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EVALUATION OF HEALTH POLICIES AND QUALITY MEASURES IN THE ERA OF VALUE-BASED CARE

A Dissertation in

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by

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ABSTRACT

High costs and poor patient outcomes are a challenge in the current healthcare system in the United States. In the last decade, health care has seen a major shift in emphasis from volume to value. Since the passage of the Affordable Care Act (ACA) in 2010, healthcare quality improvement efforts have brought together payers, providers, and policymakers implementing strategies that aim to provide the highest quality of care for the lowest cost. Moving towards this goal has led to an increasing use and evaluation of quality measures that reflect the value of care. This dissertation examines three topics related to patient outcomes commonly used as quality measures.

In the first study, I examine the impact of receiving post-acute care at a skilled nursing facility (SNF) on 30-day readmission using a regression discontinuity approach. A comparison of SNF use among Medicare Advantage (MA) and Medicare fee-for-service (FFS) showed although most MA plans are not subject to the 3-Day rule for SNF coverage, MA enrollees had lower SNF discharge rates with similar (although statistically not significant) increase in readmission rates to FFS enrollees. This finding highlights three important policy improvement opportunities. First, the potential for reducing unnecessary SNF use. Second, the need for hospitals to carefully identify the appropriate post-acute care setting for their patients that is capable of meeting the patient's needs to avoid potentially avoidable readmissions. And third, the need to revisit Medicare's SNF coverage policies to ensure all Medicare beneficiaries receive comparable SNF care, regardless of how they participate in Medicare.

In the second study, I examine the spillover effects of MA growth on FFS readmission rates for three conditions targeted by the Hospital Readmission Reduction Program (HRRP). Using the Norms Hypothesis to support the conceptual model, a comparison of the change in FFS readmission rates before and after the implementation of the HRRP did not show a differential impact of the HRRP on FFS readmissions in areas with high MA enrollment rates. This finding can inform future research to explore the possibility of MA moderating FFS readmissions for individual conditions given the three studied conditions have different risk factors and practice patterns.

Finally, in the third study, I evaluate the impact of a new kidney cancer treatment guideline on three quality indicators. This study showed a decrease in readmission and mortality rates and a shorter length of stay in the post-guidelines period among patients with stage I kidney tumors targeted by the new guidelines. The guidelines did not differentially impact the quality indicators across stage I and stage II.

This finding has important policy and clinical implications. First, the possibility of positive spillover effect of the guidelines on patients with stage II kidney cancer is suggestive of an opportunity to explore effective treatments for patients with stage II kidney tumors. Second, the availability of minimally invasive surgery techniques (i.e., laparoscopy or robotic surgery) in recent years may have contributed to enhancing quality of care and improving patient outcomes for patients with stage II kidney cancer, thus minimizing the difference in outcomes between stage I and stage II. Postoperative complications are frequent and are strongly associated with the risk of subsequent death, readmission, or length of hospital stay, all of which contribute to considerable costs of care and excess health care resource use. As the healthcare system shifts to value-based reimbursement models, achieving better quality in surgical care seems to be an essential part of the broader hospital quality improvement efforts.

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LIST OF ABBREVIATIONS

ACA: Affordable Care Act

HRRP: Hospital Readmission Reduction Program

GDP: Gross Domestic Product

CMS: Centers for Medicare and Medicaid Services

PAC: Post-Acute Care

SNF: Skilled Nursing Facility

HHA: Home Health Agency

MSPB: Medicare Spending Per Beneficiary

FFS: Fee-For-Service

BPCI: Bundled Payments for Care Improvement Initiative

RD: Regression Discontinuity

DID: Difference-In-Differences

HCUP: Healthcare Cost and Utilization Project

MA: Medicare Advantage

ER: Emergency Room

RTC: Randomized Controlled Trial

KHR: Knee and Hip Replacement

HAS: Health Service Area

SID: State Inpatient Databases

SEDD: State Emergency Department Databases

LOS: Length of Stay

PHC4: Pennsylvania Health Care Cost Containment Council

DRG: Diagnosis Related Group

MDC: Major Diagnostic Category

IV: Instrumental Variable

LATE: Local Average Treatment Effect

2SLS: Two-Stage Least Squares

CI: Confidence Interval

ALS: Amyotrophic Lateral Sclerosis

ESRD: End-Stage Renal Disease

TM: Traditional Medicare

HMO: Health Maintenance Organization

PPO: Preferred Provider Organizations

AMI: Myocardial Infarction

HF: Heart Failure

PN: Pneumonia

COPD: Chronic Obstructive Pulmonary Disease

MedPAC: Medicare Payment Advisory Commission

CJR: Medicare's Comprehensive Care for Joint Replacement

LEJR: Lower Extremity Joint Replacement

MAPR: Medicare Advantage Penetration Rate

USDA: U.S. Department of Agriculture Economic Research

RUCC: Rural-Urban Continuum Codes

CPR: Center for Rural Pennsylvania

ACO: Accountable Care Organization

VBP: Hospital Value-Based Purchasing Program

CABG: Coronary Artery Bypass Graft

THA= Total Knee Arthroplasty

TKA=Total Hip Arthroplasty

AJCC: American Joint Committee on Cancer

CT: Computed Tomography

MRI: Magnetic Resonance Imaging

PN: Partial Nephrectomy

RN: Radical Nephrectomy

CKD: Chronic Kidney Disease

AUA: American Urological Association

NCDB: National Cancer Database

CoC: Commission on Cancer

NCI: National Cancer Institute

CI: Charlson Index

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Chapter 1 Introduction

The United States currently spends around 18 percent of the country's gross domestic product (GDP) on healthcare alone[1] – the highest among developed countries.[2] Additionally, close to $1 trillion, or over 25% of total healthcare spending in the country, is not considered to add value and can be classified as "waste."[1] Yet, poor patient outcomes and quality of care remain a challenge.[3] Consequently, the focus of providers and payers is shifting to enable them to obtain better value for the money spent. Patient value can be increased either by improving patient outcomes or reducing the cost of patient care for the same outcomes, through better use of resources.[4] Moving towards this goal has led to increasing use and evaluation of quality measures that reflect the value of care.[5]

The need to improve the value of care in the United States is undeniable, and efforts to achieve this goal were accelerated by the passage of the Affordable Care Act (ACA) in 2010.[6] The introduction of value-based payment models has effectively impacted payers and providers to adopt innovative strategies in order to align payments to the concepts of improved quality and outcomes. Therefore, it is critical for payers and providers to identify the right opportunities to roll out value-based approaches. With that in mind, to successfully implement a value-based care infrastructure, it will be important to consistently evaluate and modify health policies and quality metrics that can effectively align and unite payers and providers to maximize care value.

For healthcare providers, readmissions have become a key measure with quality and financial implications.[7] Hospital readmission is often considered as a sign of poor quality of care,[8] and therefore, reducing hospital readmissions—especially those that result from poor inpatient or outpatient care—has long been a health policy goal as it represents an opportunity to lower health care costs and improve quality.[9,10] Up to 30% of the cases of hospital readmission are preventable,[11] which has led to considerable effort in reducing readmissions. The Centers for Medicare and Medicaid Services (CMS) is a major player in the efforts to reduce hospital readmissions. In the first two studies in my dissertation, I examine the relationship between two different Medicare policies and readmissions among Medicare patients above 65.

As a key element in the healthcare continuum, post-acute care (PAC) is shown to be closely related to quality improvement efforts. Skilled nursing facilities (SNF) are the most common setting for post-acute care in the United States.[12] Discharging patients to SNFs after hospitalization aims to ease the transition

from the hospital to home and prevent readmission by increasing patients' physical strength and ability to take care of themselves. Yet, 25% of Medicare patients discharged to a SNF experience readmission within 30 days.[12] In the first study, I examine the impact of receiving post-acute care at a SNF on 30-day readmission. In particular, I use the 3-Day Rule–a Medicare policy that requires the beneficiary to have a minimum of 3 days of consecutive inpatient hospital stay to qualify for SNF coverage–as an instrumental variable to understand the causal relationship between SNF and readmissions. Using a regression discontinuity (RD) approach, I compare SNF use among Medicare Advantage (MA) and Medicare fee-for-service (FFS) and how it impacts their readmissions. I find that although most MA plans are not subject to the 3-Day rule for SNF coverage, MA enrollees have lower SNF discharge rates with similar (although statistically not significant) increase in readmission rates to FFS enrollees.

The Hospital Readmissions Reduction Program (HRRP) is part of a broader strategy to reform the health care system that links providers' reimbursements to the value of the services they provide. The implementation of the HRRP has overlapped with the rapid growth of the MA in the past decade. In the second study, I examine the unintended consequences of the rapid growth of MA plans during the past decade and its potential to alter the care delivered to Medicare FFS patients, also known as the spillover effect. In this study, I compare the change in FFS readmission rates before and after the implementation of the HRRP and examine whether the HRRP had a differential impact on FFS readmissions in areas with high MA enrollment rates. Using the Norms Hypothesis to support the conceptual model, a comparison of the change in FFS readmission rates before and after the implementation of the HRRP did not show a differential impact of the HRRP on FFS readmissions in areas with high MA enrollment rates. Although I did not find evidence of MA to FFS readmission spillover effects, this study provides insight to identify managed care strategies to improve patient outcomes and quality measures as MA continues to expand.

Finally, in the third study, I evaluate the impact of a new guideline, that prioritized partial nephrectomy (PN) as the preferred treatment for stage I kidney tumors, on three quality indicators. This study showed a decrease in readmission and mortality rates and a shorter length of stay in the post-guidelines period among patients with stage I kidney tumors targeted by the new guidelines. The guidelines did not differentially impact the quality indicators across stage I and stage II. This finding has two important policy and clinical implications. First, the possibility of positive spillover effect of the guidelines on patients with stage II kidney cancer, which is suggestive of an opportunity to explore effective treatments for patients with stage II kidney tumors. Second, the availability of minimally invasive surgery techniques (i.e., laparoscopy or robotic surgery) in recent years may have contributed to

enhancing quality of care and improving patient outcomes stage II, thus minimizing the difference in outcomes between stage I and stage II. Postoperative complications are frequent and are strongly associated with the risk of subsequent death, readmission, or length of hospital stay, all of which contribute to considerable costs of care and excess health care resource use. As the healthcare system shifts to value-based reimbursement models, achieving better quality in surgical care seems to be an essential part of the broader hospital quality improvement efforts, specially for a high-cost and high-need patient population such as patients with cancer.

Chapter 2 3-Day Rule: The Effect of Skilled Nursing Facility Care on Patient Outcomes: A Regression Discontinuity Assessment of Medicare Beneficiaries

Introduction

Post-acute care (PAC) is a key element in the healthcare continuum, especially for older adults. PAC includes additional supervised care or rehabilitation services after hospital discharge, and depending on the required intensity of care, treatment may be provided in a facility or at home (Appendix A).[13] About 40% of Medicare acute inpatient hospital discharges result in PAC use, provided in four different settings: skilled nursing facilities (SNFs), home health agencies (HHAs), inpatient rehabilitation facilities, and long-term care hospitals.[14] Discharges to PAC facilities have been increasing rapidly among Medicare beneficiaries, making PAC spending the primary driver of costs in the Medicare Spending Per Beneficiary (MSPB) measure.[15] This key measure assesses Medicare Part A and Part B payments for services provided to a Medicare beneficiary.[16] The high PAC spending accounts for nearly 10 percent of all fee-for-service (FFS) expenditures.[17] Among all Medicare patients hospitalized for acute care, approximately 20% are discharged to a SNF, and nearly one-fourth of admissions to SNF result in 30-day hospital readmission.[12] Most of these readmissions are unplanned (Appendix B), i.e., acute clinical events experienced by a patient that require urgent hospital management,[18] with an estimated cost of $17.4 billion.[19,20] Despite the high spending and a significant proportion of Medicare patients being discharged to SNFs, it is uncertain what the impact of SNF care is on patient outcomes, particularly hospital readmissions.

Medicare policy has increasingly placed a greater emphasis on value-based care holding providers accountable for the cost and quality of care. As a result, reducing hospital readmissions has become a key quality improvement target for hospitals and policymakers. Following the implementation of the ACA in 2010, Medicare established new policies that aim to hold providers accountable for the cost and quality of care.[21] Examples include the Hospital Readmissions Reduction Program (2012), Accountable Care Organizations (2012), and Bundled Payments for Care Improvement (BPCI) initiative (2013) (Appendix C).[22] New Medicare policies seek to improve the quality of care by emphasizing efficient care coordination between acute and post-acute care settings and reducing hospital readmissions. Therefore, it is critical to evaluate SNF care's effect on hospital readmissions as new policies increasingly value reductions in readmission as a way to lower costs and improve quality of care.[23,24] The purpose of this study is to

evaluate the impact of SNFs, as a costly and frequently used post-acute care setting, on 30-day hospital readmissions among Medicare beneficiaries.

In this study, I use a regression discontinuity approach to evaluate the impact of SNF care on 30-day readmissions. Using a Medicare policy known as the 3-Day Rule as an instrumental variable, I examine the causal relationship between SNF use and 30-day readmission among Medicare FFS and MA beneficiaries above 65. I aim to address two research questions: First, are Medicare patients with a "qualifying hospital stay" more likely to be discharged to a SNF? And second, does SNF care affect 30-day readmission among Medicare FFS and MA patients differentially?

