finer refinements of the healthcare law. It is certain that health care leaders will be actively engaged in patient care beyond hospital walls if indeed the U.S. health care system is going to achieve the principles of Triple Aim (Berwick et al., 2015; Gabow, Halvorson, & Kaplan, 2012). As things stand, much of the push for health care change has been coming from outside the provider realm – particularly from the federal government. Evidently, hospitals continue to have a strong incentive to fill beds and many hospital executives find minimal economic incentives to reduce readmissions. To some, designing interventions to reduce readmissions is both costly and may mean decreased revenues (Berenson et al., 2012). Future readmission policy alternatives must carefully evaluate these concerns and seek proper ways to reward hospitals that implement strategies that lower avoidable readmissions.

Meanwhile, a research study by Mulvey et al. concluded that hospitals ranked by U.S. News & World Report as “America’s Best Hospitals” in “Heart & Heart Surgery” perform no better in readmission outcomes than non-ranked hospitals (Mulvey et al., 2009). Of note, rankings place much emphasize on inpatient process of care as opposed to post-discharge follow-up and care coordination. Previous research by Williams et al. found inconsistent application of evidence-based care for heart patients by U.S. News & World Report top-ranked hospitals (S. C. Williams, Koss, Morton, & Loeb, 2006). Hospital leadership with expanded role in community settings is an essential component in achieving long term improvement in care quality and superior patient outcomes. At a time of unprecedented changes in healthcare delivery in the US, how hospital
leaders govern and steer their organizations will also be crucial in sustained hospital performance and financial outlook (Gabow et al., 2012).

Furthermore, several attempts have been made to identify American hospitals with the best leadership as defined by performance in specific leadership aspects including those that address patient safety, quality metrics, and financial standing. A study by Hansen et al. showed that hospital’s patient safety climate is associated with readmission rates for patients diagnosed with AMI and HF (Hansen, Williams, & Singer, 2011). Thus, conscientious effort by hospital senior leadership to promote patient safety by for instance preventing medication errors is crucial to curtailing readmissions. Hospital leaders are tasked with designing policies and procedures that promote and sustain high standards of care while embedding a culture of safety into the group norms and values of the organization.

In addition, hospital administrators and senior leaders are responsible for identifying specific strategies that can lower readmissions in their institutions (R. E. Burke & Coleman, 2013). These strategies may range from tracking all-cause readmissions, deploying readmission prediction tools, care coordination with primary care, adopting electronic health records, and enhanced discharge planning (Ahmad et al., 2013). These stratagems may require substantial up-front investment in personnel, education, training, and care coordination. However, pressure to act may not necessarily lead to sustainable long-term solutions. Accumulating evidence also indicates that senior leaders can ensure that readmission prevention remains a top priority in their institutions by creating buy-in and developing stakeholder teams that are solely focused on reducing avoidable readmissions.
Expanded Role of Hospitals in Community Settings

Policy experts contend that to effectively address avoidable hospital readmissions, the issue must be viewed within a broader system of care that is clearly cognizant of community context (McCarthy et al., 2013). Broader system of care recognizes and appreciates the role that multiple individuals and entities play in influencing clinical outcomes. Thus, it is vital to engage every stakeholder along the patient care path in reducing readmissions. Already, hospital leaders have resisted this role citing financial burden and expanded jurisdiction that is beyond their mandate. Clearly, hospitals have a huge role to play in reducing avoidable 30-day readmissions. Yet, previous research shows that expecting hospitals to be sole solvers of readmission problems may be unfair considering that successful interventions are already taking place in community settings - supported and driven primarily by nurses, care coordinators, coaches, and social workers (Joynt, 2014). Additionally, hospitals seem ill equipped and poorly positioned for a broader role in community settings (Epstein, 2009). To be successful, hospitals must re-evaluate their business models and make investments toward creating and strengthening communities where patients live (Jha, 2013).

Hospitals could engage primary care physicians and other community level providers by sponsoring and coordinating social programs and education summits to ensure that all partners are abreast with current care guidelines, best practices, and policy changes (Kangovi & Grande, 2011). As part of system alignment, hospitals expanded role could also include ensuring that all their discharged patients are part of a home health network that can provide necessary care coordination and deter quick attempt to return to the hospital. Essentially, as we move toward Accountable Care Organizations and bundled payments, hospitals can expand their current role and become organizing entities in care coordination. More importantly, hospitals working with
outpatient stakeholders could develop creative strategies through shared responsibility to prevent unnecessary hospital admissions. Arbaje et al. designed a useful model to demonstrate the association between post-discharge environment and socioeconomic factors, and early readmission (Arbaje et al., 2008). As CMS continues to test models that require greater coordination of care, hospitals will be required to step up their responsibilities in addressing downstream challenges that influence readmissions (McCarthy et al., 2013). In coming years, it will be interesting to see if the National Quality Forum will offer recommendations to CMS and potentially alter the way hospitals are reimbursed based on their active participation in care coordination in community settings.

In conclusion, research on hospital readmissions has broadened significantly over the last few decades. Proximal patient-level risk factors associated with readmissions among Medicare beneficiaries such as severity and type of illness are now well understood. However, knowledge on how downstream factors such as neighborhood poverty and demographic composition influence hospital readmission rates is growing. To date, only one study has comprehensively assessed the role of community factors in observed variability in readmission rates among hospitals in the U.S. (Herrin et al., 2015). This current research builds on this prior work by assessing how neighborhood and associated factors influence hospital-level variability in readmission rates for three specific medical conditions – AMI, HF and PN.
Chapter 3

Methods

Data Sources and Study Population

Data for the study were obtained from CMS, the American Hospital Association (AHA), County Health Rankings and Roadmaps (CHR&R), Area Health Resources Files (AHRF) and United States Census Bureau. The 2011-2013 - inpatient, outpatient, and carrier (physician) 100% Limited Data Set (LDS) - Standard Analytic Files (SAF) were obtained from CMS. LDS files contain protected patient-level information but certain variables such as beneficiary age are ranged while other variables are encrypted or blanked. Use of Medicare data files was reviewed by the CMS Data Use Agreement (DUA) team to ensure that all federal privacy and confidentiality requirements were met. Consequently, a DUA was completed following CMS guidelines and approved for data use.

The AHA Annual Survey Database is a wide-ranging census of approximately 6,500 U.S. hospitals and over 400 hospital systems. The database captures over 900 hospital variables ranging from organizational structure to personnel and hospital facilities and services. AHA database is viewed by healthcare experts as an authoritative source of U.S. hospital data and has been deployed extensively in health service research studies.
County Health Rankings and Roadmaps (CHR&R) files are publicly available rankings that provide comprehensive data on virtually every county in the U.S. County-level measures included in CHR&R cover areas such as county social and economic indicators, physical environment, health behaviors, clinical care and quality of life. CHR&R is a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

AHRF datasets are publicly available and encompass basic county files coupled with state and national files from more than 50 sources. These databases provide a comprehensive set of data covering a broad range of socioeconomic indicators that influence access to care including income and number of primary care physicians. Additionally, the basic AHRF files contain geographic codes and descriptors which enable AHRF data to be linked with Medicare and AHA datasets.

United States Census Bureau (USCB) is a leading source of data on U.S. population. USCB data and statistics come primarily from decennial U.S. censuses. However, USCB income and poverty estimates come from several major national household surveys and programs. These surveys include Annual Social and Economic Supplement to the Current Population Survey (CPS ASEC), American Community Survey (ACS), Survey of Income and Program Participation (SIPP), and Small Area Income and Poverty Estimates (SAIPE) Program.

Variables to include in this current research and their respective sources were selected and determined based on relationships already established in extant research literature. For CMS data, waiver of consent approval by patient’s whose medical records were used as data in the study, was obtained from the Cleveland Clinic Institutional Review Board.
Study Cohort

- **Inclusion criteria**

  The study population encompassed Medicare fee-for-service patients 65 years of age and older with a principle discharge diagnosis of HF, AMI and PN discharged directly from short-term acute care hospitals in the U.S. between January 2011 and November 2013. Discharges occurring in December 2013 were excluded due to lack of full 30 days of follow-up. Cohorts were defined based on *International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM)* codes as used in the CMS publicly reported readmission measures. For acute MI codes 410.xx, excluding 410.x2; for CHF 398.91, 404.X1, 404.X3, AND 428.0-428.9; and pneumonia, 480-486. More information regarding these codes can be found in the appendix F. CMS SAF data includes information pertaining principal discharge and secondary diagnosis codes and procedure codes for each Medicare fee-for-service hospitalization. Only patients with complete hospitalization claims history for 1 year preceding admission were included in the study. Diagnosis codes obtained 12 months prior to index admission were used to gauge disease severity and comorbidity status for each participant for purposes of risk adjustment as done in CMS publicly reported readmission measures. Other inclusion criteria included live discharges only since it is only possible for patients to be re-hospitalized if they are discharged alive. The final inclusion criteria involved inclusion of patients that were discharged to a non-acute care setting such as home or skilled nursing facility.

- **Exclusion criteria**

  Patients discharged on the same-day or who died in the hospital or were transferred to another acute care facility were excluded from the study. Likewise, patients who were
discharged against medical advice (AMA) or who had less than 30 day’s enrollment in Medicare fee-for-service after hospital discharge were excluded. Patients discharged from federal hospitals and those outside the 50 states were also excluded. To provide comparative estimates of hospital performance, patients from hospitals with fewer than 25 index admissions for each condition or no readmission over the study period, were excluded from the study.

**Study Measures**

- **Primary Outcome Variable**

  The primary outcome variable was hospital-level all-cause 30-day RSRR for Medicare patients with a primary discharge diagnosis of HF, AMI and PN. Readmission was defined as occurrence of at least one hospitalization for any cause within 30 days of discharge after an index admission in any U.S. acute care hospital for the three disease conditions. Readmissions were identified from Medicare hospital claims data and all readmissions were attributed to the hospital where the patient was discharged from. Medicare data were used to determine each patient’s likelihood of readmission within 30 days after discharge adjusted for age and gender. In addition, each patient’s likelihood of readmission was adjusted using the Elixhauser risk-adjustment scheme – a tool developed and validated by Agency for Healthcare Research and Quality (AHRQ) for use with administrative data in adjusting for comorbidity (Elixhauser, Steiner, Harris, & Coffey, 1998; Southern, Quan, & Ghali, 2004). Consequently, hospital-level 30-day RSRR for each condition was determined as a rate and measured on a continuous scale.
**Explanatory County (level-2) Variables**

- **Per capita number of primary care physicians (PCPs)**

  Per capita number of primary care physicians is defined as the per person number of physicians in primary care (general practice, internal medicine, obstetrics and gynecology, or pediatrics) within the county. Evidence regarding the role of PCPs in preventing unnecessary hospitalizations is mixed. Generally, post discharge care coordination with PCPs is associated with optimal patient outcomes. However, some studies have found the opposite. Though it appears contradictory, a study by Brown et al. demonstrated a strong positive correlation between per capita rate of primary care physicians and hospital readmission rates (J. R. Brown et al., 2014). Part of the reason for such correlation is heightened care that uncovers new disease conditions that could not have been discovered if access to primary care was limited or nonexistent (Weinberger et al., 1996). However, in most cases, access to primary care, care coordination and PCP follow-up has been associated with decreased risk of 30-day hospital readmission (Brooke et al., 2014). Thus, it can be hypothesized that Medicare patients from counties with high per capita number of primary care physicians are less likely to be readmitted as compared to patients from counties with few per capita number of primary care physicians. Accordingly, hospitals located in counties with fewer numbers of PCPs are more likely to have higher readmission rates as compared to counties with higher numbers of PCPs. Per capita number of primary care physicians is measured on a continuous scale.
- **Median annual household income**

  Median annual household income is defined as the yearly (12 months) income of the householder and all other individuals 15 years old or older in a household. Income is one element of an individual’s or group’s socioeconomic status. Others may include education and occupation. Substantial evidence indicates that income, either as a single parameter or in composite with other SES factors, is a strong independent predictor of health outcomes including early unplanned hospital readmissions (Calvillo-King et al., 2013; Lindenauer et al., 2013). McGregor et al. found that among hospitalized pneumonia patients less than 65 years, low individual-level income was associated with a two-fold greater risk of hospital readmission (McGregor et al., 2006). At ZIP Code level, Agrawal et al. found that low median income was positively and independently associated with 30-day readmission risk (Agrawal et al., 2016). Another postal zip code level analysis conducted in New York state by Philbin et al. found similar results among heart failure patients – lower income patients had 18 percent higher odds of readmission as compared to high income counterparts (Philbin, Dec, Jenkins, & DiSalvo, 2001).

  However, a study by van Walraven et al. in Ottawa, Canada found no association between neighborhood household income and hospital readmission after adjusting for known patient-level factors such as length of stay, acuity of admission and patient-level comorbidities (van Walraven et al., 2013). Thus, it can be hypothesized that based on extant literature Medicare patients from low median household income counties are more likely to be readmitted as compared to patients from high median household income counties. Accordingly, hospitals located in counties with low median household income blanket are more likely to have higher readmission rates as compared to hospitals located in high median household income counties. In
this analysis, the median household income is based on the distribution of the total number of households including those with no income. This variable is measured on a continuous scale.