Background

Medicare Part A covers the full cost for skilled nursing facility for the first 20 days and provides partial coverage for days 21-100 per benefit period. A benefit period measures a patients' use of inpatient hospital and skilled nursing facility services and begins the day the patient is admitted as an inpatient. The benefit period ends when the patient has been out of the hospital or SNF for 60 days in a row.[25] Medicare beneficiaries do not have any out-of-pocket cost for the first 20 days in the SNF and then pay daily coinsurance ($185.50 coinsurance per day of each benefit period) for the 80-100th day. For days 101 and beyond, the patient is responsible for paying all of the cost.

Although Medicare does cover care provided in a SNF, there are requirements before this coverage is effective. Medicare beneficiaries must meet the "3-Day Rule" before SNF admission in order to qualify for SNF coverage. The 3-day rule requires the beneficiary to have a medically necessary 3-day-consecutive inpatient hospital stay and does not include the day of discharge or any pre-admission time spent in the emergency room (ER) or in outpatient observation in the 3-day count.[26]

Prior Literature

Previous studies have explored the relationship between SNF use and 30-day readmission; however, the results are mixed. While some studies have not found a significant relationship between SNF use and 30-day readmission,[27–29] others have reported higher[30–34] or lower[24,35–37] readmission rates among patients who use SNF care. Different study designs and study subjects can cause variability in the findings. The majority of prior research studies are observational studies that focus on the association between SNF use and readmission rather than the causal relationship. These studies have either been limited to a

single institution with small sample size or have only examined specific conditions. Such studies suffer from limited generalizability of findings and are often prone to unmeasured confounding or selection bias.[38] Confounding can be addressed by experimental (e.g., randomized trials) or quasi-experimental methods, as they assess the causal relationship by allowing for even distribution of potential confounders among treatment and control groups. Although experimental studies such as randomized controlled trials (RCTs) are often encouraged as the ideal methodology for studying causality, they are usually costly in terms of both time and money, with limited possibility to conduct a large-scale study. Besides, Angus and Deaton (2018)[39] have argued that the popularity of RCTs over other methods may have been over-emphasized.

While no randomized trial has studied the effect of SNF use on readmissions, several studies have evaluated SNF and readmissions relationship using a quasi-experimental approach. [24,28,40] For example, studies by Jin et al.(2018)[28], Rose (2020),[41] and Werner et al. (2019)[24] used difference-in-differences (DID), RD and two-stage least squares (2SLS) model with an instrumental variable approach to account for unobserved confounding, and estimate the causal relationship between SNF and readmissions. However, these studies also show mixed results.

Jin et al.(2018)[28] used the Healthcare Cost and Utilization Project (HCUP) from Florida, Arizona, New York and Washington to examine the impact of SNF on hospital readmissions. In this study, authors compare Medicare patients (65-79) with non-Medicare patients (60-79) using a DID method with the 3-Day Rule as an instrumental variable to estimate the effect of SNF on readmissions. Findings showed SNF discharge leads to lower readmission rates among a pooled sample of Medicare patients. After doing a stratified analysis by comorbidity, the authors further explain that the observed negative association between SNF and readmission rates may be driven by patients with higher comorbidity burden (with above-median Elixhauser Comorbidity Index). When focusing on patients with no comorbidity or those with low comorbidity burden, the analysis did not find any difference in readmissions between patients discharged to SNF and those discharged to other destinations. The authors highlight the importance of accounting for differences in the level of comorbidity and how it relates to SNF quality and readmission rates. For example, this study found knee and hip replacement (KHR) patients had the highest rates of discharge to SNF (over 50% of the patients discharged to SNFs) and experienced a significant increase in hospital readmissions. The authors further explain that the increase in readmission rates among KHR patients discharged to SNF is larger in the health service areas (HSAs) where the average SNFs have a lower-than-state-median occupancy rate or a higher-than-state-median total deficiency count, which may

suggest that many KHR patients go to SNF because Medicare covers the cost and there is a bed available in nearby low-quality SNFs.

Rose[41] also used the HCUP data, State Inpatient Databases (SID), and the State Emergency Department Databases (SEDD) from Florida and New York to study the impact of SNF on readmissions. Using RD, Rose also used the 3-Day Rule as an instrumental variable to study patients with 60-84 hours of inpatient stay admitted within 8 hours before and after midnight to estimate the effect of SNF discharge on Medicare readmissions. The findings suggest patients discharged to SNF are 1.1 percentage points less likely to experience 30-day readmission. Unlike Jin et al.[28], Rose did not provide further analysis with respect to comorbidities. Instead, he analyzed specific diagnoses (without including knee and hip replacement). The estimates show mixed results regarding the effect of SNF for specific diagnoses readmissions. For example, there was a negative association between SNF discharge and readmissions among patients with heart disease, a positive association with those with COPD, and no association for patients with Ischemic heart disease. Besides, most of the coefficient estimates are small (smaller than -0.0005), showing less than 0.05 percentage points lower probability of readmission for SNF users. While the overall estimation for a pooled sample of Medicare patients showed lower likelihood of readmissions among patients discharged to SNF compared to those discharged elsewhere, the sub-analysis suggests the results may vary by diagnoses.

To date, only one study has used a quasi-experimental method to examine the association between patient outcomes (e.g., readmission, mortality, and functional status) and discharge to skilled nursing facility among Medicare Advantage and traditional Medicare FFS patients separately. Werner et al. (2019)[24] used the differential distance between the beneficiary's home zip code and the closest home health agency and the closest skilled nursing facility as an instrumental variable to study how patient outcomes and Medicare spending are affected by the decision to discharge patients to home with home health care vs. to a skilled nursing facility. The authors studied two categories of readmissions: readmissions for nondiscretionary diagnoses and those that were for potentially discretionary diagnoses. Potentially discretionary hospitalizations were defined as those resulting from conditions with greater uncertainty regarding the optimal treatment and thus greater variation in the use of hospital admission, and nondiscretionary hospitalizations were those resulting from conditions or events for which a hospital admission is almost always advised, as no other setting would typically have the required resources to address the patient's acute needs. The analysis showed no difference in readmissions associated with discharge to home health care vs. discharge to an SNF for nondiscretionary readmissions. But discharge

to home health care was associated with a higher rate of readmission for discretionary readmissions compared with SNF among Medicare FFS only and no significant results for MA patients. While Werner et al.[24] provide a separate analysis for MA and FFS patients, the study uses a different instrumental variable to study the differences between SNF and home health as two post-acute care destinations.

Gaps in the Literature

The quasi-experimental studies by Jin[28] and Rose[40] examine the impact of SNF on readmissions using a pooled sample of Medicare patients without separating FFS from MA enrollees. Disentangling differences in effects between MA and FFS patients is critical for two reasons. First, Medicare FFS and MA have different policies with respect to SNF coverage. Medicare FFS requires patients to have at least three consecutive days as an inpatient to provide SNF coverage for their beneficiaries. Unlike FFS, most MA plans have waivers for the 3-Day Rule. A 2016 CMS report states, "92% of MA plans waive the three-day requirement but may implement other utilization-management methods (such as prior authorization) to limit the use of the SNF benefit".[42] In addition, while Medicare FFS provides full SNF coverage for the first 20 days, two-thirds of MA plans include cost-sharing for covered SNF days 1 through 20.[42] Therefore, the 3-Day Rule may not be an ideal instrumental variable to study the relationship between SNF use and readmission for MA patients. Second, MA and FFS patients may be different in SNF use patterns and readmission rates at baseline. Evidence has shown that FFS patients tend to be sicker on average than MA enrollees,[43] potentially making them more likely to need post-acute care following discharge or to experience higher readmissions. Medicare FFS' prospective payment systems for post-acute care provide more limited incentive to coordinate care or control costs. In contrast, MA plans provide coverage for post-acute care out of monthly capitated payments, which creates a stronger incentive to use it efficiently.[44,45] Therefore, MA programs have a financial incentive to avoid readmissions and unnecessary use of post-acute care, and MA enrollees also may avoid unnecessary SNF use due to cost-sharing for the first 20 days.[42] Additionally, the variation in payment structures may be associated with higher rates of SNF discharge among FFS patients, which may not necessarily improve their outcomes.[46] For example, a 2017 study[45] compared the use of post-acute care in skilled nursing and inpatient rehabilitation facilities by enrollees in MA and FFS after hospital discharge for three high-volume conditions: lower extremity joint replacement, stroke, and heart failure and found lower intensity of post-acute care for MA patients compared to FFS patients discharged from the same hospital, across all three conditions. MA patients also had lower rates of hospital readmission and higher rates of return to the community. A different study,[46]

compared post-acute care use among MA and FFS patients with hip fracture and found MA patients were less likely to experience a 30-day hospital readmission compared to FFS patients.

Contribution

The evidence on the impact of SNF on readmissions, even in quasi-experimental studies, is mixed, with a lot of potential for improvement. In this study, I build on previous research by Rose.[40] I use a RD approach with the 3-Day Rule as an instrumental variable to examine the impact of SNF care on 30-day readmission among Medicare patients. While I use a similar method to Rose, I make several important additions.

First, instead of examining Medicare patients as a pooled sample, I provide separate estimates for Medicare FFS and MA patients, which allows me to evaluate SNF's impact on readmissions based on payer type. This can be particularly important considering the substantial differences between MA and FFS patients, which may create differences in readmission and SNF use.

Second, I include all patients with 2-3 days of inpatient stay. The narrow length of stay trimming range in Rose's approach (60-84 hours) leaves out some patients who are still within the 2-3 days of inpatient stay, which can be critical to include in the analysis. If excluding patients outside the 60-84 hours inpatient stay leads to more comparable treatment and control group, then doing so may create selection bias in the analysis.

Finally, I provide a stratified analysis of SNF's impact on readmissions separately for Medicare FFS and MA patients for four comorbidity levels: No comorbidity, and Charlson index of 1, 2, and 3+. Multiple comorbidities and a high Charlson Comorbidity Index are shown to be associated with SNF readmissions.[47,48] By identifying comorbid patients with high risk for readmission, providers can implement appropriate interventions during hospitalization and post-acute care to decrease the risk of future readmission.

Methods

Data

I use January 2011 through December 2014, Pennsylvania inpatient discharge data, provided by the Pennsylvania Health Care Cost Containment Council (PHC4). The Council is an independent state agency that collects more than 1.7 million inpatient discharge records from Pennsylvania hospitals per year. The

data include information on Diagnosis Related Groups (DRGs), Major Diagnostic Categories (MDCs), admission type and source, 30-day readmission, diagnosis and procedure codes, discharge status, length of stay, and charges. Information on patient admission origin and payer are also included. All licensed health care facilities are responsible for providing administrative data to the PHC4. Administrative and clinical data are collected on a quarterly basis and received 90 days from the close of each quarter. The information is then used to prepare public reports for use by payers, providers, purchasers of health care, and the general public.[49]

Study Design

I use a RD approach to evaluate the impact of SNF care on 30-day readmissions. The treatment and control groups are assigned quasi-experimentally based on either being admitted just before or just after midnight, using the hour of admission as the running variable. The 3-Day Rule is then used as an instrumental variable (IV) to predict the causal impact of SNF discharge (treatment variable) on 30-day readmission (outcome variable) by comparing patients admitted just before and just after midnight.

The existing literature typically distinguishes between two types of RD designs: the sharp design, in which all subjects receive their assigned treatment or control condition, and the fuzzy design, in which some subjects do not.[50] In my model, the probability of treatment (SNF discharge) is discontinuous at the cut-off but not to the degree of a definitive 0 to 1 jump. Regardless of Medicare eligibility for SNF coverage, patient discharge status may vary. Not all patients who become eligible for SNF coverage, according to the 3-Day Rule, are discharged to a SNF. Therefore, I use a fuzzy design, in which the local average treatment effect (LATE) is estimated using an IV.[51]

To approximate randomization, I assume the hour of admission (running variable) cannot be manipulated to include or exclude specific patients. Besides, I assume that to the extent possible, the instrument satisfies two required criteria for RD: excludability, i.e., the instrument only affects the outcome through its effect on treatment status, and exchangeability, i.e., the instrument cannot be influenced by unmeasured confounders. Figure 2-1 illustrates the relationship between the instrumental variable, the treatment, and the outcome.

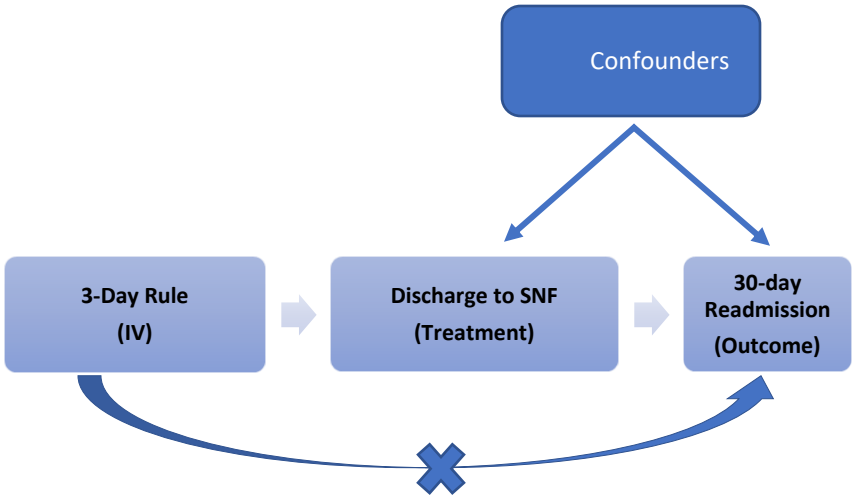


Figure 2-1: The Relationship Between Instrumental Variable, Treatment, and Outcome

Study Sample

The steps for building the study sample are shown in Figure 2-2. As the first step, I include patients with Medicare as their primary or secondary payer. Next, I exclude patients below 65 years old and dual-eligible beneficiaries (i.e., those who are enrolled in both Medicare and Medicaid) because the younger patients who are eligible for Medicare coverage due to having a disability, end-stage renal disease, or Amyotrophic Lateral Sclerosis (ALS) diagnosis, may be systematically different from beneficiaries age 65 or older.[52]

Additionally, I exclude patients that are less likely to be affected by the 3-Day Rule (i.e., LOS≤1 and LOS≥4. As shown in figures 2-3 and 2-4, LOS of 2-3 days ranges from 26-94 hours of hospital stay. This range is based on how hospitals calculate LOS, i.e., counting the number of midnights a patient stays at the hospital. The final analysis sample is restricted to the admissions within 5 hours before and after midnight.