- **Poverty rate**

  Estimate of all ages in poverty is defined as percentage of all ages below the poverty level within the county. Poverty level is a measure of neighborhood socioeconomic disadvantage and it is derived on a sample basis by comparing total family income to an income cutoff or poverty threshold after adjusting for family size, number of children, and age of family householder. Evidence regarding the role of neighborhood poverty on hospital readmissions is inconclusive. Villanueva et al. found that among patients hospitalized with cardiovascular disease (CVD) in New York city, residing in a poor neighborhood was not associated with 30-day rehospitalizations (Villanueva & Aggarwal, 2013). Nonetheless, substantial research evidence indicates that patients residing in high poverty areas experience considerable additional burdens beyond immediate family level challenges (Hu et al., 2014; Kind et al., 2014; Muennig, Fiscella, Tancredi, & Franks, 2010). As such, patients living in poor neighborhoods are more likely to lack adequate social support and other infrastructure critical for follow-up and continued care. Such patients are therefore more likely to be readmitted following discharge from an acute care hospital. Therefore, it can be hypothesized that Medicare patients from counties with high percentage estimate of all ages in poverty are more likely to be readmitted as compared to patients from counties with low estimates of all ages in poverty. Accordingly, hospitals located in counties with high estimate of all ages in poverty are more likely to have higher readmission rates as compared to counties with fewer percentage estimate of all ages in poverty. Since poverty estimate is a percentage, this variable is measured on a continuous scale.
- **Black resident population**

  Black resident population is defined as percentage of persons having origins in any of the black racial groups of Africa. It includes all persons indicating their race as Black, African American, or who provided written entries such as African American, Afro American, Kenyan, Nigerian, or Haitian. Racial disparities in readmissions are well documented in surgical patients as well. Joynt et al. also demonstrated that black elderly Medicare patients were more likely to be readmitted within 30 days after hospitalization for MI, congestive heart failure (CHF), and pneumonia (Joynt et al., 2011). Gunnell et al. found that black patients with inflammatory bowel disease were at an increased risk for readmission when compared to other races after surgery (Gunnells et al., 2016). But whether such effects are evident at neighborhood-level is unclear. Nonetheless, it can be hypothesized that an aggregate effect is possible and that Medicare patients from counties with high percentage black resident population are more likely to be readmitted as compared to patients from counties with low percentage black resident population. In turn, hospitals located in counties with high percentage black resident population are more likely to have higher readmission rates as compared to hospitals located in counties with fewer black residents. Since this variable is a percentage, it is also measured on a continuous scale.

- **Per capita number of skilled nursing facilities (SNFs)**

  Per capita number of skilled nursing facilities (SNFs) is defined as the number of Medicare certified facilities providing long-term care for the elderly or other patients requiring chronic care in a non-acute setting. SNFs play a significant role in the U.S. health care system. Largely, these facilities provide crucial transient care to Medicare patients discharged from acute
care settings. Evidence regarding effectiveness of SNFs care and how they influence hospital readmission is mixed (Neuman, Wirtalla, & Werner, 2014). Some research studies show that, due to quality deficiencies inherent in SNFs, nearly 25 percent of elderly patients admitted to SNFs for post-acute care end up being readmitted to an acute care hospital for unplanned reasons (Hakkarainen, Arbabi, Willis, Davidson, & Flum, 2016; Jencks et al., 2009; Mor, Intrator, Feng, & Grabowski, 2010). As such, hospitals located in counties with greater numbers of SNFs may experience disproportionally higher rates of re-hospitalized patients and this could explain some of the observed county-level variation in readmission rates. Other studies indicate that these findings could be attenuated by interventions such as sustained follow-up, provider communication and enhanced linkage between hospitals and SNFs (Schoenfeld et al., 2016). Yet, other studies show that, as compared to patients discharged home directly from acute care hospitalizations, patients discharged to SNFs experience higher mortality rates and overall poorer outcomes (Allen et al., 2011; Davidson et al., 2011; Kane et al., 2000; Wunsch et al., 2010). Thus, considering heightened risk of hospital readmission for patients in SNFs, it can be hypothesized that Medicare patients from counties with fewer per capita number of skilled nursing facilities are more likely to be readmitted as compared to patients from counties with higher per capita number of skilled nursing facilities. In turn, hospitals located in counties with more nursing homes may register fewer readmission rates. This variable is measured on a continuous scale.

- **Population aged 65 or older in nursing homes**

  Population aged 65 or older in nursing homes is defined as the percentage of elderly (65 years and above) in institutionalized nursing quarters. The size of population aged 65 or older in
nursing homes is partly a function of hospital discharge practice. Hospitals typically have a choice of where the patient goes following discharge. Choices may include home, home with home care, SNF, or rehabilitation center. Considering that discharge disposition to SNFs has to an extent been linked to poor outcomes, the magnitude of such effects would be distinct if the number of elderly patients in SNFs within a county is large. County measure of size of population aged 65 or older in nursing homes can therefore be considered as an important variable to county-level variation in hospital readmission rates. Thus, it can be hypothesized that hospitals located in counties with higher percentage population aged 65 or older in nursing homes are more likely to have higher readmission rates when compared to hospitals located in counties with fewer percentage population aged 65 or older in nursing homes. Since this estimate is a percentage, this variable is measured on a continuous scale.

- **Adult smoking rates**

  Adult smoking is defined as the percentage of adults that reported current smoking based on Behavioral Risk Factor Surveillance System (BRFSS) 2014 survey data. At individual patient level, cigarette smoking is a leading risk factor for morbidity and premature death in the United States (Xu, Bishop, Kennedy, Simpson, & Pechacek, 2015). Dramatic variation in total cigarette smoking prevalence across US counties is well documented ranging from 5.8 percent to 41.5 percent (Dwyer-Lindgren et al., 2014). Counties with highest rates of total cigarette smoking are primarily located in the South and in particular Kentucky, Tennessee, and West Virginia while counties in Western states such as Utah have the lowest rates. Evidence regarding the role of smoking in hospital readmission rates is inconclusive. A study by Evangelista et al. demonstrated a clear direct relationship between cigarette smoking and the risk for multiple hospital
readmissions among veterans discharged with heart failure (Evangelista, Doering, & Dracup, 2000). Among surgical patients, preoperative smoking has been strongly associated with risk of 30-day hospital readmission (Hensley et al., 2016).

Other studies have demonstrated a clear reduction in hospital readmission among hospitalized high-risk smokers with acute cardiovascular disease in settings where smoking cessation programs were implemented (Mohiuddin et al., 2007). However, a study by Logue et al. indicated that cigarette smoking does not significantly increase the risk of 30-day readmission (Logue, Smucker, & Regan, 2016). Irrespective, it can be hypothesized that since a majority of prior research studies have strongly implicated cigarette smoking to hospital readmission at individual level, a composite effect would also be observed at county level and this would help explain some of the county-level variation in readmission rates. This variable is measured on a continuous scale.

**Hospital (level-1) variables**

The motivation for introducing these level-1 hospital variables in the analysis is to assess how hospital characteristics impact the relationship between level-2 county covariates (presented above) and risk-adjusted readmission rates.

- **Ownership status**

Ownership status relates to how hospitals are owned and operated. This may include; for profit, private not-for-profit, and public not-for-profit. Depending on ownership classification, hospitals tend to have different missions and this in turn may impact how they respond to various government policies and regulations including HRRP. Both for profit and private not-for-profit
hospitals have been shown to have higher readmission rates (Epstein et al., 2011). However, a study by Joynt et al. indicated that public hospitals with limited financial and clinical resources were more likely to have higher readmission rates (Joynt & Jha, 2011).

- **Teaching status**

  A hospital is considered a teaching hospital if it has an American Medical Association (AMA)-approved residency program, is a member of the Council of Teaching Hospitals (COTH) or has a ratio of full-time equivalent interns and residents to beds of .25 or higher. Typically, teaching hospitals tend to be larger and provide care to disproportionally higher numbers of low-income patients. Accordingly, these hospitals have been associated with both higher readmission rates and higher financial penalties for excessive readmission rates (Joynt & Jha, 2013a; Singh et al., 2014).

- **Bed size**

  Bed size is operationalized as the number of short-term acute beds available in a hospital. In the US, the number of hospital beds vary considerably based on hospital location and teaching status. Consequently, bed availability may have an influence on admissions and readmissions. A study by Joynt et al. demonstrated that large teaching hospitals (400 beds and above) were more to have higher readmission rates and therefore more likely to be penalized (Joynt & Jha, 2013a). However, small hospitals with fewer resources have also been shown to have higher readmission rates (Joynt & Jha, 2011).
- **Setting**

  Setting refers to hospital location - rural versus urban. Hospitals located within metropolitan statistical areas are considered urban, while all others are considered rural. Notably, government payment policies often differ substantially based on hospital location designation. Comparatively, rural hospitals tend to be smaller and provide fewer services than urban hospitals. There is evidence that rural hospitals are more likely to provide lower post-discharge care including fewer follow-up visits effectively increasing the odds of readmission (Toth et al., 2015).

- **Region**

  Region refers to any of the four sub-divisions of continental United States - Northeast, Midwest, South, and West – as defined by the U.S. Census Bureau. Medical care practices and outcomes have been shown to vary considerably between these regions. For instance, as compared to hospitals in the West, 30-day readmissions tend to be higher among hospitals in Northeast (Epstein et al., 2011).

- **Safety-net status**

  Safety-net status relates to the amount of disproportionate Share Hospital (DSH) received by a given hospital. DSH is government compensation paid to hospitals serving a significantly disproportionate number of indigent or low-income patients (Redlener & Grant, 2009). These payments are critical in preserving access to care for indigent patients. In general, low-income patients typically tend to be sicker and their overall cost of care can be exorbitant. As such DSH payments are met to offset large hospital operating costs related to uncompensated care provided
to uninsured patients. Research studies have demonstrated unequivocally that hospitals that
disproportionately serve indigent patients have higher readmission rates and this may be
contributing to variability across hospitals in the U.S. (Gilman et al., 2015; Joynt et al., 2011;
Joynt & Jha, 2013a). On the other hand, safety-net are more likely to be high-volume teaching
hospitals with greater access to advanced treatment technologies that could improve outcomes
(Ross et al., 2012).

- **Length of Stay**

  Length of Stay (LOS) refers to mean duration of a single episode of hospitalization
calculated by dividing the sum of inpatient days by the number of patient admissions with the
same diagnosis-related group classification. Although reducing LOS has been a priority for
hospitals, there is evidence that this could result in increases in 30-day readmission rates (Bueno
et al., 2010). However, Kaboli et al. could not validate these findings among patients discharged
from 129 acute care Veterans Affairs (VA) hospitals in the U.S. (Kaboli et al., 2012).

**Statistical Analysis Plan**

**Statistical Analysis Plan for Aim 1 and 2**

**Specific Aim # 1:** To assess the amount of variability in hospital-level readmission rates that
would be explained by county of hospital location among fee-for service Medicare beneficiaries
with a primary discharge diagnosis of HF, AMI, and PN in the U.S.
H1: Among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN, a notable portion of hospital-level variability in readmission rates may be explained by county of hospital location.

Specific Aim #2: To examine how much variation in hospital readmission rates is explained by characteristics of county of hospital location among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN in the U.S.

H1: Hospital-level variation in readmission rates among fee-for-service Medicare beneficiaries with a primary discharge diagnosis of HF, AMI, and PN is associated with characteristics of hospital location including median household income, per capita number of primary care physicians, percentage resident population 65 years and over, percentage black resident population, percentage estimate of all ages in poverty, per capita number of skilled nursing facilities, percentage population aged 65 or older in nursing homes, and percentage of adults who are current smokers.

Preliminary Analysis

Preliminary Data Preparation

The data for 30-day readmission rates following HF, AMI and PN were obtained from the 2011, 2012, and 2013 CMS Standard Analytic Files. Among other information, these files contained the diagnostic codes for Medicare-eligible beneficiaries seen as inpatients over this period. Coding of the CMS data involved combining adjacent admissions such that a new admission on the same day as a discharge was treated as a continuation of the original admission. In addition, any admission occurring within 30 days of a prior admission was not included; a
beneficiary was eligible to be in the sample again after the 30-day window had passed. Following the initial preparation of the CMS data, RSRRs were calculated using the methodology of the Yale-New Haven Health Services Corporation Center for Outcomes Research and Evaluation. Comprehensive details of this methodology can be found elsewhere (Horwitz et al., 2014; Keenan et al., 2008; Krumholz et al., 2011; Lindenauer et al., 2011). Specifically, a Generalized Linear Mixed Model (GLMM) with a logit link was fit with 30-day readmission as the primary outcome - adjusting for gender, age, and Elixhauser comorbidities; this was repeated separately with Charlson comorbidities in place of the Elixhauser codes for sensitivity analysis purposes.

The model estimates provided a patient-specific readmission probability adjusted for the hospital-specific random effect as well as a readmission probability averaged over all hospitals. The ratio of these two values was then multiplied by the average predicted probability in the entire sample to determine the patient-level RSRR. Next, the mean of the patient RSRRs in each hospital was calculated to determine the hospital-level RSRR. The process was repeated for each diagnosis as well as for all three diagnoses combined.

The next step was to join the hospital-level RSRR information with the AHA hospital data, the Area Health Resource File data, county-level Census data, and County Health Rankings data. One complication was that CMS uses Social Security Administration (SSA) codes for state and counties, whereas county level data files use Federal Information Processing Standard (FIPS) codes. It was therefore necessary to employ a cross-walk to match the SSA values to the FIPS values. All hospitals without full data from the non-CMS sources were then dropped to create the final sample.
Selecting Predictor Variables for the Final Model

To only include the necessary variables in the final analysis, bivariate relationships between each county-level explanatory variable and hospital readmission were first assessed. The goal was to define a parsimonious set of county-level predictor variables that could explain inter-hospital variability in hospital readmissions rates without including many predictors. Accordingly, median household income and poverty rate were highly correlated when included in the same model while percentage population aged 65 or older in nursing homes and percentage resident population 65 years were non-significant in bivariate assessments. As such, signs of multicollinearity such as large correlations among pairs of predictor variables and estimates of coefficients varying from model to model were evaluated appropriately. However, given the limits of assessing pairwise correlations, variance inflation factors (VIF) were also examined to detect multicollinearity. Violating predictors were removed from the model and VIF assessed again. Subsequently, county-level covariates most strongly correlated with hospital readmission were included in the final model. Results of multicollinearity assessment can be found in Appendix G-1 and 2.

Model Building Process

Considering the hierarchical or clustered structure to the data (patients nested within hospitals and hospitals nested within counties), measurements on patients within a hospital or county (cluster) are more likely to be similar when compared with measurements on patients in different hospitals or different counties (clusters). As such, to assess the amount of variance in readmission rate that could be attributed to county variables and hospital characteristics, a hierarchical linear model (HLM) was deployed using proc Glimmix. HLM allowed partitioning
of variance in re-hospitalizations into components resulting from hospital and county level respectively. Similar approach has been used in previous research studies (Haymart et al., 2011; Herrin et al., 2015; Singh et al., 2014). To obtain the best fitting model, the model building process involved gradual estimation of more complex models with more variables while monitoring for improvement in model fit at each step. Analyses were performed using SAS statistical software (SAS Institute Inc, version 9.4, Cary, NC).