I further exclude patients transfers from one distinct unit of the hospital to another distinct Unit of the same hospital resulting in a separate claim to the payer. The term "distinct part" refers to a portion of a hospital that is certified to provide SNF services, which must be physically distinguishable from the hospital and fiscally separate for cost reporting purposes.[53]

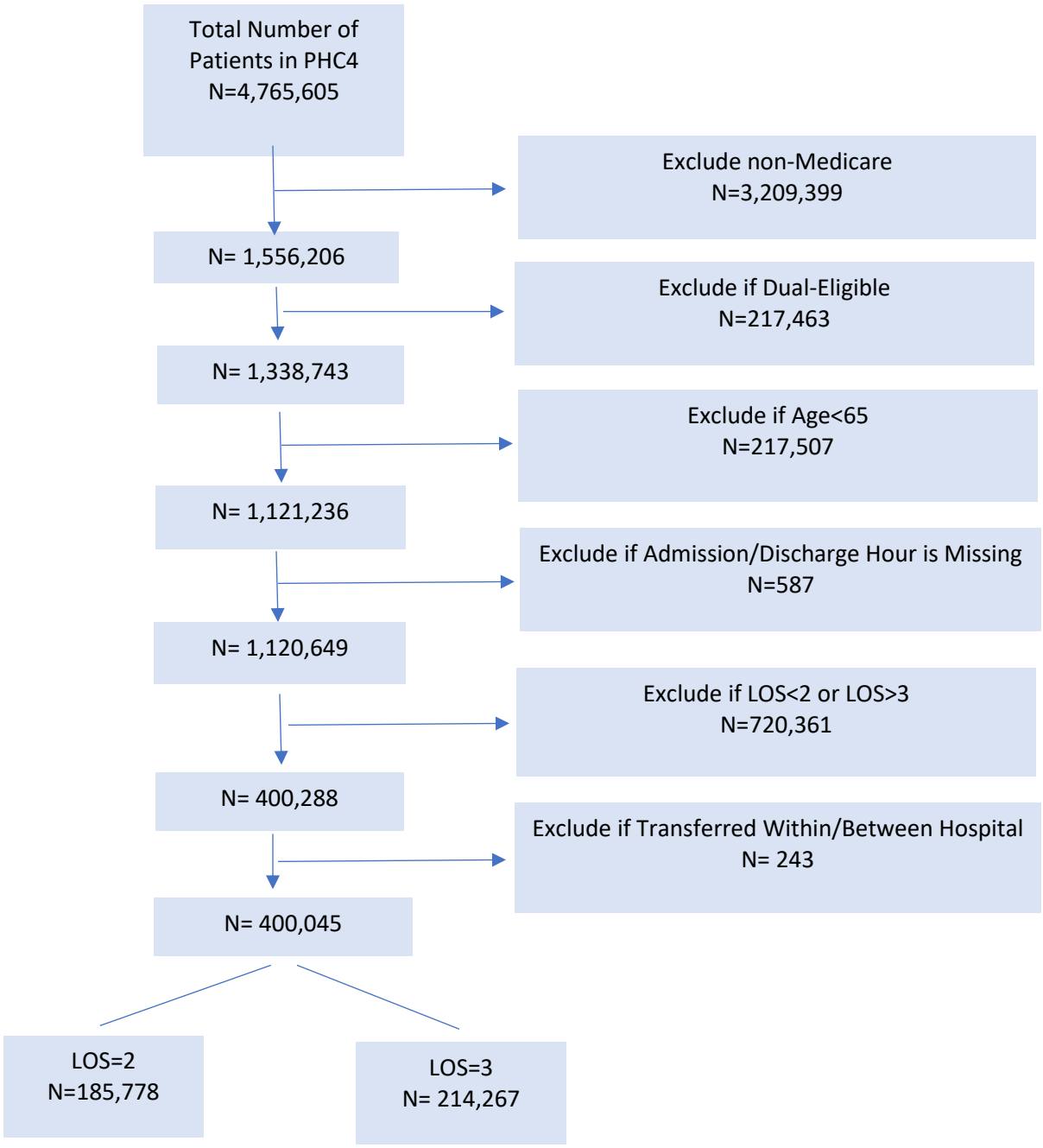


Figure 2-2: Steps for Building the Study Sample Using the PHC4 Inpatient Data 2011-2014

Note. PHC4= Pennsylvania Health Care Cost Containment Council. HRRP= Hospital Readmission Reduction Program. FFS= fee-for-service. MA= Medicare Advantage.

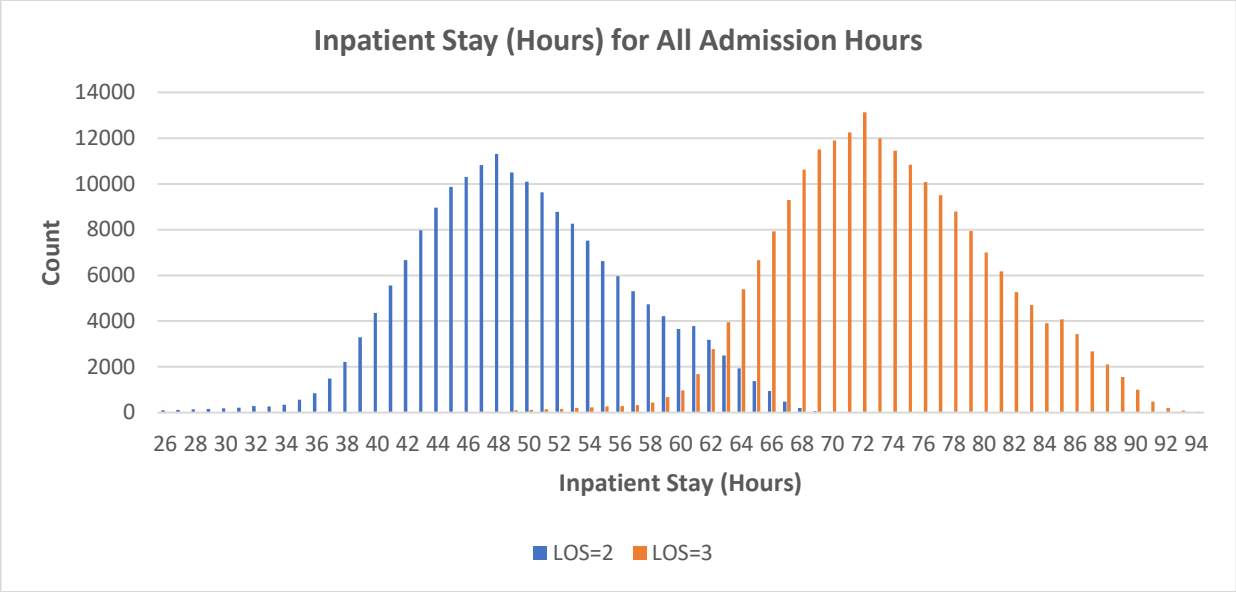


Figure 2-3: Length of stay (hours) for All Admissions

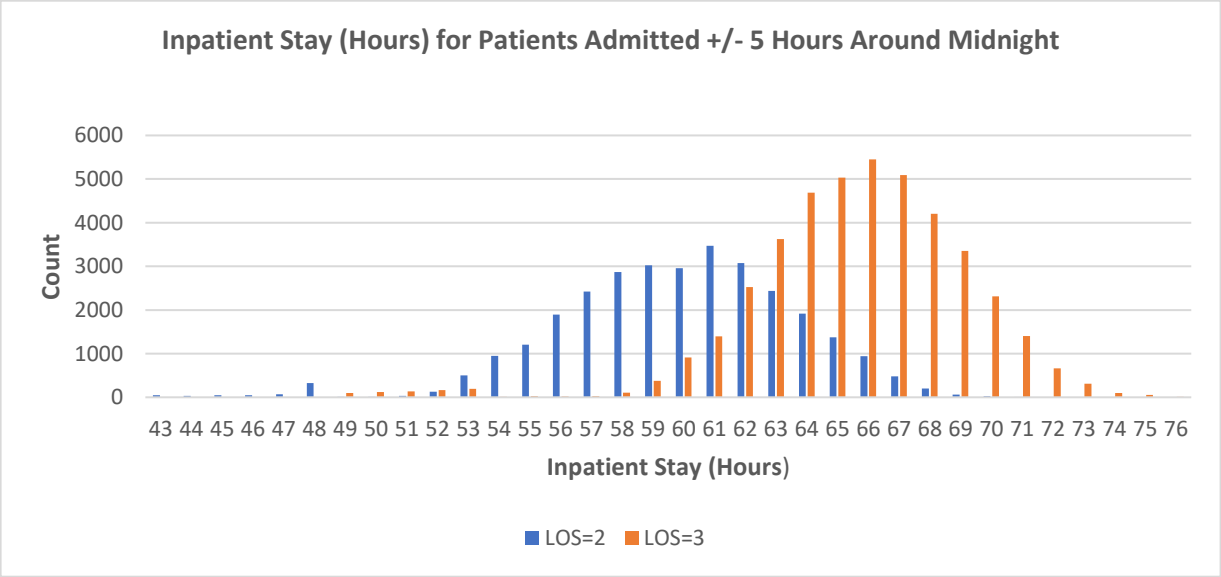


Figure 2-4: Length of Stay (hours) for Inpatient Admissions within 5 Hours Before/After Midnight

Dependent Variable

The dependent variable is all-cause 30-day readmission. The 30-day readmission is defined as a hospital stay within 30 days of discharge from the index (i.e., initial) admission. No more than one

readmission is counted within the 30-day window, but a patient can have multiple index hospitalizations within the study period (2011-2014). Following the 30-day period, a patient who experiences another hospital admission is counted as another index hospitalization, and a subsequent 30-day follow-up period begins. Another readmission can be counted within subsequent 30-day periods.[54–56]

Independent Variables of Interest

The estimation method for this study is a 2SLS model. The independent variable for stage 1 is an indicator variable for before vs. after midnight admission. The independent variable for stage 2 is discharge to SNF.

Other Covariates

Other covariates used include age as a categorical variable with three categories: 65-74, 75-84, and 85+, race (Black, White, and Other), ethnicity (Hispanic and non-Hispanic), sex, year (to account for temporal trends), and comorbidity level. A dummy variable for each year is also included to account for year fixed effects.

I control for the comorbidity level of the patients because research suggests that comorbidity is associated with readmission.[57,58] The comorbidity variable in this study is based on the Charlson Comorbidity Index. This index is based on a list of 19 conditions identified from diagnoses in hospital and physician data. Each condition is assigned a weight from 1 to 6. The index score is the sum of the weights for all identified conditions.[59] An index score of 0 indicates no comorbid conditions, while higher scores indicate a greater level of comorbidity. In this study, I define four comorbidity levels: no comorbidity (index score = 0), index score = 1, index score = 2, and index score 3 and above. Each level is defined as a binary variable (Appendix D).

Bandwidth Size

An important decision in the RD estimation is specifying the bandwidth size around the cut-off. Inevitably, the treatment and comparison groups look more similar the closer to the cut-off to which the sample is restricted.[50]. Patients admitted in the after-hours may be intrinsically at higher risk for poor patient outcomes due to a different case mix, increased severity of illness, or some other unmeasured factors as compared with patients admitted during the usual daytime hours.[60,61] Therefore, I use a narrow bandwidth of 5 hours before and after midnight (between 7 p.m. and 5 a.m.) to have a more comparable

treatment (admitted before midnight) and control (admitted after midnight) groups. Later, I perform a sensitivity test to examine if the bandwidth is robust to a narrower range (i.e., 1, 2, 3, and 4 hours before/after midnight), or a wider range (i.e., 6, 7, and 8 hours before/after midnight). Figure 2-5 shows the frequency of admission by hour, including 5 hours before and after midnight (cut-off). Although a smooth trend of readmissions would be ideal, we are less worried about manipulating the admission hour to qualify for SNF coverage because the spike in readmissions at midnight (shown as 0) includes patients admitted between 12 and 1 a.m. Additionally, the spike at 5 a.m. may be due to schedules surgeries in early morning.

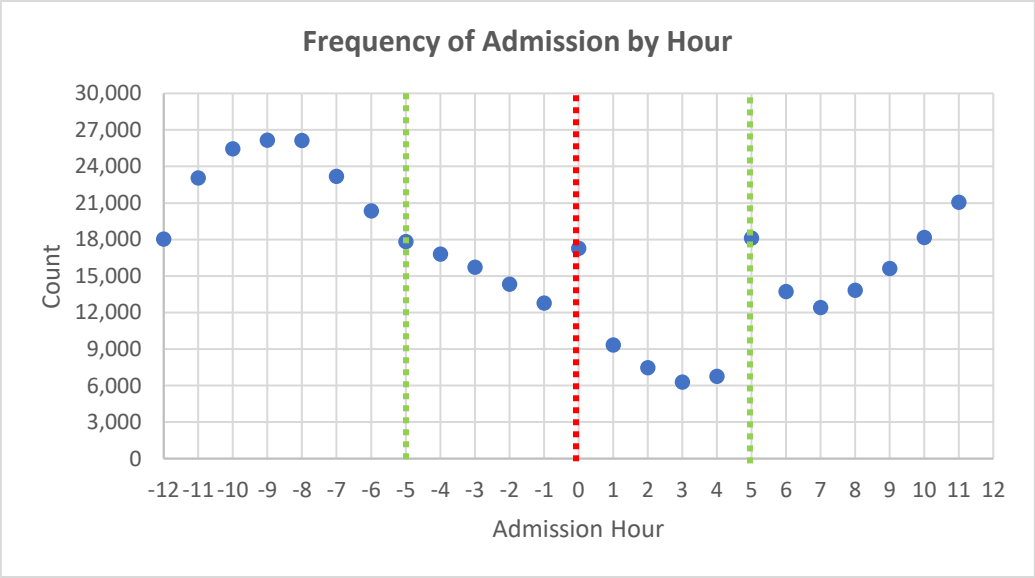


Figure 2-5: Frequency of Admission for Medicare Beneficiaries with 2-3 Days of Inpatient Stay.

Note: The green line shows the bandwidth chosen for the final sample. 0 represents midnight shown in red dashed line.

Statistical Analysis

Visual Inspection of Data

The first step in the RD analysis is a visual inspection of the data, which provides a graphical answer to whether or not there is evidence of a discontinuity (or "jump") at the cut-off. I begin with a plot to check for the presence of a discontinuity at midnight (cut-off) in the probability of being discharged to SNF (treatment). Figure 2-6 is a graphical presentation with the probability of receiving the treatment (SNF discharge) as a function of the running variable (hour of admission) within 5 hours before and after midnight (shown as 0). Ideally, we would expect to see a jump around the cut-off which creates a

discontinuity in receiving the treatment (i.e., SNF discharge). Figure 2-6 suggests the presence of a discontinuity in SNF discharge around midnight. The probability of SNF discharge is higher for the patients admitted before midnight who qualify for SNF coverage based on the 3-Day Rule requirement. For those admitted after midnight, the probability of SNF discharge is lower, creating a discontinuity around midnight as the cut-off.

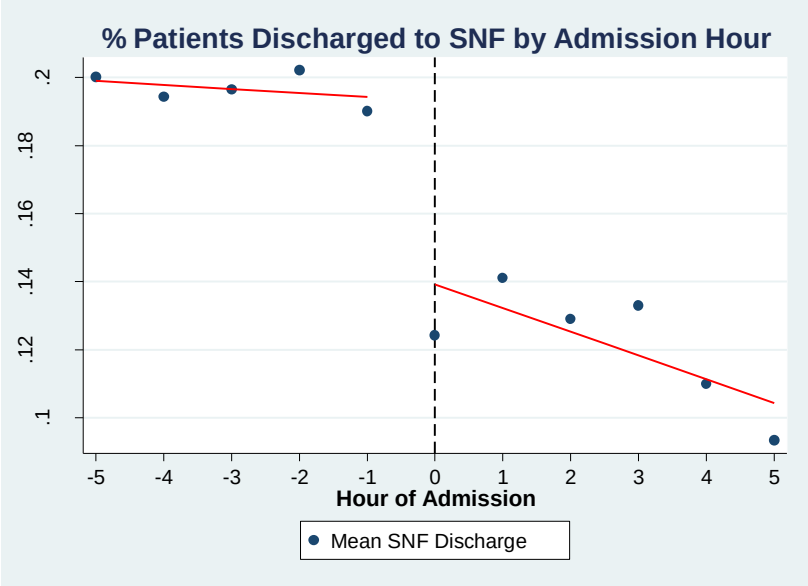


Figure 2-6: SNF Discharge Within 5 Hours Before and After Midnight

Estimation

To estimate the effect of SNF discharge on 30-day readmission using a fuzzy RD design, I use a linear probability 2SLS approach. The outcome variable in the model is a binary variable for 30-day readmission. Therefore, the predicted value from the regression is a prediction for the probability that a patient discharged to SNF had a readmission within 30 days following hospital discharge. For the first stage, I estimate a regression with SNF discharge as the dependent variable and a dummy variable for admission before vs. after midnight as the independent variable and control for the admission hour and sociodemographic characteristics of patients, including age, race, Hispanic origin, sex, and comorbidity. The regression for the first stage takes the following form:

$$P_i = \alpha + \delta\, B_i + h\, Z_i + k\, X_i + \varepsilon_i$$

where P_i is a dummy variable for SNF discharge for patient i, B_i is a dummy variable that takes a value of 1 for patient i if admitted before midnight and 0 if admitted after midnight. δ corresponds to the effect

of eligibility for SNF coverage on being discharged to SNF. To control for admission time, I include Z_i as the hour of admission for patient *i*. X_i is a vector of control variables such as age, race, Hispanic origin, sex, and comorbidities. Year fixed effects (defined as a dummy variable for each year) are also included in X_i. I save the estimated value for SNF discharge as $\hat{P}_i$, and plug it into the second stage regression equation

The regression for the second stage takes the following form:

$$y_i = \mu + \tau \hat{P}_i + h Z_i + k X_i + e_i$$

where y_i is a dummy variable for 30-day readmission, and τ shows the effect of SNF discharge on 30-day readmissions using discontinuity around midnight as an instrumental variable. X_i is a vector of control variables such as age, race, Hispanic origin, sex, and comorbidity. Year fixed effects (defined as a dummy variable for each year) are also included in X_i.

Results

Descriptive Statistics

Table 2-1 shows the descriptive statistics for this study. The study sample includes 400,045 Medicare beneficiaries above age 65, with an inpatient LOS of 2-3 days, between the years of 2011-2014 in our analysis sample. Of those patients, 197,947 patients were admitted within 5 hours before and after midnight. The patients admitted before vs. after midnight were roughly the same age. In the before midnight group, there were fewer patients with no comorbidity (22% vs. 27%) and more with severe comorbidity (32% vs. 27%) compared to the after-midnight group. Fewer patients in the before-midnight group were discharged home (52%) compared to the after-midnight group (63%), and more patients were discharged to SNF (23% vs. 10%) in the before vs. after-midnight group. The proportion of patients with Medicare FFS and MA were the same in the before and after-midnight group.

Table 0-1: Characteristics of Patients by Before/After Midnight Admission

	Before Midnight	After Midnight	p-value
Age (average)	78.62	77.04	<0.0001
65-74 (%)	34.14%	41.63%	<0.0001
75-84 (%)	39.45%	38.78%	<0.0001
85+ (%)	26.39%	19.62%	<0.0001
Male (%)	43.18%	46.31%	<0.0001
Hispanic (%)	0.80%	0.74%	0.09
Race (%)			
White	90.26%	90.09%	0.22
Black	7.64%	7.57%	0.57
Other	2.09%	2.32%	<0.001
Insurance Status			
Medicare FFS	61.66%	61.92%	0.24
Medicare Advantage	38.33%	38.07%	0.24
Comorbidity (Charlson Index)			
0 (No Comorbidity) (%)	22.12%	27.50%	<0.0001
1 (%)	25.69%	26.28%	<0.01
2 (%)	20.06%	18.91%	<0.0001
3+ (%)	32.11%	27.29%	<0.0001
Discharge Destination (%)			
SNF	20.07%	9.32%	<0.0001
HH	22.95%	23.89%	<0.0001
Home	54.18%	64.47%	<0.0001

Note: SNF: Skilled Nursing Facility, HH: Home Health. FFS: fee-for-service

Estimation Results

Table 2-2 shows the estimates from the first stage in the 2SLS model, estimating the effect of eligibility for SNF coverage on being discharged to SNF. The F-statistic values are large (greater than 10), which indicate that the 3-Midnight Rule is a strong instrument. Patients admitted before midnight were 13.05 (pooled sample, n=197,947), 15.31 (FFS subsample, n=122,372), and 9.43 (MA subsample, n=75,575) percentage points more likely to be discharged to SNF compared to those admitted after midnight.

Table 2-3 shows the second stage estimates for the effect of SNF on the probability of readmission to the hospital within 30 days of discharge. SNF discharge increased the probability of 30-day readmission by 5.3 (pooled sample) and 5.2 (FFS subsample) percentage points. SNF care did not affect the probability of 30-day readmission among MA patients.

Table 0-2: First Stage Estimates of the Effect of Admission Before Midnight on the SNF Discharge

	Pooled Sample	FFS	MA
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
Change in discharge to SNF	0.1305*** (0.1256 , 0.1353)	0.1531*** (0.1469 , 0.1592)	0.0943*** (0.0899 , 0.1020)
Admission Hour	-0.0036*** (-0.0040 , -0.0033)	-0.0035*** (-0.0039 , -0.0030)	-0.0039*** (-0.0045 , -0.0033)
Age			
65-74	-0.1881*** (-0.1920 , -0.1842)	-0.1863*** (-0.1912 , -0,1814)	-0.1894*** (-0.1958 , -0.1829)
75-84	-0.1214*** (-0.1253 , -0.1175)	-0.1217*** (-0.1266 , -0.1168)	-0.1194*** (-0.1257 , -0.1130)
85+	*Ref. Group*	*Ref. Group*	*Ref. Group*
Male	-0.0413*** (-0.0442 , -0.0383)	-0.0386*** (-0.0424 , -0.0348)	0.0451*** (-0.0499 , -0.0404)
Race			
White	-0.0014 (-0.0117 , 0.0089)	-0.0020 (-0.0144 , 0.0104)	-0.0008 (-0.0194 , 0.0178)
Black	0.0093 (-0.0022 , 0.0208)	0.0192*** (0.0053 , 0.0331)	-0.0106 (-0.0311 , 0.0099)
Other	*Ref.Group*	*Ref.Group*	*Ref.Group*
Hispanic	-0.0206* (-0.0381 , 0.0031)	-0.0173 (-0.0372 , 0.0027)	-0.0367* (-0.0730 , -0.0004)
Comorbidity (Charlson Index)			
0	0.0097*** (0.0057 , 0.0137)	0.0046 (-0.0005 , 0.0097)	0.0189*** (0.0115 , 0.0244)
1	-0.0010 (-0.0049 , 0.0030)	-0.0046 (-0.0096 , 0.0004)	0.0050 (-0.0014 , 0.0114)
2	-0.0038 (-0.0081 , 0.0005)	-0.0030 (-0.0084 , 0.0024)	-0.0045 (-0.0115 , 0.0025)
3+	*Ref. Group*	*Ref. Group*	*Ref. Group*
N	197,947	122,372	75,575
F-Statistic	1117	809	344

Note: SNF denotes skilled nursing facility, *p< 0.05; **p< 0.001; ***p< 0.000

Table 0-3: Second Stage Estimates of the Effect of SNF on the Probability of 30-Day Readmission

	Pooled Sample	FFS	MA
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
Readmission Change	0.0530** (0.0175 , 0.0855)	0.0521** (0.0131 , 0.0910)	0.0577 (-0.0203 , 0.1356)
Admission Hour	0.0005*** (0.0003 , 0.0008)	0.0002 (-0.0001 , 0.0006)	0.0010*** (0.0006 , 0.0014)
Age			
65-74	-0.0037 (-0.0115 , 0.0041)	-0.0027 (-0.0116 , 0.0061)	-0.0049 (-0.0210 , 0.0112)
75-84	-0.0012 (-0.0070 , 0.0046)	-0.0003 (-0.0071 , 0.00061)	-0.0023 (-0.0135 , 0.0088)
85+	*Ref. Group*	*Ref. Group*	*Ref. Group*
Male	0.0082*** (0.0050 , 0.0115)	0.0085*** (0.0045 , 0.0125)	0.0078** (0.0020 , 0.0137)
Race			
White	0.0100* (0.0001 , 0.0200)	0.0093 (-0.0028 , 0.0214)	0.0127 (-0.0050 , 0.0305)
Black	0.0199*** (0.0050 , 0.0115)	0.0211** (0.0075 , 0.0346)	0.0184 (-0.0012 , 0.0380)
Other	*Ref. Group*	*Ref. Group*	*Ref. Group*
Hispanic	0.0070 (-0.0099 , 0.0238)	0.0032*** (-0.0161 , 0.0226)	0.0193 (-0.0155 , 0.0541)
Comorbidity (Charlson Index)			
0	-0.0813*** (-0.0851 , -0.0774)	-0.0804*** (-0.0845 , -0.0755)	-0.0827*** (-0.0890 , 0.0765)
1	-0.0607*** (-0.0645 , -0.0569)	-0.0588*** (-0.0637 , -0.0540)	-0.0638*** (-0.0474 , -0.0240)
2	-0.0378*** (-0.0420 , -0.0337)	-0.0362*** (-0.0414 , -0.0309)	-0.0407*** (-0.0474 , -0.0340)
3+	*Ref. Group*	Ref. Group	*Ref. Group*
N	197,947	122,372	75,575

Note. *p< 0.05; **p< 0.001; ***p< 0.0001

Tables 2-4 and 2-5 present the results stratified by comorbidity level. As Table 2-4 shows, for all comorbidity and insurance groups, we see a statistically significant increase in SNF discharge among patients admitted before midnight compared to those admitted after midnight. The magnitude of increase was smaller among patients in the MA (CI, 0.0899,0.1020) subsample compared to FFS (CI, 0.1469,0.1592). Table 2-5 show the estimates from the second stage estimates of the effect of SNF care on the probability of 30-day readmission stratified by four comorbidity levels. For all four comorbidity levels, the coefficient for the effect of SNF discharge on 30-day readmission is positive but is not statistically significant in all cases.