**Model 1: One-way ANOVA with random effects**

The simplest possible random effect linear model to be assessed was one-way ANOVA with random effects. This model was characterized by randomly varying intercept (county RSRR mean, $\beta_{0j}$) with no predictors specified - typically referred to as an “empty” or fully unconditional HLM (equation 1). One-way ANOVA model produces a point estimate and confidence interval for the grand mean, $\gamma_{00}$ (see combined model below). The goal of this model was to understand how much hospital readmission rates vary between counties. To assess how much of the national variation in readmission rates is attributable to county characteristics and how much is attributable to hospital, variance was partitioned between the two levels – hospital (level 1) and county (level 2). This unconditional model was used to compute the intraclass correlation coefficient (ICC). The ICC, therefore, was the portion of total variance in readmission rate (outcome) that was attributable to county (level-2) units or that occurs between counties.

Equation 1:

**Level-1 (Hospital) model:** $\text{RSSR}_{ij} = \beta_{0j} + r_{ij}$

**Level -2 (County) model:** $\beta_{0j} = \gamma_{00} + \mu_{0j} + r_{ij}$
Combined model: \[ \text{RSSR}_{ij} = \gamma_{00} + \mu_{0j} + r_{ij} \]

where \( r_{ij} \sim N(0,\sigma^2) \) and \( \mu_{0j} \sim N(0,\tau^2) \)

- \( \text{RSSR}_{ij} \) is the 30-day RSRR for hospital \( i \) in county \( j \).
- \( \beta_{0j} \) is the average RSRR for county \( j \).
- \( r_{ij} \) is the hospital-level variance or hospital \( i \) deviation from county-level mean RSRR (\( \beta_{0j} \)).
- \( \gamma_{00} \) is the intercept or grand mean (RSRR across hospitals and across all counties).
- \( \mu_{0j} \) is the county-level variance or county \( j \) deviation from the grand mean \( \gamma_{00} \).
- The \( \sigma^2 \) parameter represents the within-group (county) variability.
- The \( \tau^2 \) parameter represents the between-group (county) variability.

Model 2: Regression with Means-as-Outcomes model

Once county variability in RSRR was ascertained in model 1 above, the next step was to start explaining this variability by introducing level-2 covariates. The aim of this second model, therefore, was to understand why there is a county difference or variability in readmission rates. To do so, county predictors strongly correlated with readmission (as determined in the preliminary analysis above) were introduced into the model. These predictors included percentage of all ages in poverty or poverty rate, per capita number of primary care physicians, percentage black only residents, per capita number of SNFs, and percentage number of adult smokers.

Equation 2:

\[ \text{Level-1 (Hospital) model: } \text{RSSR}_{ij} = \beta_{0j} + r_{ij} \]
**Level -2 (County) model:** \[ \beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Level-2 predictor } X_j) + \mu_{0j} \]

**Combined model:** \[ \text{RSSR}_{ij} = \gamma_{00} + \gamma_{01}(\text{Level-2 predictor } X_j) + \mu_{0j} + r_{ij} \]

where \( r_{ij} \sim N(0, \sigma^2) \) and \( \mu_{0j} \sim N(0, \tau^2) \)

The model above incorporated mean for each predictor (labeled as level-2 predictor \( X_j \)). As such, the slope coefficient (\( \gamma_{01} \)) associated with each predictor variable is fixed - effectively making this a conditional linear mixed model. Variance \( \mu_{0j} \) is now the residual or conditional variance in \( \beta_{0j} \) (county means) after controlling for all 5 predictors i.e \( \text{Var} (\beta_{0j}|x \text{ predictors}) \). At this point, appropriate inferences could be made. Additionally, how county-level variance and hospital-level variance changed (reduced) when county-level predictors were included in the model was determined. The proportion of variance explained by each predictor was also determined. County-level predictors explaining the greatest variability in RSRR across counties were noted as potential targets for interventional strategies aiming at reducing avoidable readmissions in the Medicare program.

To determine whether county RSRR means varied significantly once predictors were controlled for, a null hypothesis of \( \tau^2 \) was tested. When \( \tau^2 \) is was not zero that meant that after controlling for \( x \) number of predictors, significant variation among county mean RSRR still remained to be explained. In this step, also, an index of the proportion in reduction in variance or variance explained at level 2 was developed. It was expected that after accounting for county-level predictors, the correlation between pairs of RSRRs in the same county was smaller as compared to the unconditional model i.e ICC would decrease. The estimated \( \rho \) was therefore a conditional intraclass correlation coefficient that measured the degree of dependence among observations within counties that are of the same value for a given predictor.
Statistical Analysis Plan for Aim 3

Specific Aim # 3: To examine how hospital characteristics influences the relationship between county characteristics and readmission rates among fee-for service Medicare beneficiaries diagnosed with heart failure, acute myocardial infarction, and pneumonia in the United States.

H1: Among Medicare patients diagnosed with heart failure, acute myocardial infarction and pneumonia in the United States, the amount of observed variability in hospital readmission rates is largely dependent on certain hospital characteristics including ranking among the top 100 hospitals, ownership type, safety-net status, teaching status, number of beds, and setting.

Model 3: Intercepts and slopes-as-outcomes model

To assess how hospital characteristics influence the relationship between county characteristics and readmission rates, a model that incorporated both level-1 (hospital) and level-2 (county) predictors was set up. Intercepts and slopes-as-outcomes model (below) is useful in accounting for variability of the regression equations across counties when both level 1 and level 2 variables are included in the model.

Equation 3:

$$RSSR_{ij} = \gamma_{00} + \gamma_{01}(\text{County predictor } X)_{ij} + \gamma_{02}(\text{Hospital predictor } Y)_{ij} + \mu_{0j} + r_{ij}$$

where $$r_{ij} \sim N(0,\sigma^2)$$ and $$\mu_{0j} \sim N(0,\tau^2)$$

Characteristics of the hospitals included in the study were analyzed and included in a table format including their calculated risk adjusted readmission rate for the three medical conditions. The goal of this second analytic plan was to determine whether inclusion of hospital characteristics had any impact on the county effects determined in aim 1 above. In other words,
to assess how the significance of each covariate-outcome relationship change (diminish) when hospital-level variables are included in the model.

In this secondary analysis, the following hospital characteristics were included: safety-net status, ownership status (for profit, private not for profit, public not for profit), teaching status, bed size, setting (rural versus urban), LOS, DSH, and region (Northeast, Midwest, South, West). The amount of variance in hospital readmission rates explained when these adjustment variables were included in the model, was also assessed appropriately for information purposes only.
Chapter 4

Results

Following data preparation, total of 8,433,723 discharges were identified with at least 6,734,310 (80%) having one diagnosis that met the inclusion criteria (Table 2). On age, 2,600,356 (30.83%) were at least 84 years or older and 4,650,256 (55.14%) were female. Majority of identified discharges were white 7,123,948 (84.47%) compared to blacks 893,104 (10.59%). The most common diagnosis was heart failure 4,781,242 (56.69%). Of the total discharges, 1,212,820 (14.38%) were readmitted within 30 days of discharge.

Table 3 provides descriptive statistics for hospitals included in the study. A total of 5,441 hospitals were included in the study of which a majority (n=2,870; 52.75%) were Private - Not for Profit hospitals. Compared to other U.S. regions, the south had the largest number of hospitals (n=2,205; 40.53%). Only 1,470 (27.02%) of the hospitals were classified as academic medical centers or teaching hospitals. A majority of hospitals (n=3,034; 55.76%) had less than 100 beds. The variables for total beds and average length of stay were all highly skewed. Hence, the multivariate models that follow controlled for the natural log transformations of these variables. Log transformations aid in rendering severely skewed distributions more normal (Zou, Tuncali, & Silverman, 2003).
Table 2: CMS data summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>n (=8,433,723)</th>
<th>%</th>
</tr>
</thead>
<tbody>
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<td><strong>Age Range</strong></td>
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<td></td>
</tr>
<tr>
<td>65-69</td>
<td>1,277,099</td>
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</tr>
<tr>
<td>70-74</td>
<td>1,404,333</td>
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<tr>
<td>75-79</td>
<td>1,505,856</td>
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<tr>
<td>80-84</td>
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<td>19.52</td>
</tr>
<tr>
<td>&gt;84</td>
<td>2,600,356</td>
<td>30.83</td>
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<tr>
<td><strong>Gender</strong></td>
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<td></td>
</tr>
<tr>
<td>Male</td>
<td>3,783,467</td>
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</tr>
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<td>Female</td>
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<td>North American Native</td>
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<td><strong>At least one diagnosis meets inclusion criteria</strong></td>
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<td>Yes</td>
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<td><strong>Heart Failure diagnosis</strong></td>
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<td>Yes</td>
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Table 3: Hospital characteristics

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<tr>
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<td>20.89</td>
<td>16.82</td>
</tr>
<tr>
<td>• Private - For Profit</td>
<td>1377</td>
<td>25.73</td>
<td>16.93</td>
</tr>
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<td>• Private - Not for Profit</td>
<td>2856</td>
<td>53.37</td>
<td>16.81</td>
</tr>
<tr>
<td>Geography</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Rural/Micro</td>
<td>1939</td>
<td>36.24</td>
<td>16.76</td>
</tr>
<tr>
<td>• Metro</td>
<td>3412</td>
<td>63.76</td>
<td>16.89</td>
</tr>
<tr>
<td>Region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Midwest</td>
<td>1523</td>
<td>28.46</td>
<td>16.83</td>
</tr>
<tr>
<td>• Northeast</td>
<td>653</td>
<td>12.20</td>
<td>17.07</td>
</tr>
<tr>
<td>• South</td>
<td>2172</td>
<td>40.59</td>
<td>16.86</td>
</tr>
<tr>
<td>• West</td>
<td>1003</td>
<td>18.74</td>
<td>16.65</td>
</tr>
<tr>
<td>Teaching status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Non-teaching</td>
<td>3907</td>
<td>73.01</td>
<td>16.79</td>
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<tr>
<td>• Teaching</td>
<td>1444</td>
<td>26.99</td>
<td>16.95</td>
</tr>
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<td>Beds</td>
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<tr>
<td>• 51-100</td>
<td>2988</td>
<td>55.84</td>
<td>16.78</td>
</tr>
<tr>
<td>• 101-200</td>
<td>1049</td>
<td>19.60</td>
<td>16.83</td>
</tr>
<tr>
<td>• 201-300</td>
<td>535</td>
<td>10.00</td>
<td>16.89</td>
</tr>
<tr>
<td>• 301+</td>
<td>779</td>
<td>14.56</td>
<td>17.03</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>Median</th>
<th>Lower Quartile</th>
<th>Upper Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of Stay (LOS)</td>
<td>5351</td>
<td>4.37</td>
<td>3.62</td>
<td>5.41</td>
</tr>
<tr>
<td>Disproportionate Share Hospital (DSH)</td>
<td>3192</td>
<td>26.24</td>
<td>18.13</td>
<td>35.59</td>
</tr>
</tbody>
</table>

Table 4 shows the number of hospitals per county in the entire dataset. Thus, the final study sample consisted of 5,351 providers nested in 2,466 counties. Of note, over half of the counties in the study sample (64 percent) had only one hospital, which made it challenging to separate out the within- versus the between-county variance with high degree of certainty for a large portion of the cases. As a sensitivity measure, all counties with a single hospital were excluded from the final study sample and data re-analyzed. The results were comparable.
Irrespective, it is still necessary to use caution when interpreting the results, understanding that the variance at both levels may have been over- or under-estimated due to the large number of counties with a single hospital.

In the literature, how large a cluster sample should be (in this case the number of hospitals within a county) to accurately determine the within cluster (county) variance is unclear (McNeish, Stapleton, & Silverman, 2016; McNeish & Stapleton, 2016a; McNeish & Stapleton, 2016b; Schunck, 2016). However, a level two sample size of at least 50 or above has been suggested (Maas & Hox, 2004; Maas & Hox, 2005). A large enough sample is essential in accurately estimating regression coefficients, the variance components, and the standard errors. Of note, in multilevel modeling, group level sample size is the most critical considering that it is always smaller than the level-1 sample size.

Table 4: Distribution of providers per county in the entire dataset (range 1-58)

<table>
<thead>
<tr>
<th>Count</th>
<th>No. of Providers</th>
<th>%</th>
<th>* No. of FIPS</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>5351</td>
<td>100</td>
<td>2466</td>
<td>100</td>
</tr>
<tr>
<td>1 only</td>
<td>1581</td>
<td>29</td>
<td>1581</td>
<td>64</td>
</tr>
<tr>
<td>2+</td>
<td>3860</td>
<td>71</td>
<td>885</td>
<td>36</td>
</tr>
<tr>
<td>3+</td>
<td>2996</td>
<td>55</td>
<td>453</td>
<td>18</td>
</tr>
<tr>
<td>4+</td>
<td>2501</td>
<td>46</td>
<td>288</td>
<td>12</td>
</tr>
<tr>
<td>5+</td>
<td>2229</td>
<td>41</td>
<td>220</td>
<td>9</td>
</tr>
<tr>
<td>6+</td>
<td>1944</td>
<td>36</td>
<td>163</td>
<td>7</td>
</tr>
<tr>
<td>10+</td>
<td>1275</td>
<td>23</td>
<td>70</td>
<td>3</td>
</tr>
<tr>
<td>15+</td>
<td>826</td>
<td>15</td>
<td>31</td>
<td>1</td>
</tr>
<tr>
<td>20+</td>
<td>610</td>
<td>11</td>
<td>18</td>
<td>1</td>
</tr>
</tbody>
</table>

*FIPS denotes Federal Information Processing Standard; a five-digit code that uniquely identifies counties and county equivalents in the U.S.

Table 5 below provides descriptive statistics for county-level predictors included in the study. In total, 8 county-level variables were hypothesized to have strong influence on hospital readmissions. However, due to multicollinearity issues and problems with model convergence, not all the variables in Table 4 were included as covariates in the full HLM models. Specifically,
median household income, percent 65 and over in nursing home and percentage of county population 65 years and over were removed from the final multivariate model due to strong multicollinearity with other county level variables (Appendix G-1 and 2).