Table 0-4: First Stage Estimates of the Effect of Admission Before Midnight on SNF Discharge Stratified by Comorbidity

	No Comorbidity			Charlson Index Score=1			Charlson Index Score=2			Charlson Index Score=3+		
	Pooled	**FFS**	**MA**	**Pooled**	**FFS**	**MA**	**Pooled**	**FFS**	**MA**	**Pooled**	**FFS**	**MA**
Variable	**Coef. (95% CI)**			**Coef. (95% CI)**			**Coef. (95% CI)**			**Coef. (95% CI)**		
Change in SNF Discharge	0.1604*** (0.105,0.170)	0.1957*** (0.183,0.208)	0.1075*** (0.091,0.123)	0.1230*** (0.123,0.150)	0.1633*** (0.151,0,175)	0.1069*** (0.092,0.121)	0.1181*** (0.107,0.128)	0.1414*** (0.127,0.155)	0.0798*** (0.062,0,096)	0.1043*** (0.095,0.113)	0.01193*** (0.107,0.130)	0.0792*** (0.064,0.093)
Admission Hour	-0.0046*** (-0.005,-0.003)	-0.0042*** (-0.005,-0.003)	-0.0052*** (-0.006,-0.004)	-0.0045*** (-0.005,-0.003)	-0.0042*** (-0.005,-0.003)	-0.0050*** (-0.006,-0.003)	0.0029*** (-0.003,-0.002)	-0.0031*** (-0.004,-0.002)	-0.0027*** (-0.004,-0.001)	-0.0026*** (-0.003,-0.001)	-0.0026*** (-0.003,-0.001)	-0.0028*** (-0.003,-0.001)
Age												
65-74	-0.2171*** (-0.225,-0.209)	-0.209*** (-0.219,-0.200)	-0.2257*** (-0.238,-0.212)	-0.1894*** (0.197,0.181)	-0.1893*** (-0.198,-0.179)	0.189*** (0.202,-0.177)	-0.1857*** (-0.194,-0.176)	-0.1845*** (-0.195,-0.173)	-0.1859*** (-0.200,-0.17)	-0.1617*** (-0.69,0.154)	-0.1625*** (-0.171,0.153)	-0.1574*** (-0.169,-0.145)
75-84	-0.1347*** (-0.142,-0.126)	-0.1340*** (-0.143,-0.124)	-0.1362*** (-0.149,0.123)	-0.1275*** (-0.135,-0.119)	-0.1264*** (-0.136,-0.116)	-0.128*** (-0.140,-0.116)	-0.1169*** (-0.125,-0.108)	-0.1107*** (-0.121,-0.099)	-0.1242*** (-0.138,-0.110)	-0.1079*** (-0.115,-0.100)	0.1142*** (-0.123,-0.105)	-0.0940*** (-0.105,-0.082)
85+	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Male	-0.0468*** (-0.052,-0.040)	-0.0392*** (-0.046,-0.031)	-0.0574*** (-0.067,-0.047)	-0.0405*** (-0.046,-0.034)	-0.0353*** (-0.042-0.028)	-0.0481*** (-0.057,-0.038)	-0.0356*** (-0.042,-0.028)	-0.0361*** (-0.-0.04,-0.027)	-0.0346*** (-0.045,-0.024)	-0.0400*** (-0.045,0.034)	-0.0412*** (-0.048,-0.034)	-0.0377*** (-0.046,-0.028)
Race												
White	-0.0069 (-0.026,0.013)	-0.0107 (-0.034,0.013)	-0.0031*** (-0.038,-0.032)	0.0013 (-0.018,0.020)	0.0021 (-0.021,0.025)	-0.0023 (-0.037,0.032)	0.0087 (-0.014,0.032)	0.0071 (-0.021,0.035)	0.0112 (-0.030,0.052)	-0.0063 (-0.026,0.014)	-0.0056 (-0.030,0.018)	-0.0050 (-0.042,0.032)
Black	-0.0037 (-0.0270.019)	0.0071 (-0.021,0.031)	-0.0253 (-0.066,0.015)	0.011 (-0.010,0.033)	0.0353* (0.0005,0.05)	-0.0166 (-0.056,0.22)	0.0276* (0.001,0.0533)	0.034* (0.003,0.006)	0.0123 (-0.033,0.057)	0.0018 (0.020,0.023)	0.0094 (-0.017,0.036)	-0.0128 (-0.052,-0,027)
Other	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Hispanic	0.0091 (-0.030,0.048)	-0.0046 (-0.049,0.040)	0.0458*** (-0.034,0.126)	-0.037* (-0.071,-0.002)	-0.0275 (-0.067,0.012)	-0.0628 (-0.130,0.004)	-0.0084 (-0.047,0.030)	0.0058 (-0.039,0.051)	-0.0640 (-0.143,0.014)	-0.0331* (-0.063,-0.003)	-0.0315 (-0.065,0.002)	-0.0485 (-0.115,0.018)
F-Statistic	626	474	190	480	346	150	319	229	97	350	251	103
N	50,161	30,243	19,918	51,562	31,423	20,139	38,356	24,004	14,352	57,868	36,702	21,166

Note: SNF denotes skilled nursing facility, *p< 0.05; **p< 0.001; ***p< 0.0001

Table 0-5: Second Stage Estimates of the Effect of SNF Discharge on 30-day Readmissions Stratified by Comorbidity

	No Comorbidity			Charlson Index Score=1			Charlson Index Score=2			Charlson Index Score=3+		
	Pooled	**FFS**	**MA**	**Pooled**	**FFS**	**MA**	**Pooled**	**FFS**	**MA**	**Pooled**	**FFS**	**MA**
Variable	**Coef. (95% CI)**			**Coef. (95% CI)**			**Coef. (95% CI)**			**Coef. (95% CI)**		
Readmission Change	0.0469 (-0.002,0.096)	0.0400 (-0.012.0.092)	0.0676 (-0.046,0.181)	0.0178 (-0.041,0.077)	0.0183 (-0.048,0.085)	0.0186 (-0.105,0.142)	0.0839 (-0.007,0.175)	0.0685 (-0.028,0.165)	0.1337 (-0.084,0.352)	0.0701 (-0.023,0.163)	0.0839 (-0.019,0.187)	0.0359 (-0.165,0.137)
Admission Hour	0.0006* (0.0001,0.001)	0.0004 (-0.0002,0.0001)	0.0009 (0.0002,0.001)	0.0001 (-0.0003,0.0006)	-0.0003 (-0.001.0.0004)	0.0008* (0.0001,0.0015)	0.0005 (-0.001,0.001)	0.0005 (-0.0004,0.001)	0.0006 (-0.0003,0.35)	0.0007* (0.0001,0.001)	0.0003 (-0.0005,0.001)	0.0015** (0.0006,0.002)
Age												
65-74	-0.0234*** (-0.036,-0.010)	-0.0220*** (-0.036,-0.007)	-0.0236 (-0.051,0.004)	-0.0242*** (-0.037,-0.010)	-0.0226** (-0.038,-0.006)	-0.0264* (-0.052,-0.0002)	0.0014 (-0.017,0.20)	-0.0020 (-0.023,0.019)	0.0118 (-0.031,0.05)	0.0278** (0.010,0.045)	0.0295** (0.009,0.049)	0.0226 (-0.012,0.057)
75-84	-0.0085 (-0.036,-0.010)	-0.0058 (-0.016,0.005)	-0.0117 (-0.030,0.007)	-0.0090 (-0.019,0.001)	-0.0047 (-0.017,0.007)	-0.0152 (-0.034,0.004)	-0.0054 (-0.019,0.008)	-0.0093 (-0.24,0.006)	0.0050 (-0.025,0.035)	0.0134* (0.0005,0.02)	0.0130 (-0.002,0.028)	0.0131 (-010,0.036)
85+	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Male	0.0089** (0.003,0.014)	0.0091*** (0.002,0.015)	0.0092 (-0.001,0.019)	0.0060* (0.0001,0.011)	0.0036 (-0.003,0.010)	0.0096 (-0.0007,0.019)	0.0096* (0.002,0.017)	0.0107* (0.001,0.019)	0.0084 (-0.004,0.021)	0.0096** (0.002,0.016)	0.0120** (0.003,0.020)	0.0051 (-0.007,0.017)
Race												
White	0.0041 (-0.012,0.020)	-0.0026 (-0.022,0.017)	0.0190 (-0.008,0.046)	0.0116 (-006,0.029)	0.0061 (-0.015,0.027)	0.0264 (-0.005,0.057)	0.0118 (-0.11,0.035)	0.0231 (-0.004,0.051)	-0.0129 (-0.055,0.029)	0.0126 (-0.009,0.035)	0.0130 (-0.013,0.039)	0.0081 (-0.033,0.050)
Black	0.0108 (-0.008,0.029)	0.0007 (-0.022,0.024)	0.0323 (-0.0001,0.06)	0.0170 (-0.003,0.37)	0.0109 (-0.013,0.035)	0.0321 (-0.003,0.067)	0.0177 (-0.008,0.043)	0.0309 (-0.0003,0.062)	-0.0104 (-0.056,0.035)	0.0269* (0.002,0.051)	0.0334* (0.004,0.062)	0.0094 (-0.035,0.054)
Other	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Hispanic	0.0011 (-0.031,0.033)	-0.0157 (-0.053,0.021)	0.0483 (-0.015,0.111)	0.0087 (-0.022,0.040)	-0.0060 (-0.042,0.030)	0.0496 (-0.010,0.109)	-0.0071 (-0.46,0.032)	-0.0155 (-0.060,0.029)	0.0250 (-0.055,0.105)	0.0151 (-0.017,0.047)	0.0273 (-0.009,0.063)	-0.0391 (-0.114,0.036)
N	50,161	30,243	19,918	51,562	31,423	20,139	38,356	24,004	14,352	57,868	36,702	21,166

Note: SNF denotes skilled nursing facility, *p< 0.05; **p< 0.001; ***p< 0.000

Falsification and Robustness Tests

The main analysis sample includes Medicare patients with 2-3 days of inpatient stay. To show that the choice of length of stay is appropriate for the choice of the 3-Day Rule as the instrumental variable, I calculate the first stage estimates for three groups of patients as a falsification test. First, I examine the association between admission before midnight and SNF discharge for 60-64-year-old patients with commercial insurance, and Medicaid patients under 65. As presented in table 2-6 below, the probability of SNF discharge for patients admitted before midnight for the privately insured (ages 60-64), and Medicaid patients was 2.39 and 5.21 percentage points higher compared to those admitted after midnight. Next, I examine age 65+ Medicare patients with an inpatient length of stay of fewer than two days. As expected, before midnight admission has minimal impact on the probability of SNF discharge 0.47 percentage points for the pooled sample, 0.64 percentage points for FFS, and (not statistically significant) 0.18 percentage points for MA (Table 2-6). Although the association is positive, the magnitude is not large compared to the main estimates (13.05 percentage points for the pooled sample, 15.31 for the FFS and 9.43 percentage points for MA).

Table 0-6: Falsification Tests

	Private (60-64)	**Medicaid**	**Medicare with LOS=1**		
			Pooled	*FFS*	*MA*
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
Change in discharge to SNF	0.0239*** (0.0188 , 0.029)	0.0521*** (0.037 , 0.067)	0.0047*** (0.001,0.008)	0.0064*** (0.002 , 0.010)	0.0018 (-0.003 , 0.007)
Change in Readmissions	0.0048 (-0.338 , 0.347)	0.03197 (-0.040 , 0.679)	0.9463 (-0.327 , 2.22)	0.8234 (-0.333 , 1.98)	1.55 (-4.97 , 8.07)
N	51,187	15,607	151,603	99,214	52,389

Note: SNF denotes skilled nursing facility, *p< 0.05; **p< 0.001; ***p< 0.000

To show the robustness to bandwidth, I calculate the change in the probability of SNF discharge for admission before vs. after midnight using narrower and wider than what was used in the main analysis. The estimates for all bandwidths are close to the main analysis (+/- 5 hours) and statistically significant (Table 2-7).

Table 0-7: Robustness to Bandwidth for the Probability of SNF Discharge

	Change in Discharge to SNF		
Bandwidth	**Pooled**	**FFS**	**MA**
+/-1	0.116***	0.137***	0.081***
+/-2	0.1230***	0.1460***	0.086***
+/-3	0.1238***	0.1452***	0.089***
+/-4	0.1232***	0.1433***	0.908***
+/-6	0.1263***	0.1485***	0.090***
+/-7	0.129***	0.1520***	0.093***
+/-8	0.130***	0.153***	0.094***

Note: **p< 0.05; ***p< 0.001

Discussion

This study examined the impact of receiving post-acute care at a SNF on 30-day readmission among Medicare patients ages 65 and older. Using a RD approach with the 3-Day Rule as an instrumental variable, I find that patients that have a 2-3 days of inpatient stay, and thus are eligible for SNF coverage by Medicare, are more likely to be discharged to a SNF. Overall, I find that a SNF discharge led to a significant increase in 30-day readmission. One possible explanation for this finding may be premature discharge. If patients leave the hospital too soon before they are ready for SNF, or if SNF is not capable of meeting the patient's medical needs, it might increase the risk for readmission and make patient care difficult. Assessing the patients' post-acute care needs is critical for reducing avoidable readmissions. Even if a patient is medically ready for discharge, discharging the patient to the most appropriate post-acute care setting is important. Besides a patient's medical needs, it is critical to take functional, and social aspects of the patient's illness into account.[62] Some examples include patient cognitive status, patient activity level and functional status, the nature of the patient's current home and suitability for the patient's conditions (e.g., presence of stairways, cleanliness), availability of family or companion support, ability to obtain medications and services, availability of transportation from hospital to home and for follow-up visits, availability of services in the community to assist the patient with ongoing care, etc.[63]

I find that a SNF discharge significantly increased the likelihood of readmissions among Medicare FFS patients. However, for MA patients, while the estimated effect was similar in magnitude, the estimate was not statistically significant. Although the lack of statistical significance does not rule out the impact of SNF on readmissions among MA patients, the wide confidence interval suggests more variability and less

precise estimates. Additionally, because MA plans participate in PHC4 voluntarily, the sample size may not have been large enough to detect a statistically significant impact of SNF on readmissions among MA patients.

The different estimates for FFS vs. MA subgroups may be due to various reasons: First, Medicare FFS and Medicare Advantage have different policies with respect to SNF coverage. Medicare FFS requires patients to have at least three consecutive days as an inpatient to provide SNF coverage for their beneficiaries. On the other hand, as discussed earlier, 92% of MA plans waive the three-day requirement, and therefore, unlike FFS, most MA patients may not be subject to the 3-Day Rule.[64,42] Second, MA beneficiaries are more likely to be younger and healthier[65,66] and FFS patients may be sicker on average than MA enrollees[43] resulting in more need for PAC following discharge or higher risk of readmissions.[67] Besides, beneficiaries' individual health risk factors can influence selection into Medicare FFS over MA due to the less restrictive provider networks.[68]

Third, despite the traditional FFS reimbursement model, which promotes the quantity of services, the MA programs tie payments for care delivery to the quality and efficiency of care provided.[44] Therefore, MA programs have a financial incentive to avoid readmissions and unnecessary use of post-acute care. This variation in payment structures may cause higher rates of SNF discharge among FFS patients, which may not necessarily improve their outcomes, e.g., higher readmission rates compares to MA beneficiaries.[46] A stratified analysis of Medicare FFS and MA patients at four different levels of comorbidity did not show any difference in readmissions based on comorbidity, which may indicate the impact of comorbidities may be more on the probability of admission or length of stay.

This study has several limitations. First, our analysis is limited to patients with a very specific length of stay (2-3 days). Therefore, the findings may not apply to patients with shorter or longer length of stay. Second, while the RD design examines the causal relationship between SNF care and readmission, this approach may not fully address unobserved confounding. One confounding factor which is difficult to observe or measure is patient preferences. For example, patients are free to choose which SNF they prefer to be discharged to and may have preferences such as language competency or proximity to home or family members. These preferences can potentially lead patients to select a SNF less based on quality measures meaning they may end up choosing a SNF that is more likely to result in readmission to the hospital.[14] Third, beneficiaries in Medicare FFS who are “aligned” to ACOs may benefit from ACOs’ waiver of the three-day inpatient hospital requirement.[69] Therefore, our estimates for the FFS subsample may

not truly reflect the impact of SNF on readmissions. Fourth, the study period (2011-2014) overlaps with the implementation of a few value-based programs, most of which focus on care coordination and readmission reduction. During this period, hospitals may have used post-acute care to decrease the length of stay and replace inpatient care with skilled nursing care to prevent readmissions.[70,71] However, a recent analysis of the trends in the use of post-acute care showed that PAC use did not appear to change after the ACA.[72] Therefore, this time overlap may have little potential to influence the true estimate of the impact of SNF on readmissions. Fifth, I did not have access to the mortality data after discharge. Therefore, I was not able to account for patients who may have died within 30 days of discharge, thereby potentially censoring their potential readmission. Sixth, the results of this study are only applicable to Medicare patients above 65. Therefore, the findings may not be generalizable to Medicare patients below 65 or patients with other insurance types with different payment incentives. Finally, the data used in this study represents one state and may not be reflective of the relationship between SNF and readmissions in other states or at the national level.

Conclusion and Policy Implications

This study contributes useful information to the literature and has important policy implications. Our study suggests that SNF discharge increases the probability of 30-day readmission among both Medicare FFS and MA enrollees. A comparison of MA and Medicare FFS use of SNF showed that although most MA plans are not subject to the 3-Day rule for SNF coverage, MA enrollees had lower SNF discharge rates with similar (although statistically not significant) readmission rates to FFS enrollees. This finding suggests there is an opportunity to reduce SNF use, which is a costly and frequently used post-acute care setting. In addition, unnecessary or inappropriate use of SNF care may not lead to overall cost-savings if it results in readmission and more subsequent health care utilization. Besides, to manage avoidable readmissions, it is important for hospitals to carefully identify the appropriate post-acute care setting for their patients. SNF may not be the most appropriate option for some patients and discharging patients to SNF only because Medicare pays for it, may result in readmissions that could potentially be avoided.[28]

As Medicare is shifting away from FFS reimbursement, an increasing share of its beneficiaries are electing MA over traditional Medicare. A core strategy of managed care plans is to provide more closely coordinated care than individuals would otherwise receive in an unmanaged health care plan, with the ultimate goal of reducing costs and resource use. However, with the similar readmission rates for FFS and

MA enrollees shown in our study, it may be worth to revisit managed care strategies that aim to reduce readmission rates among MA enrollees in post-acute care settings.

Since March 2020, CMS has waived the 3-Day requirement during the health emergency and coronavirus pandemic[73] which illustrates an opportunity to repeal the Medicare 3-Day Rule to ensure all Medicare beneficiaries receive comparable SNF care, regardless of how they participate in Medicare.

The positive association between SNF care and readmission rates shown in this study may reflect poor coordination of care or inadequate recognition of post-discharge needs. Our study provides a new perspective to policymakers and healthcare providers to identify the optimal clinical setting for different patient sub-groups with different payer types. With recent efforts to move towards value-based payment systems, hospitals are encouraged to deliver care efficiently across the continuum of care, including outpatient, inpatient, and transitions of care, and reducing unnecessary readmissions is a critical step in achieving this goal. Therefore, a better understanding of the outcomes among Medicare subgroups can help manage unnecessary Medicare spending and potentially avoidable readmissions more efficiently.

Chapter 3 The Differential Impact of the Hospital Readmission Reduction Program (HRRP) on Readmissions in Counties with High vs. Low Medicare Advantage Penetration Rate in Pennsylvania

Introduction

Medicare is a federal health insurance program created in 1965 for all people ages 65 and older, certain younger people with disabilities such as ALS, and people with end-stage renal disease (ESRD).[74] For over 30 years, the Medicare program has offered two insurance coverage options: traditional Medicare (TM), also referred to as Medicare FFS, and Medicare Advantage (MA). The MA program offers beneficiaries the opportunity to voluntarily enroll in a commercial managed care plan as an alternative to TM. While traditional Medicare has plenty to offer, a market for quality private health plans has emerged, giving insurers to provide coverage in the form of MA plans.

According to CMS, "MA Plans, are an "all in one" alternative to TM offered by private companies approved by Medicare. These "bundled" plans include Medicare Part A (including inpatient stays, skilled nursing facility care, some home health visits, and hospice care) and Medicare Part B (including physician visits, outpatient services, preventive care, and some home health visits),[75] and often Medicare prescription drug coverage (Part D).[76] CMS also notes that most MA plans may provide supplemental benefits such as preventive dental care, vision and hearing assistance, or health and wellness programs, benefits that are not provided by TM. Beneficiaries can choose from several types of MA plans, with Health Maintenance Organizations (HMOs) and Preferred Provider Organizations (PPOs) accounting for the majority of total MA enrollment.

MA plans provide all Medicare-covered services (other than hospice) but differ from TM in several respects.[77] One major difference between TM and MA is in their payment structure. In TM, health care providers are directly reimbursed by the government, receiving a separate fee for each service they deliver (fee-for-service) with exceptions like payment systems based on Diagnosis-Related Groups (DRGs) where Medicare pays hospitals a flat rate per case for a procedure or diagnosis rather than the number of days of stay in hospital.[78] Critics of this system argue that DRGs encourage inappropriate early discharge of patients before optimal patient education and follow-up care have been provided, and alter diagnoses to higher cost units of service.[79] In contrast, when a Medicare beneficiary is covered through MA, the

healthcare provider will get reimbursed by privately run plans that receive monthly premiums (capitated payments) from the government to provide healthcare coverage to their enrollees.[80] The TM payment system incentivizes volume over value, which can drive overuse, waste, or inappropriate use of services. In contrast, capitated payments create the incentive for MA plans to structure their benefits and covered medical services toward delivering care in the most cost-effective way.[81,82]

One of the policy goals of the MA program is to improve the efficiency of care delivered to enrollees through better insurance design, limiting the incentives to deliver additional services inherent in FFS payment, and the use of care management tools increasingly seen in the private sector.[83] MA plans use utilization management as a tool to control service use and spending.[81,82,84] For example, MA enrollees may be required to use a defined network of providers or pay more for out-of-network care. Through establishing networks, MA plans may limit access to costlier providers and review claims to eliminate unnecessary costs. To achieve high-quality outcomes, MA plans make efforts to identify the highest-performing providers and use provider incentives to direct care appropriately.[85] MA plans pursue value-based contracts (including full-risk contracting with primary-care providers) and make efforts to identify cost drivers (e.g., patient leakage to competing providers outside the network, use of high-cost facilities and specialists, and readmission rates).[85] Overall, the differences in plan design between MA and TM plans may result in different utilization patterns among MA enrollees compared to TM.

Over the past decade, MA enrollment has grown rapidly from 24% of Medicare beneficiaries in 2010 to 39% in 2020– 24.1 million people out of 62.0 million Medicare beneficiaries overall.[77,86] The rapid expansion of Medicare Advantage has raised the question about the effects of this growth beyond MA enrollees, potentially influencing care for TM patients as well. This is a common phenomenon referred to as “externalities” or “spillover effects”. The concept of spillover effects has been the subject of many studies in economics and health policy.[87] Beyond the effect of care management on MA enrollees themselves, there is also the possibility that better care management might have wider-ranging effects: by shifting financial incentives and physician practices, a large number of patients covered by insurance plans that promote better management could generate spillover effects that change the utilization of other patients in the health-care system.

Evidence suggests important MA spillover effects on different TM outcomes such as expenditures and quality,[88–97] mortality,[91] hospital utilization,[89,91,92] length of stay,[92,98] outpatient visits,[88,98] treatment intensity,[91,99], etc. While there is suggestive evidence that higher MA enrollment rates in an area may lead

to lower spending and potentially higher quality for other patients in the same area,[83,90,92] very few studies have explored the possibility of high MA penetration rate affecting TM readmissions.

Conceptual Framework

Nearly 20% of Medicare patients are re-hospitalized within 30 days of discharge[56], which is a major contributor to resource use and spending. Readmissions can be driven by multiple factors, including poor hospital care, insufficient discharge planning, uncoordinated transition care or inadequate post-discharge care, poor communication from hospital team members to post-acute care providers, etc.[100–103] Research suggests that some strategies may help patients and providers to avoid readmissions. Studies have shown that assessing patient discharge needs, assisting patients to manage their medications or their transitions from hospital to post-acute care, and linking patients to necessary follow-up care may reduce readmissions.[13,100–108] For example, pharmacist-directed interventions that combine medication reconciliation with education and post-discharge follow-up have been shown to prevent adverse drug events and reduce readmissions.[106,109] Another study showed a program that included linkage to community resources and care coordination with long-term care facilities, as well as medication reconciliation and follow-up phone calls were able to reduce readmissions.[106]

MA plans and providers serving MA beneficiaries may utilize managed care strategies and invest in improving the care processes and additional care coordination to avoid costly hospitalizations and readmissions. In addition, although population health is not an explicit strategy for reducing readmissions, MA plans may invest more in wellness programs, early intervention (e.g., management of chronic conditions such as diabetes or high blood pressure), preventive care, or minimizing disease progression to improve or maintain enrollee health with the goal of reducing unnecessary hospitalizations or readmissions.[43]

Many spillover studies in the context of healthcare delivery and policy have used the "Norms Hypothesis", developed by Newhouse and Marquis[110] in 1978, to explain the mechanism behind the spillover effects. The Norms Hypothesis suggests that physicians' practice styles are driven by their patients' average or typical health insurance coverage and that physicians tend to practice similarly for all patients regardless of what type of insurance they have. Evidence suggests that for physicians, the mix of patients in their local area, as well as the overall characteristics of their patient panels, influences physicians' care choices.[111] Beyond a physician's panel, physicians' practice styles can also be influenced

through peer effects and learning. Thus, even physicians with few managed care patients may change their practice styles in areas with high levels of managed care among their peers.[98]

I use the Norms Hypothesis to create the conceptual framework for this study. If the Norms Hypothesis is true, as more patients enroll in Medicare Advantage, providers tend to standardize their care processes over time and treat all patients the same regardless of payer source. The rapid growth of MA has the potential to increase the efficiency of healthcare delivery.[98] Therefore, more efficient care processes and better care management (e.g., better care coordination, more emphasis on preventive care, etc.) brought about by increases in MA penetration could, by changing provider behavior, "spill over" onto traditional Medicare patients treated by the same providers, with a potential to reduce readmissions.[110] Figure 3-1 illustrated the conceptual framework for this study.