Table 5: Descriptive statistics for county-level predictors across all 5,351 providers

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>Median</th>
<th>Lower Quartile</th>
<th>Upper Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poverty percent, all ages</td>
<td>5350</td>
<td>16.20</td>
<td>12.50</td>
<td>19.40</td>
</tr>
<tr>
<td>Median household income</td>
<td>5350</td>
<td>48635</td>
<td>42125</td>
<td>55686</td>
</tr>
<tr>
<td>Percent smokers</td>
<td>5350</td>
<td>17.00</td>
<td>15.00</td>
<td>19.90</td>
</tr>
<tr>
<td>Primary care physician rate</td>
<td>5323</td>
<td>69.22</td>
<td>49.37</td>
<td>88.97</td>
</tr>
<tr>
<td>Percent 65 and over</td>
<td>5350</td>
<td>15.24</td>
<td>12.71</td>
<td>18.02</td>
</tr>
<tr>
<td>Percent African American</td>
<td>5350</td>
<td>5.90</td>
<td>1.43</td>
<td>16.59</td>
</tr>
<tr>
<td>No. of skilled nursing facilities</td>
<td>5351</td>
<td>7.00</td>
<td>3.00</td>
<td>24.00</td>
</tr>
<tr>
<td>Percent &gt; 65 years in SNFs</td>
<td>5351</td>
<td>3.93</td>
<td>2.86</td>
<td>5.14</td>
</tr>
</tbody>
</table>

Table 6 presents the RSRRs by outcome using Elixhauser and Charlson comorbidities as adjusters in the RSRR calculations (Charlson for sensitivity analyses). Elixhauser and Charlson adjusted results were nearly identical, with only the minimum and maximum values differing. The correlation between the Elixhauser and Charlson estimates was .996 for all four outcomes (correlation results not shown). As such, only Elixhauser adjustment was deployed in the rest of the analysis.
<table>
<thead>
<tr>
<th>Elixhauser Adjusted:</th>
<th>n</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMI</td>
<td>4730</td>
<td>16.840</td>
<td>0.988</td>
<td>12.410</td>
<td>21.864</td>
</tr>
<tr>
<td>HF</td>
<td>5319</td>
<td>19.368</td>
<td>1.997</td>
<td>12.913</td>
<td>32.097</td>
</tr>
<tr>
<td>PN</td>
<td>5206</td>
<td>16.507</td>
<td>1.772</td>
<td>11.473</td>
<td>30.665</td>
</tr>
<tr>
<td>All</td>
<td>5351</td>
<td>18.116</td>
<td>2.094</td>
<td>12.063</td>
<td>30.627</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Charlson Adjusted:</th>
<th>n</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMI</td>
<td>4730</td>
<td>16.839</td>
<td>0.979</td>
<td>12.412</td>
<td>21.871</td>
</tr>
<tr>
<td>HF</td>
<td>5319</td>
<td>19.354</td>
<td>1.961</td>
<td>12.909</td>
<td>31.589</td>
</tr>
<tr>
<td>PN</td>
<td>5206</td>
<td>16.502</td>
<td>1.746</td>
<td>11.612</td>
<td>29.291</td>
</tr>
<tr>
<td>All</td>
<td>5351</td>
<td>18.099</td>
<td>2.049</td>
<td>12.085</td>
<td>29.816</td>
</tr>
</tbody>
</table>
The mean AMI RSRR was estimated at 16.84 percent based on Elixhauser adjustment scheme (figure 6). The peak – representing the most common RSRR values – occurs at approximately 17 percent. Wide spread variation in RSRRs is noticeable - from about 12 percent to 21 percent. Distribution of RSRRs appears symmetrical with uniform distribution of data values on the left and the right side of the mean. No outliers are noticeable.
For HF, the mean RSRR was estimated at 19.37 percent based on Elixhauser adjustment scheme (figure 7). The peak – representing the most common RSRR values – occurs at approximately 19 percent. Just like in AMI, wide spread variation in RSRRs is noticeable. In this case, the values spread from about 13 percent to 30 percent. Also, the distribution of RSRRs appears slightly skewed to the right. That is relative to the peak value, the sample values are slightly clustered on the right side of the histogram. No outliers are noticeable.
For pneumonia, the mean RSRR was estimated at 16.51 percent based on Elixhauser adjustment scheme (figure 8). The peak – representing the most common RSRR values – occurs at approximately 16 percent. Just like in AMI and HF, wide variation in RSRRs is noticeable - from about 11 percent to 25 percent. Largely, the distribution of RSRRs appears symmetrical although a slight right skew is noticeable. The distribution, however, has no noticeable outliers.
Finally, figure 9 represents combined RSRR distribution for the three disease conditions. Just like individual histograms, the distribution of sample data appears relatively symmetrical with no outliers. The peak occurs at RSRR of approximately 18 percent. The distribution of combined RSRRs demonstrates a slight right skew relative to the peak. In other words, a majority of hospitals had their combined RSRRs between 18 and 25 percent and the maximum value was 30.63 percent.
Figures 10 to 13 are U.S. maps showing the location and percentage RSRRs (shown on the legend) of each provider (hospital) included in AMI, HF and PN analysis. The maps demonstrate a trend whereby hospitals with RSRR greater than national mean of 18 percent are located in large urban centers such as Los Angeles, New York, Detroit and Miami. In addition, high RSRRs are noticeable among providers located along the Appalachia region that stretches from Southern tier of New York through West Virginia, East and Southern Ohio, Kentucky, Tennessee, Georgia, Alabama, and Mississippi.
Figure 10: Map of AMI RSRR by hospital location
Figure 11: Map of HF RSRR by hospital location
Figure 12: Map of PN RSRR by hospital location
Figure 13: Map of hospital-wide RSRRs by hospital location
Table 7 presents the intra-class correlation coefficients (ICCs) that resulted from estimating the “empty” or unconditional models. Thus, the ICC values represent the proportion of total variability in the respective outcome (AMI, HF or PN) attributable to county where the hospital is located. HF had the highest ICC suggesting that 37.3 percent of HF variability in RSRR is due to county-level factors where hospitals are located. Overall (all three conditions combined), ICC was estimated at 38.74 percent. Once again, the Elixhauser and Charlson adjustments yielded comparable results. Only Elixhauser results are shown in table 7.

Table 7: Unconditional ICC

<table>
<thead>
<tr>
<th>Disease Condition</th>
<th>County-Level Variance</th>
<th>Hospital-Level Variance</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>• AMI</td>
<td>0.1311</td>
<td>0.8123</td>
<td>0.1389</td>
</tr>
<tr>
<td>• Heart Failure</td>
<td>1.5082</td>
<td>2.5344</td>
<td>0.3731</td>
</tr>
<tr>
<td>• Pneumonia</td>
<td>0.8184</td>
<td>2.2677</td>
<td>0.2651</td>
</tr>
<tr>
<td>• All combined</td>
<td>1.7226</td>
<td>2.7236</td>
<td>0.3874</td>
</tr>
</tbody>
</table>

Tables 8-11 present the results of HLM models fit including county and hospital-level variables based on the Elixhauser adjusted RSRR estimates. Each table contains a first model that includes only county-level predictors and the second (fully-adjusted) model adds the hospital-level predictors. The tables also include (at the bottom) the variance component estimates for the county random effect and hospital-level residual. Since hospital-level effects are not the major focus of this study, the hospital-level mixed model results are not shown.

Table 8 below shows the results for AMI diagnosis. Overall, the estimate for all ages in poverty is non-significant in both models (p-value = 0.1121 in the fully adjusted model). The results however show that, as compared to hospitals located in counties with fewer individuals in poverty, hospitals located in counties with greater numbers of all ages in poverty (quintile 4 and 5) are more likely to have higher readmission rates. The relationship between AMI and the
county-level number of primary care physicians is also not significant in both partial and fully adjusted models. The variable percentage African American resident population is associated with significantly higher readmission rates in both partial and fully adjusted models with demonstrable strong effect in the third quintile. This suggests that hospitals located in counties with higher numbers of African Americans are more likely to have higher readmission rates and consequently more likely to be financially penalized for inordinate AMI re-hospitalizations.

Additionally, the number of skilled nursing facilities per capita and percentage number of smokers are both positively and independently associated with AMI readmission rates. Of note, as compared to all other variables included in the model, the number of skilled nursing facilities had the strongest effect. That is, among hospitals located in the highest quintile, an increase in the number of skilled nursing facilities per capita by 1 unit, increases AMI readmission rates by 0.505 (CI: 0.264, 0.746). Similarly, a 1 percent increase in the number of smokers increases AMI readmission rates by 0.254 percent (CI: 0.052, 0.455) among hospitals located in counties with highest numbers of adult smokers (quintile 5).
Table 8: Mixed models results AMI

<table>
<thead>
<tr>
<th></th>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
</tr>
<tr>
<td>Socioeconomic factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimate of all ages in poverty</td>
<td>0.2624</td>
<td></td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
<td></td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>-0.084</td>
<td>-0.182</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>-0.052</td>
<td>-0.158</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>0.018</td>
<td>-0.092</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>-0.015</td>
<td>-0.135</td>
</tr>
<tr>
<td>Access to primary care factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of primary care physicians (PCPs) per capita</td>
<td>0.2109</td>
<td></td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
<td></td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>0.015</td>
<td>-0.078</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>-0.051</td>
<td>-0.153</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>-0.100</td>
<td>-0.205</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>-0.064</td>
<td>-0.173</td>
</tr>
<tr>
<td>Demographic factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage African American</td>
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<td></td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
<td></td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>0.009</td>
<td>-0.085</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>0.163</td>
<td>0.057</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>0.270</td>
<td>0.159</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>0.129</td>
<td>0.010</td>
</tr>
</tbody>
</table>
### Table 8 continued

<table>
<thead>
<tr>
<th>Access to skilled nursing home care factors</th>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
</tr>
<tr>
<td>Number of skilled nursing facilities per capita</td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>• Quintile 1 (lowest) Ref</td>
<td>0.025</td>
<td>-0.060</td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>-0.064</td>
<td>-0.165</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>0.048</td>
<td>-0.071</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>0.048</td>
<td>-0.071</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>0.428</td>
<td>0.286</td>
</tr>
</tbody>
</table>

**Behavioral factors**

<table>
<thead>
<tr>
<th>Smoking percentage</th>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
</tr>
<tr>
<td>• Quintile 1 (lowest) Ref</td>
<td>0.106</td>
<td>-0.004</td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>0.117</td>
<td>0.005</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>0.103</td>
<td>-0.014</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>0.277</td>
<td>0.148</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>0.277</td>
<td>0.148</td>
</tr>
</tbody>
</table>

**Random Effects**

<table>
<thead>
<tr>
<th></th>
<th>SE</th>
<th>p-Value</th>
<th>SE</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>County</td>
<td>0.097</td>
<td>&lt;.0001</td>
<td>0.170</td>
<td>0.026</td>
</tr>
<tr>
<td>Hospital</td>
<td>0.816</td>
<td>&lt;.0001</td>
<td>1.123</td>
<td>0.034</td>
</tr>
</tbody>
</table>

**All p-values reported at 95% CI or Significant at p<.05**
Table 9 below presents a similar analysis for HF. Estimate of all ages in poverty is significant in the partially adjusted model but this significance disappears in the fully adjusted model. Quintile-level results suggest that hospitals located in high poverty counties are more likely to have higher HF readmission rates as compared to hospitals located in counties with fewer individuals in poverty. The number of PCPs per capita is independently and positively associated with fewer readmission rates with demonstrable strong effects in counties with higher numbers of PCPs. On the other hand, percentage African American is independently and negatively associated with HF readmissions across all quintiles. A very strong effect is noted in quintile 4 such that a 1 percent increase in African American resident population increases HF readmissions by 0.904 (CI: 0.531,1.278). Indeed, compared to all other variables included in the model, percentage African American population appears to have the strongest effect in increasing readmission rates for HF.

Per capita number of skilled nursing facilities and smoking percentage were both independently and significantly associated with HF readmission rates. In the fully adjusted model and among hospitals located in the highest quintile, the number of SNFs per capita is associated with higher readmission rates. Smoking is positively associated with HF readmissions across all categories but the strongest effect is evident in counties with the highest number of smokers (quintile 5). Overall, inclusion of hospital characteristics appears to have little to no effect on the association between county-level predictor variables and HF readmission rates.
Table 9: Mixed models results HF

<table>
<thead>
<tr>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
</tr>
<tr>
<td><strong>Socioeconomic factors</strong></td>
<td></td>
</tr>
<tr>
<td>Estimate of all ages in poverty</td>
<td>0.0059</td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>0.076</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>-0.055</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>0.101</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>0.375</td>
</tr>
<tr>
<td><strong>Access to primary care factors</strong></td>
<td></td>
</tr>
<tr>
<td>Number of primary care physicians (PCPs) per capita</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>-0.089</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>-0.299</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>-0.467</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>-0.437</td>
</tr>
<tr>
<td><strong>Demographic factors</strong></td>
<td></td>
</tr>
<tr>
<td>Percentage African American</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>• Quintile 1 (lowest)</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quintile 2</td>
<td>0.323</td>
</tr>
<tr>
<td>• Quintile 3</td>
<td>0.856</td>
</tr>
<tr>
<td>• Quintile 4</td>
<td>1.098</td>
</tr>
<tr>
<td>• Quintile 5 (Highest)</td>
<td>0.560</td>
</tr>
</tbody>
</table>
Table 9 continued

<table>
<thead>
<tr>
<th>Access to skilled nursing home care factors</th>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
</tr>
<tr>
<td>Number of skilled nursing facilities per capita</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Quintile 1 (lowest)</td>
<td>-0.129</td>
<td>-0.298</td>
</tr>
<tr>
<td>- Quintile 2</td>
<td>-0.328</td>
<td>-0.534</td>
</tr>
<tr>
<td>- Quintile 3</td>
<td>0.077</td>
<td>-0.181</td>
</tr>
<tr>
<td>- Quintile 4</td>
<td>0.844</td>
<td>0.506</td>
</tr>
<tr>
<td>- Quintile 5 (Highest)</td>
<td>1.057</td>
<td>0.784</td>
</tr>
<tr>
<td>Behavioral factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoking percentage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Quintile 1 (lowest)</td>
<td>0.094</td>
<td>-0.143</td>
</tr>
<tr>
<td>- Quintile 2</td>
<td>0.135</td>
<td>-0.105</td>
</tr>
<tr>
<td>- Quintile 3</td>
<td>0.322</td>
<td>0.072</td>
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<td>- Quintile 4</td>
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<td>p-Value</td>
</tr>
<tr>
<td>County</td>
<td>1.005</td>
<td>0.081</td>
</tr>
<tr>
<td>Hospital</td>
<td>2.535</td>
<td>0.065</td>
</tr>
</tbody>
</table>

**All p-values reported at 95% CI or Significant at p<.05**
Table 10 considers RSRR for pneumonia. Percentage estimate of all ages in poverty is not statistically or independently associated with pneumonia readmission rates in both partial and fully adjusted models. In terms of the direction of the relationship, percentage estimate of all ages in poverty is associated with increased readmission rates in quintiles 4 and 5 while lower quintiles are negatively associated with readmissions. On the other hand, the number PCPs per capita is associated with fewer pneumonia readmissions except in the lower quintiles. The greatest effect is noticeable among quintile 4 counties; a 1 unit increase in the number of PCPs per capita decreases pneumonia readmission rates by 0.391 (CI: -0.666, -0.115).