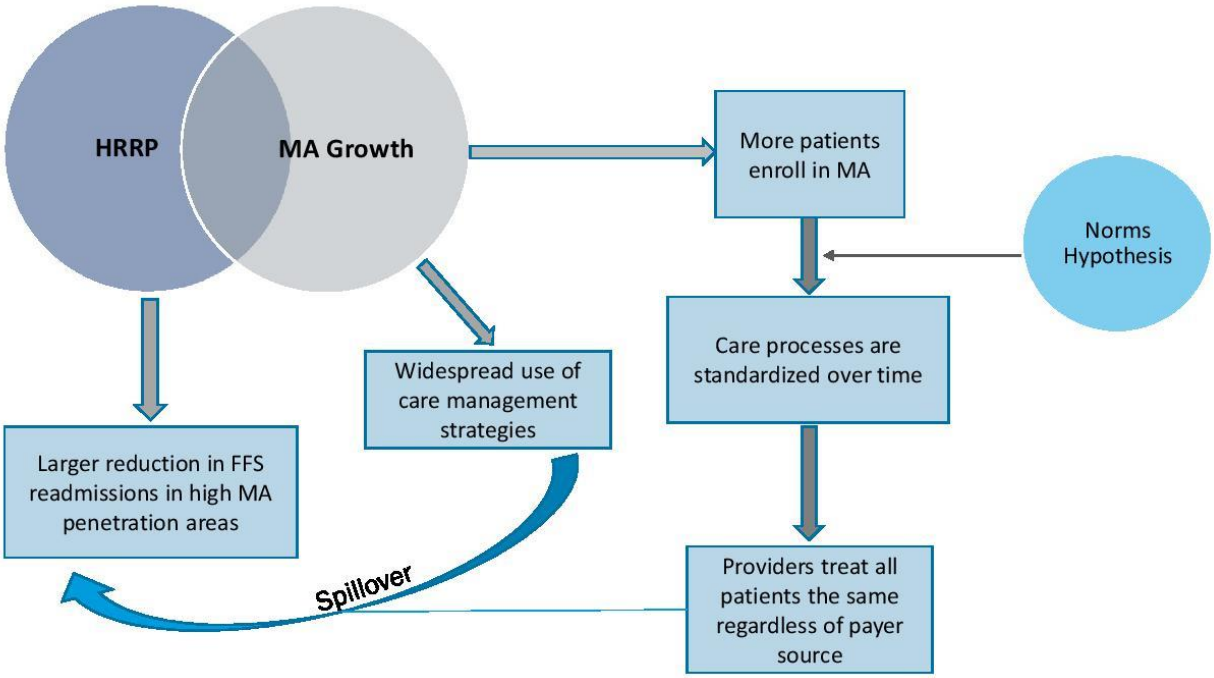


Figure 3-1: Conceptual Framework

Note. HRRP= Hospital Readmission Reduction Program. MA= Medicare Advantage. FFE= fee-for-service

The Hospital Readmission Reduction Program

One area where studying the MA spillover effects on TM readmissions is particularly relevant is the HRRP. The HRRP is "a Medicare value-based purchasing program that encourages hospitals to improve communication and care coordination to better engage patients and caregivers in discharge plans and, in turn, reduce avoidable readmissions." The HRRP was first implemented in October 2012 to provide incentives to hospitals to decrease their readmission rates by instituting penalties for hospitals with high readmission rates among Medicare patients. HRRP started with targeting the readmissions among TM patients with three specific conditions: acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN). (Figure 3-2). Since 2015, the HRRP has added chronic obstructive pulmonary disease (COPD), elective total hip arthroplasty, and total knee arthroplasty to the list of conditions for which hospitals may be penalized for excess 30-day readmissions. [112] The first round of HRRP penalties was announced in August 2012 based on readmissions that occurred between July 2008 and June 2011; penalties were applied to Medicare reimbursements that occurred in 2013. For example, if a hospital received the maximum penalty of 1 percent in the first round of penalties, all subsequent Medicare reimbursements that occurred between October 2012 and September 2013 would be reduced by 1 percent. The penalties expanded to a maximum of 3 percent in the third year.[113]

In January 2018, Medicare Payment Advisory Commission (MedPAC) analysts presented findings of their analysis on the HRRP ahead of their report due to Congress in June. According to their data, both unadjusted and risk-adjusted readmission rates declined for conditions covered by the HRRP. Earlier studies also examined the HRRP-related improvement in readmissions.[114–121,122–125] For example, research shows readmissions for targeted conditions fell from 21.5% in 2007 to 17.8% in 2015.[10] Additionally, readmissions for targeted conditions fell significantly faster at hospitals that were subject to the HRRP than those that were not, and readmissions for conditions covered by the HRRP were reduced more than non-covered conditions.[126] Although these data were promising, due to the complicated nature of the HRRP, the program has faced questions and criticisms. Research has raised the concern that some readmission reductions seen after implementation of HRRP may be attributed to changes in the way admitted patients were coded for the severity of illness rather than the program itself.[127,128] Additionally, some critics of the HRRP policy effect on readmissions state that the declines in excess readmissions--after implementation of the HRRP can partly be explained by "regression to the mean", attributing the improvements in readmissions experienced at poor-performing hospitals to a lower probability of observing extreme values when the outcome is measured multiple times.[128–131] Nevertheless, despite the

debates on whether the HRRP has been successful in reducing readmissions, research continues to study the HRRP from different angles.

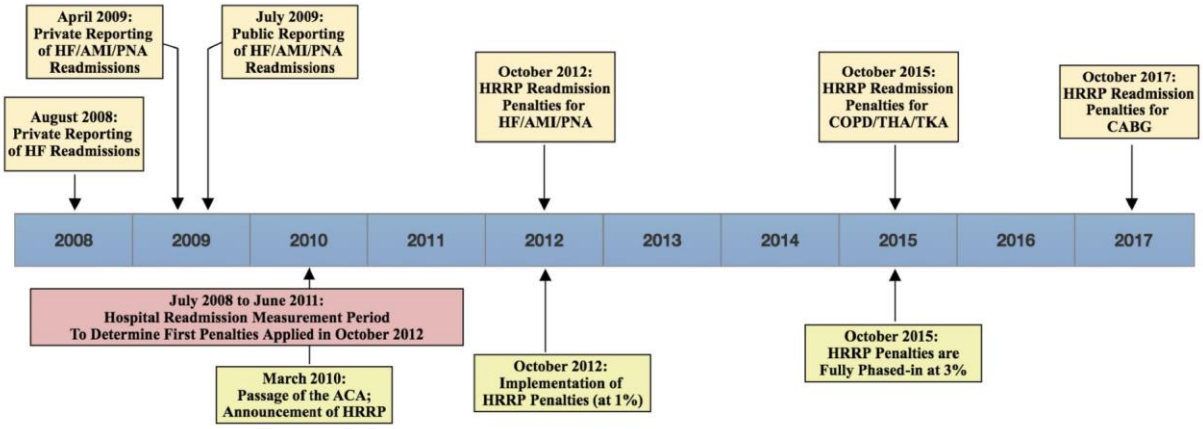


Figure 3-2: Timeline for Implementation of the Hospital Readmission Reduction Program

Note. HF=heart failure, AMI=acute myocardial infarction, PNA=pneumonia, COPD=chronic obstructive pulmonary disease, CABG= coronary artery bypass graft, THA= total knee arthroplasty, TKA=total hip arthroplasty.

Prior Literature

Recognizing that most physicians and healthcare providers today treat a variety of patients with a variety of insurance arrangements, the Norms Hypothesis has set the theoretical background for a number of empirical studies related to the spillover effects and physician behavior. Landon (2017)[132] discusses two alternative scenarios related to how physicians might respond to changes in financial incentives. One scenario suggests that physicians will customize their decision-making for each patient based on the incentives associated with that patient's payer. The alternative scenario, which is the focus of this paper, suggests that physicians will develop a relatively uniform approach to care that is consistent with their overall financial incentives without customizing their treatment decisions based on the payment arrangements for the patient in front of them. This scenario is consistent with the "Norms Hypothesis" introduced by Newhouse and Marquis in (1978).[110]

MA Penetration Spillover Effects

Evidence suggests that managed care penetration, in general, is associated with a decrease in Medicare FFS expenditures.[93–97] The first estimates of such spillovers were published by Baker et al.

(1999).[95] Using 1990-1994 data, this study showed an increase in HMO market share (Medicare and non-Medicare) from 10% to 20%, will decrease Medicare FFS expenditures for Part A services by 2% and Part B services by 1.5%. The authors' explanation for this result is that managed care contributed to reductions in the number or intensity of services received by patients covered by traditional Medicare.[95] This study explains two broad mechanisms through which managed care could affect non-Medicare patients: first, by system-wide changes in the availability of medical infrastructure, clinicians, and new medical technology, and second, through physician behavior change treating FFS patients the way they treat managed care patients (Norms Hypothesis).

Chernew et al. (2008)[93] used 1994–2001 Medicare Current Beneficiary Survey data to identify the effect of Medicare HMO penetration on FFS expenditures. Findings showed each percentage point increase in Medicare HMO market penetration led to a one percent decrease in annual, per capita TM spending. The spending reduction was for both inpatient and outpatient care and was concentrated among TM beneficiaries with at least one chronic condition.

Another study that has discussed MA to TM spillover effects with reference to MA penetration was done by Glied and Zivin (2002).[99] This study explored how doctors behave when some (but not all) of their patients are in managed care. Specifically, the authors studied how practice-level managed care penetration affects treatment intensity. This study revealed that with a diverse pool of patients with different insurance types, visit duration remains constant across patients (FFS, HMO, Medicare, Medicaid) within a practice, which is counterintuitive to the idea that some payers are more profitable than others. For medications, prescription patterns appeared to be different among various insurance holders but converging to the patterns for managed care patients as managed care penetration increased. The findings of this study are consistent with the Norms Hypothesis that physicians set a practice-wide rule on the basis of the overall payer mix. However, the patient mix may vary among different practices. Therefore, practice-level findings may not hold true in a system-wide analysis.

The literature has also examined the MA to TM spillover effects on hospital utilization. Two studies by Baicker et al. in 2013[92] and 2015[98] explored MA spillover effects on TM and the commercially insured younger by examining the effects of greater managed care penetration on hospital utilization and spending. The authors did not find any association between hospitalizations and MA penetration, but MA penetration was associated with lower costs, shorter stays per hospitalization, and increases in outpatient visits for TM and younger privately insured patients. Although a decrease in length of stay and an increase

in outpatient visits may indirectly imply a decrease in inpatient readmissions, none of these two studies used readmissions as a measure of hospital use.

Callison (2016)[91] used 2003-2009 Health Care Utilization Project's State Inpatient Databases (SID) data to examine the relationship between MA market penetration and TM treatment intensity for patients hospitalized with AMI. The findings of this study indicate that increases in MA penetration lead to reduced treatment intensity for FFS AMI patients through reductions in the average number of inpatient procedures, surgical treatments to restore blood flow to the heart, and indicators for, particularly intensive inpatient interventions. Additionally, these reductions in utilization and treatment intensity appear to negatively impact the health of FFS patients, resulting in an increase in inpatient mortality.

Henke et al. (2018)[89] investigated the relationship between MA growth and inpatient hospital costs and utilization for all Medicare patients (TM and MA) before and after the ACA. The authors found evidence of MA enrollment growth leading to modest reductions in inpatient costs per enrollee for the entire Medicare population aged 65 or older. The association was particularly strong for non-urgent admissions. After the ACA, the impact of MA enrollment growth on costs and utilization diminished. The authors state that one potential reason for this finding is that other initiatives introduced or expanded under the ACA—for example, Accountable Care Organizations and the HRRP—may have improved outcomes for non-MA patients over the same timeframe.

Feyman et al. (2020)[133] extend prior work by identifying the relationship between county-level changes in MA market penetration and TM utilization and spending (spillovers). The authors estimate that a one percentage point increase in county-level MA penetration results in a $64 (0.7%) reduction in standardized per-enrollee TM spending.

The literature suggests that a shift in provider behavior might not be seen until a high enough proportion of patients are in a certain group so as to make the change in behavior worthwhile.[132] Two studies have examined whether a threshold exists for MA penetration above which providers start to measurably change the way they deliver care in a manner in which there is the possibility of spillover effects to happen.[90,98] Johnson et al. (2016)[90] suggest that a provider is unlikely to change the way he or she delivers care in response to pressure from insurers covering a small number of patients. However, as more and more patients enroll in managed care, plans' influence over providers may grow. In their analysis of MA to TM spillover effects, they found no significant relationship between MA penetration and

Medicare FFS costs in counties with low baseline penetration. However, in counties with the highest baseline penetration (the upper 25%), they found a significant negative association between managed care penetration rate and FFS Medicare costs. Baicker et al.[98] also estimate a threshold model, examining whether the effect of penetration is different above versus below a threshold and find a nonlinear relationship between managed care penetration and expenditures which is consistent with an earlier study that showed a nonlinear relationship between FFS expenditures and HMO market share.[94]

Other Spillover Studies

Research suggests clinicians' responses to payment reforms are not limited by payer[110,132,134–136] and that the effect of a policy can be broader than the target population. For instance, a recent NBER paper by Barnett et al. (2020)[136] examined spillovers of a Medicare intervention to commercial insurance. The intervention was a randomized controlled trial conducted by Medicare, which sent warning letters to doctors who heavily prescribed the most popular antipsychotic medication, quetiapine. The authors examined the spillover effects of these letters on commercial insurance patients covered by three of the five largest insurers in the U.S. Those patients were not mentioned in, nor were they the focus of, the Medicare letter. Even though the letters did not mention commercial insurance, they reduced prescribing to commercially insured patients by 12%. The authors hypothesize that physicians experience high costs to setting insurer-specific medical practice styles and may be unable or unwilling to distinguish insurers when determining how they treat patients. Consistent with the Norms Hypothesis, the results imply that when physicians develop styles of practicing medicine, those styles are not insurer-specific.