Percentage African American resident population is positively and independently associated with higher pneumonia readmission rates. Similar to HF, the strongest demographic effect was noted among hospitals in the fourth quintile. The number of skilled nursing facilities per capita is associated with higher pneumonia readmissions rates in the highest quintile meaning that increasing per capita SNFs by 1 unit in increases pneumonia re-hospitalizations by 0.403 (CI: -0.005, 0.810). Overall, smoking is positively and independently associated with higher pneumonia readmission rates except in the lowest quintile. Hospitals located in counties with highest numbers of adult smokers are associated with the greatest increase in pneumonia re-hospitalizations such that a 1 percentage increase in the number of smokers increases readmission rate by 0.663 percent (CI: 0.327, 0.999).
### Table 10: Mixed models results PN

<table>
<thead>
<tr>
<th></th>
<th>County-level predictors only</th>
<th></th>
<th>County and hospital level predictors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
<td>Upper CI</td>
<td>p-Value</td>
</tr>
</tbody>
</table>

**Socioeconomic factor**

Estimate of all ages in poverty | 0.0997     | 0.0535
- Quintile 1 (lowest) | Ref | Ref
- Quintile 2 | 0.002 | -0.188 | 0.191 | 0.9874 | -0.041 | -0.298 | 0.215 | 0.7524
- Quintile 3 | 0.116 | -0.082 | 0.314 | 0.2507 | 0.286 | -0.006 | 0.578 | 0.0549
- Quintile 4 | 0.233 | 0.020 | 0.445 | 0.0319 | 0.277 | -0.047 | 0.600 | 0.0935
- Quintile 5 (Highest) | Ref | Ref

**Access to primary care factor**

Number of primary care physicians (PCPs) per capita | 0.0125     | 0.0019
- Quintile 1 (lowest) | Ref | Ref
- Quintile 2 | 0.018 | -0.142 | 0.179 | 0.8237 | 0.074 | -0.167 | 0.316 | 0.5448
- Quintile 3 | -0.086 | -0.266 | 0.094 | 0.3476 | -0.020 | -0.282 | 0.242 | 0.8826
- Quintile 4 | -0.274 | -0.460 | -0.088 | 0.0039 | -0.391 | -0.666 | -0.115 | 0.0055
- Quintile 5 (Highest) | -0.200 | -0.394 | -0.006 | 0.0433 | -0.309 | -0.594 | -0.025 | 0.0331

**Demographic factor**

Percentage African American | <.0001     | <.0001
- Quintile 1 (lowest) | Ref | Ref
- Quintile 2 | 0.198 | 0.033 | 0.362 | 0.0186 | 0.278 | 0.007 | 0.550 | 0.0443
- Quintile 3 | 0.706 | 0.520 | 0.892 | <.0001 | 0.593 | 0.294 | 0.891 | 0.0001
- Quintile 4 | 0.836 | 0.639 | 1.032 | <.0001 | 0.670 | 0.344 | 0.996 | <.0001
- Quintile 5 (Highest) | 0.410 | 0.202 | 0.618 | 0.0001 | 0.121 | -0.228 | 0.471 | 0.4959
Table 10 continued

<table>
<thead>
<tr>
<th></th>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Lower CI</td>
</tr>
<tr>
<td><strong>Access to skilled nursing home care factor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of skilled nursing facilities per capita</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile 1 (lowest)</td>
<td>Ref</td>
<td></td>
</tr>
<tr>
<td>Quintile 2</td>
<td>-0.089</td>
<td>-0.236</td>
</tr>
<tr>
<td>Quintile 3</td>
<td>-0.163</td>
<td>-0.340</td>
</tr>
<tr>
<td>Quintile 4</td>
<td>0.257</td>
<td>0.042</td>
</tr>
<tr>
<td>Quintile 5 (Highest)</td>
<td>0.856</td>
<td>0.586</td>
</tr>
<tr>
<td><strong>Behavioral factor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smoking percentage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile 1 (lowest)</td>
<td>Ref</td>
<td></td>
</tr>
<tr>
<td>Quintile 2</td>
<td>0.109</td>
<td>-0.090</td>
</tr>
<tr>
<td>Quintile 3</td>
<td>0.180</td>
<td>-0.022</td>
</tr>
<tr>
<td>Quintile 4</td>
<td>0.265</td>
<td>0.055</td>
</tr>
<tr>
<td>Quintile 5 (Highest)</td>
<td>0.864</td>
<td>0.634</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td>SE</td>
<td>p-Value</td>
</tr>
<tr>
<td>County</td>
<td>0.522</td>
<td>0.053</td>
</tr>
<tr>
<td>Hospital</td>
<td>2.264</td>
<td>0.055</td>
</tr>
</tbody>
</table>

**All p-values reported at 95% CI or Significant at p<.05**
Finally, Table 11 below considers all three disease conditions together. Of the five county-level predictors included in the model, only the estimate of all ages in poverty is not statistically significant in the fully adjusted model. However, estimate of all ages in poverty is associated with higher readmission rates among counties with higher percentage of poverty. The number of PCPs per capita is negatively and independently associated with lower readmission rates. Percentage African American resident population is positively and independently associated with higher readmission rates in both partial and fully-adjusted models. The strongest effect is observed at the fourth quintile of the fully adjusted model where a 1 percentage increase in black only resident population is associated with 0.639 (CI: 0.366, 0.911) increase in readmissions.

The number of skilled nursing facilities per capita is associated with independent and statistically significant increase in re-hospitalizations in counties with the highest number of SNFs per capita. Smoking remained a statistically significant predictor of hospital readmissions in both models. Hospitals located in counties with high percentage number of adult smokers (quintile 5) are more likely to experience higher readmission rates overall. For instance, a 1 percentage increase in the number of smokers is associated with a 0.907 (CI: 0.536, 1.279) increase in readmission rates in counties with the highest number of smokers (quintile 5).
Table 11: Mixed models - all three medical conditions combined

<table>
<thead>
<tr>
<th>County-level predictors only</th>
<th>County and hospital level predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
</tr>
</tbody>
</table>

**Socioeconomic factors**

<table>
<thead>
<tr>
<th>Estimate of all ages in poverty</th>
<th>0.0041</th>
<th>0.0585</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Quartile 1 (lowest)</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quartile 2</td>
<td>0.081</td>
<td>-0.128</td>
</tr>
<tr>
<td>• Quartile 3</td>
<td>-0.002</td>
<td>-0.233</td>
</tr>
<tr>
<td>• Quartile 4</td>
<td>0.155</td>
<td>-0.086</td>
</tr>
<tr>
<td>• Quartile 5 (Highest)</td>
<td>0.435</td>
<td>0.178</td>
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</table>

**Access to primary care factors**

<table>
<thead>
<tr>
<th>Number of primary care physicians (PCPs) per capita</th>
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<th>&lt;.0001</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Quartile 1 (lowest)</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quartile 2</td>
<td>-0.103</td>
<td>-0.294</td>
</tr>
<tr>
<td>• Quartile 3</td>
<td>-0.338</td>
<td>-0.554</td>
</tr>
<tr>
<td>• Quartile 4</td>
<td>-0.509</td>
<td>-0.734</td>
</tr>
<tr>
<td>• Quartile 5 (Highest)</td>
<td>-0.464</td>
<td>-0.700</td>
</tr>
</tbody>
</table>

**Demographic factors**

<table>
<thead>
<tr>
<th>Percentage African American</th>
<th>&lt;.0001</th>
<th>&lt;.0001</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Quartile 1 (lowest)</td>
<td>Ref</td>
<td>Ref</td>
</tr>
<tr>
<td>• Quartile 2</td>
<td>0.346</td>
<td>0.149</td>
</tr>
<tr>
<td>• Quartile 3</td>
<td>0.982</td>
<td>0.758</td>
</tr>
<tr>
<td>• Quartile 4</td>
<td>1.213</td>
<td>0.974</td>
</tr>
<tr>
<td>• Quartile 5 (Highest)</td>
<td>0.651</td>
<td>0.399</td>
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### Table 11 continued

<table>
<thead>
<tr>
<th>Access to skilled nursing home care factors</th>
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<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of skilled nursing facilities per capita</td>
<td>County-level predictors only</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>County and hospital level predictors</td>
</tr>
<tr>
<td>Quintile 1 (lowest)</td>
<td>Ref</td>
<td>&lt;.0001</td>
<td></td>
<td></td>
<td>&lt;.0001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile 2</td>
<td>-0.137</td>
<td>-0.311</td>
<td>0.037</td>
<td>0.1235</td>
<td>-0.247</td>
<td>-0.512</td>
<td>0.017</td>
<td>0.0671</td>
<td></td>
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<tr>
<td>Quintile 3</td>
<td>-0.294</td>
<td>-0.508</td>
<td>-0.080</td>
<td>0.0071</td>
<td>-0.547</td>
<td>-0.870</td>
<td>-0.225</td>
<td>0.0009</td>
<td></td>
</tr>
<tr>
<td>Quintile 4</td>
<td>0.182</td>
<td>-0.084</td>
<td>0.448</td>
<td>0.1808</td>
<td>-0.157</td>
<td>-0.543</td>
<td>0.229</td>
<td>0.4238</td>
<td></td>
</tr>
<tr>
<td>Quintile 5 (Highest)</td>
<td>0.978</td>
<td>0.630</td>
<td>1.327</td>
<td>&lt;.0001</td>
<td>0.716</td>
<td>0.235</td>
<td>1.196</td>
<td>0.0035</td>
<td></td>
</tr>
</tbody>
</table>

| Behavioral factors |  |  |  |  |  |  |  |  |  |
| Smoking percentage | County-level predictors only |  |  |  |  |  |  |  | County and hospital level predictors |
| Quintile 1 (lowest) | Ref | <.0001 |  |  |  |  | <.0001 |  |  |
| Quintile 2 | 0.095 | -0.149 | 0.339 | 0.4457 | -0.007 | -0.345 | 0.331 | 0.9678 |
| Quintile 3 | 0.170 | -0.077 | 0.418 | 0.1771 | 0.100 | -0.240 | 0.440 | 0.5642 |
| Quintile 4 | 0.372 | 0.114 | 0.630 | 0.0048 | 0.038 | -0.317 | 0.393 | 0.8344 |
| Quintile 5 (Highest) | 1.158 | 0.876 | 1.439 | <.0001 | 0.895 | 0.507 | 1.284 | <.0001 |

<table>
<thead>
<tr>
<th>Random Effects</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>County</td>
<td>1.075</td>
<td>0.088</td>
<td>&lt;.0001</td>
<td>1.417</td>
<td>0.125</td>
<td>&lt;.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>2.728</td>
<td>0.069</td>
<td>&lt;.0001</td>
<td>2.492</td>
<td>0.085</td>
<td>&lt;.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**All p-values reported at 95% CI or Significant at p<.05**
A key research question underlying this work is how much variability these county-level predictors can account for in different RSRR measures. Table 11 below presents this information and shows that the models account for quite a bit of county-level variability but very little hospital variability. These numbers are calculated as the percent reduction in the variance components for each level relative to the empty model. In the conditional model that includes county-level factors, RSRR variability that can be attributed to the county ranges from 10.6 percent in Elixhauser-adjusted AMI to 28.5 percent in HF. Thus, the greatest reduction in ICC was in pneumonia diagnosis at 29.3 percent while AMI and PN had the least reduction at 23.4 percent each. In combined model, county-level variables included in this study accounted for 27 percent reduction in RSRR variability.

Table 12: Conditional ICC and reduction in variance over empty model

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Variance changes after including county-level covariates</th>
<th>ICC Reduction over unconditional model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>County</td>
<td>Hospital</td>
</tr>
<tr>
<td>AMI</td>
<td>0.097</td>
<td>0.815</td>
</tr>
<tr>
<td>HF</td>
<td>1.012</td>
<td>2.533</td>
</tr>
<tr>
<td>PN</td>
<td>0.523</td>
<td>2.263</td>
</tr>
<tr>
<td>ALL</td>
<td>1.075</td>
<td>2.728</td>
</tr>
</tbody>
</table>
Sensitivity Analyses

Two sensitivity analyses were performed. First, to examine the effect on county-level variances, hospitals with a single hospital were excluded from the data sample and remaining providers re-analyzed. The results were comparable and therefore the results presented above include all counties and associated hospitals that data was available. Second, to investigate the effect of comorbidity adjustment on RSRR, Charlson adjustment was run concurrently with Elixhauser adjustment. The results were relatively similar. Therefore, only Elixhauser adjusted results are presented.
Chapter 5

Discussion

This 3-year nationally representative retrospective cohort study of the relationship between contextual-level factors and hospital-level risk standardized readmission rates had four key findings. First, for AMI, HF and PN 13.9, 37.3 and 26.5 percent respectively of variability in hospital-level RSRRs could be attributed to the county of hospital location. Second, county-level per capita number of PCPs, percentage African-American resident population, the number of skilled nursing facilities per capita, and adult smoking percentage were found to be statistically and independently associated with re-hospitalization across all three disease categories. Third, after accounting for other readmission-related county-level predictor variables, poverty rate was not found to be associated with re-hospitalizations. However, high poverty rate was consistently associated with higher readmission rates even though the overall relationship was not significant. Fourth, inclusion of hospital characteristics did not appear to have substantial effect on the relationships between various county-level covariates and hospital readmission rates.

First, for AMI, HF and PN, 13.9, 37.3 and 26.5 percent respectively of variability in hospital-level RSRR could be attributed to the neighborhood of hospital location. Further, for all three disease conditions combined, 39 percent of variability in RSRR could be attributed to the county of hospital location (Table 7). These findings, though modest, are consistent with a previous research study by Herrin et al that determined that 58 percent of variability in hospital-level readmission rates was at the county level (Herrin et al., 2015; Nuckols, 2015). Findings
from these studies amplify the role of neighborhood factors in observed variability in hospital-level readmission rates. The results therefore suggest that outcome measures such as AMI, HF and PN RSRRs should appropriately account for neighborhood factors to avoid penalizing hospitals for factors that may be beyond their control. The results also suggest that CMS policies such as HRRP that unilaterally hold hospitals accountable for excess readmissions maybe insufficient in lowering readmission rates.

Noteworthy, there are several methodological and approach differences between Herrin et al. study and the current study that can potentially explain the differences in the size of overall variability noted between the two studies. First, Herrin at al. study deployed publicly available AMI, HF and PN pooled RSRR (from Hospital Compare website) as a dependent variable while this study assesses RSRR for each medical condition separately plus all three conditions combined based on administrative claims CMS raw data. Yet, it is still unclear why current study ICC finding of 39 percent differs with Herrin et al. 58 percent finding for the three medical conditions combined. Secondly, there are differences involving sample size. Analytic sample for the current study was comprised of all hospitals that RSRR could be determined based on a priori inclusion criteria – 5,351 hospitals nested in 2,466 counties (Table 4). As such, the sample for the present study included counties with a single hospital. However, a sensitivity analysis was conducted and results for analysis including and excluding counties with a single hospital were comparable. Herrin et al. study included all hospitals (4,073 hospitals nested in 2,254 counties) that had publicly reported RSRRs for any of the three medical conditions. Third, Herrin et al. study was conducted using data from pre-ACA period when hospitals had no incentive to lower readmission rates. It is clearly possible that the current study results reflect some impact of ACA readmission policies such as HRRP (Zuckerman et al., 2016).
Results of this study indicate that the influence of county factors on RSRRs varies by medical condition. HF diagnosis had the highest ICC (37.31 percent) while AMI had the lowest (13.89 percent) - highlighting important differences in how context influences 30-day re-hospitalizations in specific disease conditions. There are a few reasons why HF would be so strongly influenced by county-level factors relative to AMI and PN. First, unlike acute conditions, chronic diseases like HF tend to persist for a long time. As such, patient recovery process is more likely to be influenced by non-hospital factors such as consistent access to primary care (Graham et al., 2015). Without proper care coordination and follow-up in community settings, patients’ odds of re-hospitalization increase sharply. Notwithstanding, HF is the most common cause of hospital readmission in the Medicare program with approximately 1 in 4 re-hospitalizations within 30 days of discharge (Krumholz et al., 2009). Other research studies have demonstrated a strong link between HF re-hospitalization and SES (Eapen et al., 2015; Hawkins, Jhund, McMurray, & Capewell, 2012; Philbin et al., 2001; Rathore et al., 2006). Even though precise mechanisms are unknown, differential access to primary care may contribute to increased HF re-hospitalizations (Philbin et al., 2001). Notably, also, HF represents the endpoint of various modifiable pathophysiological processes many of which are difficult to disentangle (Hawkins et al., 2012). Largely, modifying residential environments may be an important step in lowering HF readmission rates even though broader focus on prevailing social and economic forces is seriously challenged by increasing economic and residential segregation in the U.S. (Kershaw, Osypuk, Do, De Chavez, & Diez Roux, 2015).

Meanwhile, the null or unconditional model with no covariates showed that approximately 37.3 percent of variation in HF hospital readmission rates is attributable to county-level factors (Table 7). When the 5 neighborhood factors were included in the model, the
percentage variation fell to 28.4 percent, a 23.9 percent reduction. However, of the three medical
conditions, PN had the largest reduction in variance at 29.3 percent. This demonstrates the
powerful influence of these five county factors on variability in readmission rates in the
Medicare program. As a potential area to expand this research, there are certainly many other
community-level factors not included in this analysis (due to availability of data limitations) that
could potentially explain some of the remaining 28.4 percent county-level variation in HF. Such
factors may include food insecurity, availability of physician specialists and distances to
community clinicians including PCPs and nurse practitioners. Most importantly, alternative
unmeasured mechanisms at the hospital and patient may be involved in mediating excess risk.

In regard to the association between RSRRs and neighborhood factors, five county-level
covariates were assessed. The first county-level variable that was considered was the percentage
African American resident population in a county. This variable emerged as a strong independent
and statistically significant predictor of 30-day hospital readmissions. Research studies have
shown that black patients are more likely to be Medicaid recipients and uninsured (Bhalla &
Kalkut, 2010; Joynt & Jha, 2013a; Lochner & Shoff, 2015). A study by Joynt et al. suggested
that black race may be associated with higher hospital readmission rates because black patients
tend to seek care in hospitals where care quality is sub-optimal (Joynt et al., 2011). As such, the
fact that hospitals located in counties with higher African American resident population are more
likely to experience higher readmission rates is not entirely astounding. Previous research studies
have found similar strong effects of race on readmission rates (Joynt et al., 2011; Krumholz &
Bernheim, 2014; Rathore et al., 2003; Wan et al., 2015). However, one study found a protective
effect (Singh et al., 2014). As such it is not completely clear which position is truly
representative of the effect of race on readmission rates.
Besides seeking care in poorly performing hospitals, other mechanisms may be responsible for disproportionate re-hospitalizations observed among minority black patients. These mechanisms include limited access to high-quality outpatient care, financial constraints and prevailing social norms (Baicker et al., 2004; Fiscella, Franks, Doescher, & Saver, 2002; Greysen et al., 2014; Jones et al., 2015; Qian et al., 2013). Even so, the underlying mechanisms that predispose blacks to increased risk of hospital readmission have not been adequately explored. Nonetheless, it is clear from this research that concerns regarding unfair performance assessment of safety-net hospitals due to failure to account for patients’ race or socioeconomic factors may indeed be valid (Lipstein & Dunagan, 2014). In the current CMS readmission model, race is not being adjusted for when determining hospital specific RSRRs. CMS and policy experts have argued that race adjustment would mean that lower quality of care is acceptable in hospitals serving disadvantaged minority patients (Krumholz & Bernheim, 2014).

Another county-level variable that was considered in this study is per capita number of SNFs. This variable was found to be associated with a statistically significant increase in Medicare re-hospitalizations. That is, as the county-level number of SNFs per capita increased, readmission rates for all three disease conditions increased – even after controlling for related county and hospital level variables. These findings may suggest a link between the quality of care in SNFs and 30-day risk of hospital readmission (Konetzka, Polsky, & Werner, 2013). CMS is planning to soon start penalizing SNFs for excessive hospital readmission rates (Carnahan, Unroe, & Torke, 2016). Previous research indicates that approximately 1 in 5 Medicare beneficiaries in the U.S. are discharged to SNF following an acute care hospitalization (Allen et al., 2011). Of these, 23.5 percent are readmitted to the hospital within 30 days at a cost of over 4 billion (Mor et al., 2010).
Alternatively, the findings may suggest that hospitals located in counties with higher numbers of SNFs maybe more incentivized to discharge their patients to SNFs relative to home care. Consequently, more Medicare patients in SNFs may mean a potential larger pool of those who are likely to be readmitted to an acute care hospital within 30-days of discharge. Notable, relative to Medicaid nursing facilities and home care, SNFs remain the most likely source of unplanned hospital readmissions in the Medicare program (Medicare Payment Advisory Commission, 2012). These findings are supported by previous work that found a strong association between discharge to SNF and increased rate of re-hospitalization among Medicare patients diagnosed with heart failure (Allen et al., 2011). However, a study by Ogunnaya et al. found no correlation between SNFs quality ratings and HF readmission rates (Ogunnaya et al., 2015).

In surgical Medicare patients, hospital-SNF linkages characterized by efficient communication between providers have been found to meaningfully reduce hospital readmission rates (Schoenfeld et al., 2016). Granted, in the U.S. SNFs occupy an important access to care position by providing critical short-term skilled nursing and rehabilitation services to Medicare beneficiaries. However, current findings underscore the need to optimize quality of care in SNFs. Even so, it is important for SNF and hospital providers to work together to improve care transitions and overall care coordination for patients entering SNFs from acute care settings (Berkowitz et al., 2013; Jacobs, 2011; Meehan TP et al., 2015; Neuman et al., 2014).

Smoking rate was another variable assessed in this study. Figure 14 below shows county-level smoking rates for all counties included in this study. High adult smoking rates can be observed along the Appalachia region. Current research study results indicated that the percentage number of smokers within a county is significantly and independently associated with
30-day risk of hospital readmission in the Medicare program. In previous research studies, living in a disadvantaged neighborhood has been associated with increased rate of individual-level cigarette smoking and poor health outcomes (Calvillo-King et al., 2013; Chuang, Cubbin, Ahn, & Winkleby, 2005; Diez-Roux et al., 1997). At individual level, smokers have been shown to have a higher risk of readmission when compared to non-smokers or never smokers (Gorina, Pratt, Kramarow, & Elgaddal, 2015).

Moreover, even though smoking rates vary substantially between counties (figure 14) research studies have shown unequivocally that cigarette smoking remains a leading risk factor for morbidity and mortality across the U.S. (Dwyer-Lindgren et al., 2014; Mokdad, Marks, Stroup, & Gerberding, 2004). Details on how smoking causes disease and other health consequences of smoking have been discussed extensively elsewhere (U.S. Department of Health and Human Services, 2010; U.S. Department of Health and Human Services, 2014).

Additionally, neighborhood cigarette smoking rates may be related to hospital readmission through a variety of other mechanisms. One pathway may be that living in a poor neighborhood increases the risk of smoking, in turn affecting individual health and consequently heightening the chances of hospital admission and readmission. Other factors may include heightened publicity and easy access to cigarettes. Research studies have also demonstrated a strong relationship between cigarette smoking rates and income, educational achievement and race (Dwyer-Lindgren et al., 2014; Wetter et al., 2005).
Figure 14: County-level smoking rates (%)
Other reasons that may predispose individuals in a neighborhood to smoke include stressors and resources to deal with stressors, and social norms and interactions that impact values and consumption habits. These and other mechanisms and related interactions are beyond the scope of this work. What this research provides is important insights regarding a possible independent role of county-level smoking rates on 30-day readmission risk among Medicare patients diagnosed with HF, AMI and PN. In addition, findings from this study posit that progress in reducing 30-day readmission rates in Medicare program will indeed be limited if communities with high smoking rates are not included in the national health policy agenda.

Another county-level variable included in this study was the per capita number of PCPs. Consistent with previous research studies, findings from this research indicate that within county per capita number of PCPs is associated with lower hospital-level readmission rates. PCP consultation and follow-up following an acute hospital stay is a critical component of care continuity. Indeed, it is only through primary care appointments that early signs of worsening disease or medication non-compliance can be detected and addressed - curtailing any potential re-hospitalization. Generally, post discharge care coordination with PCPs is associated with optimal patient outcomes. Notably, in this current study, the U.S. regions along the Appalachia appear to have fewer PCPs when compared to other U.S. regions (see map in Appendix H). A study by Brooke et al. indicated that access to primary care, care coordination and PCP follow-up is associated with decreased risk of 30-day hospital readmission (Brooke et al., 2014). However, some studies have found the opposite. Though rather contradictory, a study by Brown et al. demonstrated a strong positive correlation between per capita rate of primary care physicians and hospital readmission rates (J. R. Brown et al., 2014). Part of the reason for this is heightened care that uncovers new disease conditions that would otherwise not have been
detected if access to primary care was limited or nonexistent (Weinberger et al., 1996). Largely, access to primary care, care coordination, and PCP follow-up have been associated with decreased risk of 30-day hospital readmission (Brooke et al., 2014).

A final variable that was considered is poverty rate. This study found that county poverty rate was not associated with 30-day re-hospitalization independent of other known neighborhood-level factors. That is, after adjusting for county and hospital-level predictors, county-level poverty rate remained statistically non-significant across all three disease categories. It is entirely possible that some of the covariates included in the final model are indeed mediators of the relationship between poverty and RSRRs. Adjustment for the mediator may mask the total impact of poverty rate (Christenfeld, Sloan, Carroll, & Greenland, 2004). Nonetheless, current results show that poverty rate was consistently associated with higher readmission rates among counties with higher percentage of poverty even though the overall relationship was not significant. In previous research studies, neighborhood poverty and low SES have been consistently attributed to poor health outcomes including unplanned hospital readmissions and mortality (Hu et al., 2014; Winkleby & Cubbin, 2003).

The likely causal pathways under which poverty and broader social context influence unplanned hospital readmissions are complex but may include factors such as lack of transportation to primary care medical appointments, inability to meet copayments, and lack of proper social support systems. Remarkably, these mechanisms seem to have no effect on hospital readmissions in the Medicare cohort included in this study although interactions were not assessed. Of note, use of single constructs - such as poverty or income - in predicting and explaining hospital readmissions remains a contested area and research findings on utility of such constructs is mixed (Philbin et al., 2001; Shavers, 2007; van Walraven et al., 2013).
Granted, neighborhood socioeconomic disadvantage is an intricate theoretical concept to define and measure (Hu et al., 2014; Phelan, Link, & Tehranifar, 2010; Shavers, 2007). A recent study demonstrated that accounting for patients’ socioeconomic status had no effect on hospital readmission rates regardless of the SES measure used or diagnosis type studied (Bernheim et al., 2016). These findings illuminate the uncertainty surrounding the decision of whether to categorically risk-adjust hospital readmission rates for patients’ SES.

Nonetheless, several experts have called for further adjustment of RSRR to include patients’ socioeconomic status and other demographic factors. Findings from this study support that position. Overall, of the five county-level variables in the final multivariate model, the variables that mattered the most, with significant findings in all three disease categories were per capita number of PCPs, percentage African American population, the number of skilled nursing facilities per capita, and adult smoking rates. As such, CMS should probably consider including these four factors in future risk adjustment models involving AMI, HF and PN medical conditions among Medicare beneficiaries. Even though poverty rate was statistically significant in bivariate assessment, this variable remained non-significant across all three medical conditions when included with other county- and hospital-level variables. This finding suggests that additional research regarding the proper role of contextual variables such as poverty rates on RSRRs is indeed required.

Finally, findings from this study indicate that following the passage of ACA and during a period of rapid decrease in RSRRs (figure 2), county-level factors continued to play a significant role in observed variability in 30-day RSRRs. However, the impact of county-level factors on combined AMI, HF and PN RSRR was not as great as suggested in previous work by Herrin et al. (Herrin et al., 2015). The period between years 2010 and 2013, when data for the current
study were collected, was characterized by heightened hospital activities such as increased patient follow-up and care coordination to reduce readmission rates and consequently avoid potential financial penalties (Farrell et al., 2015; Hansen et al., 2013; Heeke et al., 2014; Lu et al., 2016). Even so, additional post-ACA period research studies are required to ascertain the proper role of hospital neighborhood factors in 30-day readmission rates.

**Implications for Health Policy**

Findings from this study underscore the importance of neighborhood factors in explaining variability in hospital-level RSRRs among Medicare patients. The results suggest that unilateral policy focus on patient or hospital-level risk factors may be insufficient in reducing variability in hospital readmission rates in the Medicare program. Greater focus on contextual social and behavioral factors is warranted. As such, hospital discharge and transitional care decisions should carefully evaluate patients’ social conditions and prioritize interventions appropriately. Accordingly, interventional strategies pursued must adequately locate and address modifiable risk factors such as barriers to care in the communities where patients live. More than ever before, hospitals are now required to actively start identifying and addressing risk factors in communities where their patients live (L. G. Burke & Jha, 2015).

Findings from this study call for greater support for broader health policy solutions that integrate patient, hospital, and contextual-level interventions. Specifically, readmission policy solutions must ensure that hospitals serving vulnerable populations are not unfairly targeted with financial penalties. NQF recently recommended adjusting for social determinants of health when determining financial penalties and this current work supports that position (National Quality Forum, 2014). Furthermore, this work suggests that focusing resources on improving
neighborhoods health through programs such as smoking cessation is crucial in minimizing both
hospital readmissions and associated variability in readmission rates. Figures 13 and 14
demonstrate a striking similarity suggesting that hospitals with high readmission rates are also
located in counties with high adult smokers. Hospital readmission policy ideas must be broad
enough to incorporate such patterns when strategizing interventions.

Moreover, this research work has implications on broader provider-payer cooperation in
addressing readmissions by emphasizing the need for innovative approaches to collecting
broader set of variables beyond clinical characteristics that can be included with administrative
Medicare data sets (Padhukasahasram et al., 2015). Currently, patient SES indicators such as
income, employment and education level are not routinely collected. To reasonably confront
questions related to variability in RSRRs, these variables must be captured during routine clinical
appointments and adequately integrated with clinical and administrative data.

Further, findings from this study have implications on provider-provider cooperation and
benchmarking to improve patient care. Comparison of hospital-specific readmission metrics with
industry bests will be fundamental in the years ahead. Indeed, in a report to Congress in June
2013, MedPAC suggested incorporating such a comparison in RSRR computation process
(Medicare Payment Advisory Commission, 2013). Since hospitals performing poorly in
readmissions are targets for quality improvement, hospitals in the lower performance quartile can
develop learning partnerships or alliances with advanced or better-performing hospitals. (Leape,
2015). To efficiently do so, hospital leaders must engage community providers, enhance
connections, and continuously improve care coordination.

The fact that several county level covariates included in this study appear to have similar
associations with RSRRs across the three medical conditions, suggests the systemic nature of
neighborhood effects – a multiplicity of interrelated neighborhood factors operating through interrelated mechanisms to affect RSRRs (Cubbin, Pedregon, Egerter, & Braveman, 2008; Diez Roux & Mair, 2010; Diez Roux, 2016). As such, the most impactful interventions are the ones that can activate change holistically. That is, policies that simultaneously improve hospital quality of care, discharge processes, coordination of care, enhance primary care and deter harmful behaviors such as cigarette smoking. Yet, rigorous research on the effectiveness of different interventions and real policies is required to not only enhance understanding of causation but also to stimulate development of better policies in future.

In summary, findings from this study have provided evidence on the link between county-level PCP rates and 30-day RSRRs to recommend design and implementation of policies which support greater PCP availability and access in community settings. In addition, findings from this study have provided evidence on the link between county-level African American population and 30-day RSRR to recommend strengthening policies that minimize residential segregation by race or social class. County or state-level housing or urban zoning policies may seem distant from health care realm but findings from this study suggest that such policies may have tremendous effect on clinical outcomes including 30-day readmission rates. (Diez Roux & Mair, 2010). Moreover, this study provides evidence of the link between county-level NSFs and 30-day RSRRs, effectively suggesting a need for enhancement of policies that can improve quality of care in SNFs. On smoking, current findings suggest that strengthening policies that deter smoking is fundamental in addressing early 30-day re-hospitalizations in the Medicare program.
**Limitations**

This study has limitations that will need to be considered in assessing findings. First, due to data limitations, individual-level SES indicators and other healthcare system factors such as spending patterns could neither be measured nor controlled for. As such, it is not clear whether noted effects are likely to persist once individual-level SES attributes or other health system factors are controlled for. Granted, it is partially or entirely possible that neighborhood effects noted in this work are just proxies of unmeasured aspects of individual attributes (Geronimus & Bound, 1998; Pickett & Pearl, 2001; Soobader, LeClere, Hadden, & Maury, 2001). However, Bikdeli et al. showed that as compared to individual SES status, neighborhood SES may be a strong predictor of re-hospitalization in HF (Bikdeli et al., 2014). Overall, context measures may not be representative of accurate individual attributes and residual confounding of results because of omitted individual-level covariates such as individual-level SES indicators could be ruled out.

Second, neighborhood was operationally defined as county of hospital location. County as a proxy of neighborhood may be too spacious. Indeed, there are suggestions that poverty at the census block group level is more robustly associated with health outcomes when compared to poverty at county level (Pickett & Pearl, 2001). Accumulated body of research has shown that use of census block-groups that consist of approximately 1000 residents is more ideal in assessing the effects of neighborhoods on health outcomes (Diez Roux et al., 2001; Diez-Roux et al., 1997). On a similar note, in this study county-level variables were regarded as direct indicators of group properties, exerting their influence uniformly on all persons within the county. Granted, there has been considerable criticism leveled at use of derived neighborhood variables as indirect measures of neighborhood properties.
Third, in being able to detect any county-level effects, ensuring variation in the ecological exposure is an indispensable requirement. Our identification of moderate ecological effects as compared to a previous similar study by Herrin et al. may be partly a result of cross-sectional (one point in time) nature of the study design. It is possible that a longitudinal design that for instance assesses poverty at several points in time would detect even greater variation. Due to data limitations, our research design could not accommodate a longitudinal research design. Moreover, considering that this is a cross-sectional observational study, any relationships identified cannot be interpreted as causal but may provide important insights regarding variability in readmission rates across hospitals in the U.S for Medicare patients with a principle discharge diagnosis of AMI, HF and PN.

Fifth, analysis was conducted using Medicare data and therefore findings may not be generalized to patient’s age 65 or less. Also, study findings reflect the experience of Medicare FFS patients diagnosed with AMI, HF and PN only. As such, findings may not necessarily be generalizable to other populations or disease conditions including patients seen in federal hospitals such as Veterans Affairs (VA). In addition, Medicare data used in the study were from 2011 to 2013 and therefore may not be truly representative of the current healthcare environment in 2016.

Finally, the method used to identify county-level variables to be included in this study relied heavily on associations noted in extant literature. Granted, application of multi-level statistical methods should be strongly predicated on theoretical framework. But still, it is possible that deployment of other methods such principle components analysis (PCA) may have yielded better estimates of county effects (Herrin et al., 2015; Winkleby & Cubbin, 2003). Most importantly,
no ecological study is perfect and as Tu et al. indicates, the strength of inference is purely based on other relatively similar studies finding the same results (Tu & Ko, 2008).

**Conclusion**

Findings from this study underscore the importance of county-level factors in influencing variability in RSRRs in the Medicare program. The findings indicate that the influence of county-level factors varies by medical condition. HF was identified as the medical condition most influenced by county-level factors such as the number of PCPs, percent African American resident population, the number of skilled nursing facilities per capita, and adult smoking rates. Even though poverty rate was associated with RSRRs in bivariate assessments, this variable remained non-significant across all disease categories when included with other county- and hospital-level variables. Current variability in readmission rates in the Medicare program can be optimally addressed if county-level factors are recognized and included in future risk adjustment models. Most importantly, hospitals can adopt public health-minded strategies such as committing resources in community settings to promote better health for Medicare patients.
## APPENDICES

### Appendix A: Conceptual Definitions and Theoretical Origins of Model Components

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary Outcome Variable:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Readmission rate</td>
<td>Risk-adjusted odds of all-cause readmission for heart failure, myocardial infarction and pneumonia</td>
<td>Literature on all-cause hospital readmissions</td>
</tr>
<tr>
<td>County-level variables:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary Care Physicians (PCPs)</td>
<td>Physician who provides both the first contact for a person with an undiagnosed health concern as well as continuing care.</td>
<td>Hospital and health-system literature</td>
</tr>
<tr>
<td>Median annual household income</td>
<td>Income of the householder and all other individuals 15 years old and over in a household over 12 months.</td>
<td>Literature on health care disparities</td>
</tr>
<tr>
<td>Estimate of all ages in poverty</td>
<td>Percentage of all ages below the poverty level within the county. Poverty level is derived on a sample basis by comparing total family income to an income cutoff or poverty threshold after adjusting for family size, number of children, and age of family householder.</td>
<td>Literature on health care disparities</td>
</tr>
<tr>
<td>Percentage African American</td>
<td>Defined as percentage of persons having origins in any of the black racial groups of Africa. It includes all persons indicating their race as Black, African American, or who provided written entries such as African American, Afro American, Kenyan, Nigerian, or Haitian.</td>
<td>Literature on health care disparities</td>
</tr>
<tr>
<td>Per capita number of skilled nursing facilities (SNFs)</td>
<td>Defined as the number of Medicare certified facilities providing long-term care for the elderly or other patients requiring chronic care in a non-acute setting.</td>
<td>Literature on health care disparities and access to care</td>
</tr>
<tr>
<td>Population aged 65 or older in nursing homes</td>
<td>Defined as the percentage of elderly (65 years and above) in institutionalized nursing quarters.</td>
<td>Access to post-acute care literature</td>
</tr>
</tbody>
</table>
## Appendix A continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adult smoking</td>
<td>Defined as the percentage of adults that reported current smoking based on Behavioral Risk Factor Surveillance System (BRFSS) 2014 survey data.</td>
<td>Behavioral health literature</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Hospital-level variables

- **Safety-net status**
  - Providing significant level of care to low-income, uninsured and vulnerable populations.
  - Literature on Medicaid utilization and safety-net status

- **Length of stay (LOS)**
  - Mean hospital index hospitalization LOS for heart failure, heart attack and pneumonia
  - Length of stay literature

- **Ownership**
  - Type of ownership
  - Hospital ownership literature

- **Teaching status**
  - Council of teaching hospitals membership or affiliation with a medical school
  - Hospital ownership literature

- **Bed size**
  - Number of beds based on American Hospital Association data
  - Hospital ownership literature

- **Setting**
  - Location of the hospital based on American Hospital Association classification
  - Hospital ownership literature

- **Region**
  - Geographical location of the hospital based on American Hospital Association classification
  - Hospital ownership literature
## Appendix B: Operational Definitions and measurement Format of Study Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Definition</th>
<th>Value</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary Outcome Variable:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Readmission rate</td>
<td>Dependent</td>
<td>Hospital-level risk-adjusted odds of all-cause readmission for heart failure, myocardial infarction and pneumonia</td>
<td>Continuous</td>
<td>Medicare SAF datasets</td>
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<tr>
<td><strong>County-level variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Primary Care Physicians (PCPs)</td>
<td>Independent</td>
<td>Per capita rate of physicians in primary care</td>
<td>Continuous</td>
<td>County Health Rankings and Roadmaps</td>
</tr>
<tr>
<td>• Median annual household income</td>
<td>Independent</td>
<td>Income of the householder and all other individuals 15 years old and over in a household over 12 months.</td>
<td>Continuous</td>
<td>U.S. Census Bureau</td>
</tr>
<tr>
<td>• Estimate of all ages in poverty</td>
<td>Independent</td>
<td>Percentage of all ages below the poverty level within the county.</td>
<td>Continuous</td>
<td>U.S. Census Bureau</td>
</tr>
<tr>
<td>• Percentage African American</td>
<td>Independent</td>
<td>Percentage of persons having origins in any of the black racial groups of Africa</td>
<td>Continuous</td>
<td>County Health Rankings and Roadmaps</td>
</tr>
<tr>
<td>• Number of skilled nursing facilities (SNFs)</td>
<td>Independent</td>
<td>The number of Medicare certified facilities providing long-term care for the elderly or other patients requiring chronic care in a non-acute setting.</td>
<td>Continuous</td>
<td>Area Health Resource Files</td>
</tr>
<tr>
<td>• Population aged 65 or older in nursing homes</td>
<td>Independent</td>
<td>The percentage of elderly (65 years and above) in institutionalized nursing quarters.</td>
<td>Continuous</td>
<td>Area Health Resource Files</td>
</tr>
<tr>
<td>• Adult smoking</td>
<td>Independent</td>
<td>Behavioral Risk Factor Surveillance System reported adults smoking rates</td>
<td>Continuous</td>
<td>County Health Rankings and Roadmaps</td>
</tr>
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</table>
### Appendix B continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Definition</th>
<th>Value</th>
<th>Data Source</th>
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</thead>
<tbody>
<tr>
<td><strong>Hospital-level variables</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Safety-net status</td>
<td>Hospital (level-1) variable</td>
<td>Amount of disproportionate Share Hospital (DSH) received.</td>
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<td>Medicare Denominator files</td>
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<tr>
<td>• Average Length of Stay (ALOS)</td>
<td>Hospital (level-1) variable</td>
<td>Mean duration of a single episode of hospitalization calculated by dividing the sum of inpatient days by the number of patient’s admissions with the same diagnosis-related group classification</td>
<td>Continuous</td>
<td>American Hospital Association (AHA) Medicare data</td>
</tr>
<tr>
<td>• Ownership</td>
<td>Hospital (level-1) variable</td>
<td>Private - For profit, private Not for profit, public</td>
<td>Categorical (3 levels)</td>
<td>American Hospital Association (AHA) Annual survey</td>
</tr>
<tr>
<td>• Teaching status</td>
<td>Hospital (level-1) variable</td>
<td>Council of teaching hospitals membership or affiliation with a medical school</td>
<td>Binary</td>
<td>American Hospital Association (AHA) Annual survey</td>
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<tr>
<td>• Bed size</td>
<td>Hospital (level-1) variable</td>
<td>Number of acute care beds based on American Hospital Association data</td>
<td>Categorical</td>
<td>American Hospital Association (AHA) Annual survey</td>
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<tr>
<td>• Geography</td>
<td>Hospital (level-1) variable</td>
<td>Rural versus urban</td>
<td>Binary</td>
<td>American Hospital Association (AHA) Annual survey</td>
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<tr>
<td>• Region</td>
<td>Hospital (level-1) variable</td>
<td>Geographical location of the hospital based on American Hospital Association classification</td>
<td>Categorical (4 levels)</td>
<td>American Hospital Association (AHA) Annual survey</td>
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</table>
## Appendix C: Number of All Beneficiaries by State

<table>
<thead>
<tr>
<th>Provider State</th>
<th>Frequency</th>
<th>Percent</th>
<th>Cumulative Frequency</th>
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<tr>
<td>Alabama</td>
<td>165306</td>
<td>1.96</td>
<td>165306</td>
</tr>
<tr>
<td>Alaska</td>
<td>10123</td>
<td>0.12</td>
<td>175429</td>
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<tr>
<td>Arizona</td>
<td>117252</td>
<td>1.39</td>
<td>292681</td>
</tr>
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<td>Arkansas</td>
<td>113367</td>
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<td>406048</td>
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<tr>
<td>California</td>
<td>585512</td>
<td>6.94</td>
<td>991560</td>
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<td>Colorado</td>
<td>71749</td>
<td>0.85</td>
<td>1063309</td>
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<tr>
<td>Connecticut</td>
<td>113632</td>
<td>1.35</td>
<td>1176941</td>
</tr>
<tr>
<td>Delaware</td>
<td>30629</td>
<td>0.36</td>
<td>1207570</td>
</tr>
<tr>
<td>District of Columbia</td>
<td>22494</td>
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<td>1230064</td>
</tr>
<tr>
<td>Florida</td>
<td>582986</td>
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<td>1813050</td>
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<tr>
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<td>220667</td>
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<td>2033717</td>
</tr>
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<td>0.18</td>
<td>2049079</td>
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## Appendix F-1: ICD-9-CM Codes for AMI Cohort

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<td>410.80</td>
<td>Acute myocardial infarction of other specified sites, episode of care unspecified</td>
</tr>
<tr>
<td>410.81</td>
<td>Acute myocardial infarction of other specified sites, initial episode of care</td>
</tr>
<tr>
<td>410.90</td>
<td>Acute myocardial infarction of unspecified site, episode of care unspecified</td>
</tr>
<tr>
<td>410.91</td>
<td>Acute myocardial infarction of unspecified site, initial episode of care</td>
</tr>
</tbody>
</table>
## Appendix F-2: ICD-9-CM Codes for HF Cohort

<table>
<thead>
<tr>
<th>Diagnosis Codes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>402.01</td>
<td>Malignant hypertensive heart disease with heart failure</td>
</tr>
<tr>
<td>402.11</td>
<td>Benign hypertensive heart disease with heart failure</td>
</tr>
<tr>
<td>402.91</td>
<td>Unspecified hypertensive heart disease with heart failure</td>
</tr>
<tr>
<td>404.01</td>
<td>Hypertensive heart and chronic kidney disease, malignant, with heart failure</td>
</tr>
<tr>
<td></td>
<td>and with chronic kidney disease stage I through stage IV, or unspecified</td>
</tr>
<tr>
<td>404.03</td>
<td>Hypertensive heart and chronic kidney disease, malignant, with heart failure</td>
</tr>
<tr>
<td></td>
<td>and with chronic kidney disease stage V or end stage renal disease</td>
</tr>
<tr>
<td>404.11</td>
<td>Hypertensive heart and chronic kidney disease, benign, with heart failure</td>
</tr>
<tr>
<td></td>
<td>and with chronic kidney disease stage I through stage IV, or unspecified</td>
</tr>
<tr>
<td>404.13</td>
<td>Hypertensive heart and chronic kidney disease, benign, with heart failure</td>
</tr>
<tr>
<td></td>
<td>and chronic kidney disease stage V or end stage renal disease</td>
</tr>
<tr>
<td>404.91</td>
<td>Hypertensive heart and chronic kidney disease, unspecified, with heart</td>
</tr>
<tr>
<td></td>
<td>failure and with chronic kidney disease stage I through stage IV, or</td>
</tr>
<tr>
<td></td>
<td>unspecified</td>
</tr>
<tr>
<td>404.93</td>
<td>Hypertensive heart and chronic kidney disease, unspecified, with heart</td>
</tr>
<tr>
<td></td>
<td>failure and chronic kidney disease stage V or end stage renal disease</td>
</tr>
<tr>
<td>428.0</td>
<td>Congestive heart failure, unspecified</td>
</tr>
<tr>
<td>428.1</td>
<td>Left heart failure</td>
</tr>
<tr>
<td>428.20</td>
<td>Systolic heart failure, unspecified</td>
</tr>
<tr>
<td>428.21</td>
<td>Acute systolic heart failure</td>
</tr>
<tr>
<td>428.22</td>
<td>Chronic systolic heart failure</td>
</tr>
<tr>
<td>428.23</td>
<td>Acute on chronic systolic heart failure</td>
</tr>
<tr>
<td>428.30</td>
<td>Diastolic heart failure, unspecified</td>
</tr>
<tr>
<td>428.31</td>
<td>Acute diastolic heart failure</td>
</tr>
<tr>
<td>428.32</td>
<td>Chronic diastolic heart failure</td>
</tr>
<tr>
<td>428.33</td>
<td>Acute on chronic diastolic heart failure</td>
</tr>
<tr>
<td>428.40</td>
<td>Combined systolic and diastolic heart failure, unspecified</td>
</tr>
<tr>
<td>428.41</td>
<td>Acute combined systolic and diastolic heart failure</td>
</tr>
<tr>
<td>428.42</td>
<td>Chronic combined systolic and diastolic heart failure</td>
</tr>
<tr>
<td>428.43</td>
<td>Acute on chronic combined systolic and diastolic heart failure</td>
</tr>
<tr>
<td>428.9</td>
<td>Heart failure, unspecified</td>
</tr>
</tbody>
</table>
### Appendix F-3: ICD-9-CM Codes for PN Cohort

<table>
<thead>
<tr>
<th>ICD-9-CM Diagnosis Codes</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>480.0</td>
<td>Pneumonia due to adenovirus</td>
</tr>
<tr>
<td>480.1</td>
<td>Pneumonia due to respiratory syncytial virus</td>
</tr>
<tr>
<td>480.2</td>
<td>Pneumonia due to parainfluenza virus</td>
</tr>
<tr>
<td>480.3</td>
<td>Pneumonia due to SARS-associated coronavirus</td>
</tr>
<tr>
<td>480.8</td>
<td>Pneumonia due to other virus not elsewhere classified</td>
</tr>
<tr>
<td>480.9</td>
<td>Viral pneumonia, unspecified</td>
</tr>
<tr>
<td>481</td>
<td>Pneumococcal pneumonia [Streptococcus pneumoniae pneumonia]</td>
</tr>
<tr>
<td>482.0</td>
<td>Pneumonia due to Klebsiella pneumoniae</td>
</tr>
<tr>
<td>482.1</td>
<td>Pneumonia due to Pseudomonas</td>
</tr>
<tr>
<td>482.2</td>
<td>Pneumonia due to Hemophilus influenzae [H. influenzae]</td>
</tr>
<tr>
<td>482.30</td>
<td>Pneumonia due to Streptococcus, unspecified</td>
</tr>
<tr>
<td>482.31</td>
<td>Pneumonia due to Streptococcus, group A</td>
</tr>
<tr>
<td>482.32</td>
<td>Pneumonia due to Streptococcus, group B</td>
</tr>
<tr>
<td>482.39</td>
<td>Pneumonia due to other Streptococcus</td>
</tr>
<tr>
<td>482.40</td>
<td>Pneumonia due to Staphylococcus, unspecified</td>
</tr>
<tr>
<td>482.41</td>
<td>Methicillin susceptible pneumonia due to Staphylococcus aureus</td>
</tr>
<tr>
<td>482.42</td>
<td>Methicillin resistant pneumonia due to Staphylococcus aureus</td>
</tr>
<tr>
<td>482.49</td>
<td>Other Staphylococcus pneumonia</td>
</tr>
<tr>
<td>482.81</td>
<td>Pneumonia due to anaerobes</td>
</tr>
<tr>
<td>482.82</td>
<td>Pneumonia due to escherichia coli [E. coli]</td>
</tr>
<tr>
<td>482.83</td>
<td>Pneumonia due to other gram-negative bacteria</td>
</tr>
<tr>
<td>482.84</td>
<td>Pneumonia due to Legionnaires' disease</td>
</tr>
<tr>
<td>482.89</td>
<td>Pneumonia due to other specified bacteria</td>
</tr>
<tr>
<td>482.9</td>
<td>Bacterial pneumonia, unspecified</td>
</tr>
<tr>
<td>483.0</td>
<td>Pneumonia due to mycoplasma pneumoniae</td>
</tr>
<tr>
<td>483.1</td>
<td>Pneumonia due to chlamydia</td>
</tr>
<tr>
<td>483.8</td>
<td>Pneumonia due to other specified organism</td>
</tr>
<tr>
<td>485</td>
<td>Bronchopneumonia, organism unspecified</td>
</tr>
<tr>
<td>486</td>
<td>Pneumonia, organism unspecified</td>
</tr>
<tr>
<td>487.0</td>
<td>Influenza with pneumonia</td>
</tr>
<tr>
<td>488.11</td>
<td>Influenza due to identified 2009 H1N1 influenza virus with pneumonia</td>
</tr>
<tr>
<td>507.0</td>
<td>Pneumonitis due to inhalation of food or vomitus</td>
</tr>
</tbody>
</table>
Appendix G-1: Assessment of Multicollinearity – all predictors included in the model (High VIF and high Condition Index)

<table>
<thead>
<tr>
<th>Parameter Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
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<tr>
<td>Intercept</td>
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<tr>
<td>PercPovAllAges</td>
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<tr>
<td>MedianHIncome</td>
</tr>
<tr>
<td>PCP_Rate</td>
</tr>
<tr>
<td>Age65plusperc</td>
</tr>
<tr>
<td>percAfAm</td>
</tr>
<tr>
<td>SNF_2013</td>
</tr>
<tr>
<td>perc65plusinmuring</td>
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<tr>
<td>SmokersPerc</td>
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</table>

<table>
<thead>
<tr>
<th>Collinearity Diagnostics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
</tr>
<tr>
<td>1</td>
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</tr>
<tr>
<td>5</td>
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<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
</tbody>
</table>
### Appendix G-2: Assessment of Multicollinearity – with only 5 predictor variables in the model

#### Parameter Estimates

| Variable          | Label                                      | DF | Parameter Estimate | Standard Error | t Value | Pr > |t| | Tolerance | Variance Inflation |
|-------------------|--------------------------------------------|----|--------------------|----------------|---------|-------|---|-----------|-------------------|
| Intercept         | Intercept                                  | 1  | 13.06141           | 0.12729        | 102.61  | <.0001|   |           |                   |
| PercPovAllAges    | Poverty Percent, All Ages                  | 1  | 0.01037            | 0.00480        | 2.16    | 0.0309|   | 0.54266   | 1.84276           |
| PCP_Rate          | Primary Care Physician Rate                | 1  | -0.00251           | 0.00067829     | -3.70   | 0.0002|   | 0.89332   | 1.11942           |
| percAfAm          | % African American                         | 1  | 0.00885            | 0.00164        | 5.39    | <.0001|   | 0.76320   | 1.31028           |
| SNF_2013          | # Skilled Nursing Facilities 2013          | 1  | 0.00529            | 0.00039327     | 13.45   | <.0001|   | 0.84032   | 1.19003           |
| SmokersPerc       | % Smokers                                  | 1  | 0.06979            | 0.00714        | 9.77    | <.0001|   | 0.56521   | 1.76925           |

#### Collinearity Diagnostics

<table>
<thead>
<tr>
<th>Number</th>
<th>Eigenvalue</th>
<th>Condition Index</th>
<th>Intercept</th>
<th>PercPovAllAges</th>
<th>PCP_Rate</th>
<th>percAfAm</th>
<th>SNF_2013</th>
<th>SmokersPerc</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>4.51094</td>
<td>1.00000</td>
<td>0.00111</td>
<td>0.00254</td>
<td>0.0584</td>
<td>0.01299</td>
<td>0.00890</td>
<td>0.00110</td>
</tr>
<tr>
<td>2</td>
<td>0.79184</td>
<td>2.38680</td>
<td>0.00030166</td>
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<td>3</td>
<td>0.48639</td>
<td>3.04538</td>
<td>0.00316</td>
<td>0.00017107</td>
<td>0.02187</td>
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<td>0.00042789</td>
<td>0.00146</td>
</tr>
<tr>
<td>4</td>
<td>0.16242</td>
<td>5.26999</td>
<td>0.00089894</td>
<td>0.07807</td>
<td>0.55901</td>
<td>0.06241</td>
<td>0.03176</td>
<td>0.01232</td>
</tr>
<tr>
<td>5</td>
<td>0.03491</td>
<td>11.36697</td>
<td>0.16757</td>
<td>0.84277</td>
<td>0.27153</td>
<td>0.12717</td>
<td>0.02360</td>
<td>0.10041</td>
</tr>
<tr>
<td>6</td>
<td>0.01350</td>
<td>18.27925</td>
<td>0.82696</td>
<td>0.07539</td>
<td>0.14161</td>
<td>0.02489</td>
<td>0.12194</td>
<td>0.88367</td>
</tr>
</tbody>
</table>
Figure 15: Appendix H: Number of Primary Care Doctors per Capita by County
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