A few studies have focused on Medicare's Comprehensive Care for Joint Replacement ("CJR") program, devoted to lowering extremity joint replacements (LEJRs), i.e., hip and knee arthroplasty for beneficiaries enrolled in traditional Medicare. The model began on April 1, 2016, and will run through September 30, 2021. As of January 1, 2021, approximately 432 hospitals in 67 different MSAs (metropolitan statistical areas) are participating in this CJR model. The system for payment, known as the Inpatient Prospective Payment System (IPPS), categorizes cases into diagnoses-related groups (DRGs) that are then weighted based on resources used to treat Medicare beneficiaries in those groups.[137] The CJR model holds participant hospitals financially accountable for the quality and cost of a CJR episode of care and incentivizes increased coordination of care among hospitals, physicians, and post-acute care providers.

A recent study by researchers at RAND[135] in 2020 used the CJR model to estimate the spillover effects of the model onto MA and the non-elderly commercially insured. Consistent with the "Norms Hypothesis," the authors found that the CJR program leads to meaningful direct and indirect changes in provider behavior towards MA and non-elderly commercially insured. Specifically, the authors found changes in post-acute care treatment decisions across all three payer populations (TM, MA, and commercial), reflecting a 20–40% decrease in inpatient rehabilitation facility (IRF) use for traditional Medicare and a 50–60% decrease among MA when compared to their pre-CJR levels. The non-elderly, commercially insured LEJR patients did not show an immediate spillover effect but instead, began to receive less IRF care after the CJR program had been in place for one year. This study also found suggestive evidence that the program creates spillovers for similar surgical procedures that are not covered by the CJR program (i.e., non-LEJR procedures performed by LEJR surgeons), which has the potential to benefit patients and payers beyond the scope of a targeted payment reform intervention.

Similarly, Einav et al. (2020)[134] estimate that the CJR had effects of similar magnitude on the healthcare experience of non-targeted, privately insured Medicare Advantage patients. Consistent with these two studies, Wilcock et al. (2020)[138] studied the association between the CJR and post-acute care use among patients with MA coverage. Findings showed for patients who underwent a lower extremity joint replacement, Medicare's CJR program reduced the use of institutional post-acute care among patients affected by the program (traditional Medicare) and those not affected by the program (enrolled in MA plans). This study's finding is consistent with prior research in which clinicians' responses to payment reforms were not limited by payer[110,132,134–136] and suggests that the effect of a policy can be broader than the target population.

Studies Related to MA Penetration and TM Readmissions

Most relevant to our research are three studies by Kulkarni et al. (2012),[139] Baicker et al. (2015),[98]and Park et al. (2020).[88]

Kulkarni et al. used 2006-2008 data to examine whether the MA penetration rate is associated with mortality and readmission rates among FFS patients. Their findings indicate that the risk-adjusted readmission and mortality rates for heart failure, AMI, and pneumonia do not differ systematically with MA penetration. Although this study focuses on the same conditions that are also targeted by the HRRP, the data used is from before the HRRP period. In addition, it seems that the study period is before the

rapid growth of MA (the median MA penetration rate in their study period was 17.0%). Therefore, a study with more recent data on MA penetration may lead to different findings, which can be important if the Norms Hypothesis plays a role in the spillover effects.

Baicker et al. (2015)[98] found that in areas with a greater enrollment of Medicare beneficiaries in managed care, Medicare FFS beneficiaries have fewer days in the hospital and more outpatient visits. The authors also examine 30-day readmissions as a sign of the quality of care delivered in the initial hospitalization and post-discharge period. They find a decline that is not statistically significant in hospital readmissions as MA managed care penetration increases (comparable in magnitude to the decline in hospitalizations overall, which is also not statistically significant).

A more recent study by Park et al. (2020)[88] assessed whether MA growth from 2010 to 2017 had a spillover to per capita spending, emergency department visits, and readmission rates among FFS beneficiaries. This study did not find any association between FFS readmission rates and MA penetration. However, when results were stratified by the number of chronic conditions, the authors found a positive association between MA penetration and FFS readmission rates among patients with zero or one chronic condition. The authors state that this observed relationship may be because MA plans may not have identified effective strategies to reduce readmission rates among their own beneficiaries, which is against the hypothesis for my study. However, if Park's explanation for the positive association between MA penetration and readmissions is true, we would expect to see a stronger or at least the same level of association between MA penetration and readmission for patients with higher comorbidity levels because this group of patients may have more complex conditions that need better care coordination. Yet, this association was only observed among patients with a lower comorbidity burden. Although Perk et al. used more recent data (two years before and 5 years after the HRRP), the main focus is on the extent to which comorbidities may impact spillover effects, so Park et al. do not analyze changes in FFS readmission rates before vs. after the introduction of the HRRP in relation to MA penetration rates. Besides, while the analysis is stratified by the numbers of chronic conditions (i.e., 0, 1. 2-3, 4-5, and 6+), the use of a pooled data source limited authors' ability to assess any specific conditions, i.e., heart failure, AMI, or pneumonia, which are the HRRP target conditions.

Gaps in the Literature and Contribution

The rapid growth of MA during the past decade overlaps with the implementation of the HRRP. Therefore, a critical question related to the implementation of the HRRP is whether and the extent to which MA rates may have impacted the HRRP even though the HRRP only targeted Medicare FFS patients.

The majority of research on MA to TM spillover effects is based on pre-HRRP data with a limited focus on readmissions. The available literature on MA penetration spillover effects on TM readmissions shows mixed evidence. While some studies suggest no overall association between MA penetration rate and FFS readmissions,[19,52] one study found a positive association between MA penetration and readmissions among FFS patients with zero to one chronic condition, and another study found a (statistically insignificant) decline in hospital readmissions.[98] None of these studies, however, have examined the relationship between MA penetration and FFS readmissions before and after the implementation of the HRRP.

In this study, I examine the MA spillover effects on TM readmissions within the context of the HRRP. More specifically, I examine whether the change in readmissions from before to after the HRRP among Medicare FFS patients is different in counties with higher vs. lower MA penetration rates. The analysis focuses on the three specific conditions targeted by the HRRP: HF, AMI, and PN. I hypothesize that Medicare FFS patients in counties with high MA penetration will experience a larger reduction in readmissions in the post-HRRP period compared to Medicare FFS patients with the same conditions in counties with low MA penetration.

Methods

Data

I use January 2011 through December 2014 Pennsylvania inpatient discharge data provided by the Pennsylvania Health Care Cost Containment Council (PHC4). The Council is an independent state agency that collects more than 1.7 million inpatient discharge records from Pennsylvania hospitals per year. All licensed health care facilities are responsible for providing administrative data to the PHC4. Administrative and clinical data are collected on a quarterly basis and received 90 days from the close of each quarter. The information is then used to prepare public reports for use by payers, providers, purchasers of health care, and the general public. There are more than 70 data fields available, which include clinical, utilization, and administrative data. Some examples of these include information such as Diagnosis

Related Groups (DRGs), Major Diagnostic Categories (MDCs), admission type and source, diagnosis and procedure codes, discharge status, length of stay, and charges. Information on patient origin, payer, physician, and facility is also included.[49]

Study Sample

This study focuses on the HRRP target population, which are TM patients admitted to the hospital with at least one of three target conditions: heart failure, AMI, and pneumonia. Since the HRRP began in October 2012, additional medical conditions have been targeted. After 2015, hospitals also are being penalized for excess 30-day readmissions for patients with chronic obstructive pulmonary disease (COPD), elective total hip arthroplasty, and total knee arthroplasty, but I only focus on heart failure, AMI, and pneumonia because my study period is 2011-2014. The steps for building my study sample are shown in Figure 3-3.

I use the PHC4 inpatient data to identify individuals ages 65 and older admitted to a Pennsylvania hospital between January 2011 and December 2014. As the first step, I exclude the admissions that happened in 2015 for two reasons. First, because for the year 2015, only the first quarter of data is available, and second, to avoid any confounding effect of additional conditions added to the HRRP after October 2015. I exclude patients (<1000 patients) that were admitted to a Pennsylvania hospital but lived in a state other than Pennsylvania. The reason for excluding non-PA residents is because the county-level MA penetration rate that I use in my analysis is defined based on the county of residence, and for non-PA residents, the county is specified as a missing value. Because the HRRP's focus is on TM, as the next step, I exclude patients whose primary payer is not TM. I also exclude patients discharged against medical advice because they are not eligible for penalties in HRRP.[140,141,142]

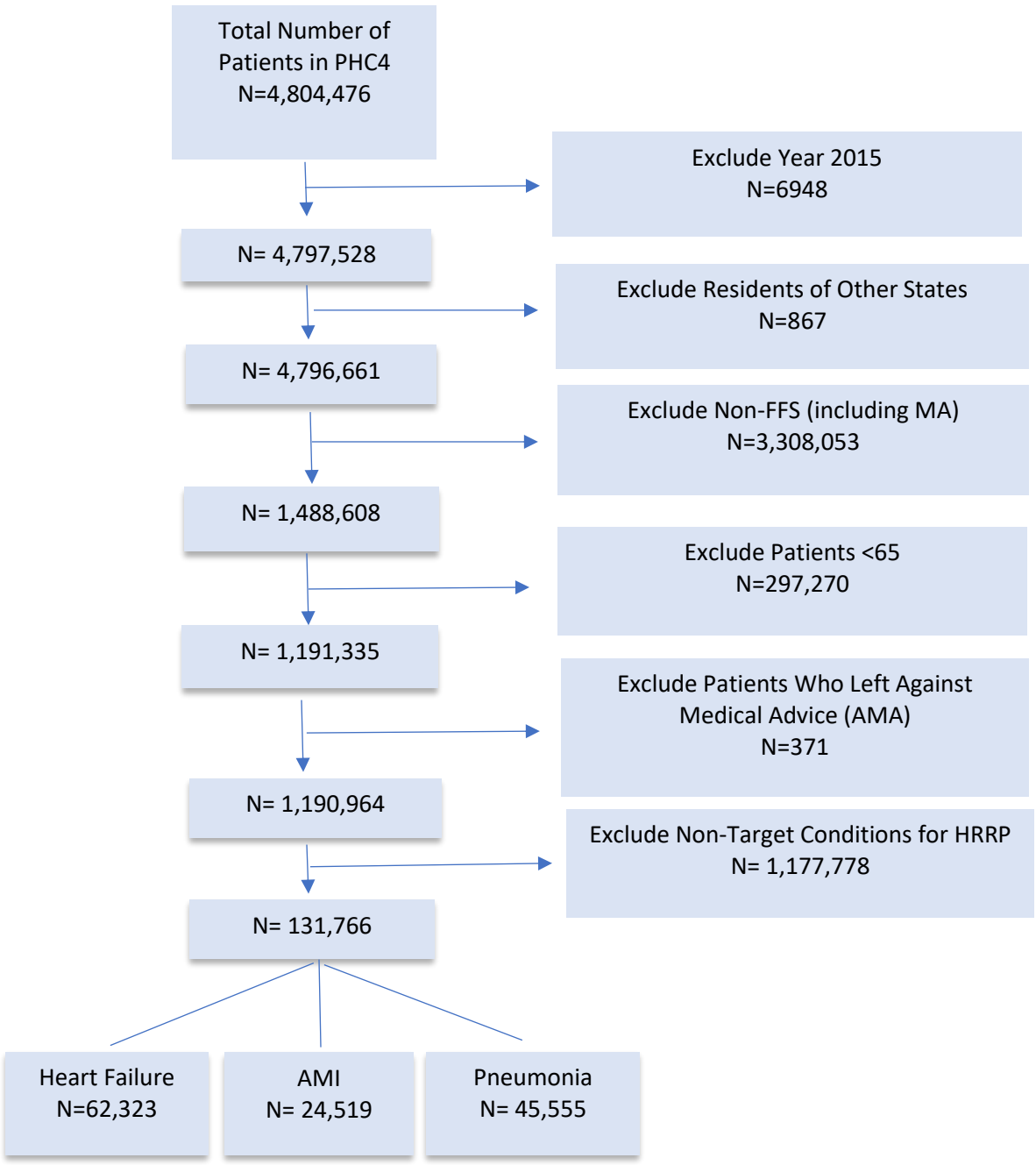


Figure 3-3: Steps for Building the Study Sample Using the PHC4 Inpatient Data 2011-2014

Note. PHC4= Pennsylvania Health Care Cost Containment Council. HRRP= Hospital Readmission Reduction Program. FFS= fee-for-service. MA= Medicare Advantage.

Dependent Variable

The dependent variable (outcome) is all-cause 30-day readmission. The 30-day readmission outcome is defined as a hospital stay within 30 days of discharge from the initial admission. No more than one readmission is counted within the 30-day window, but a patient can have multiple index hospitalizations within the study period (2011-2014). Following the 30-day period, a patient who experiences another hospital admission is counted as another index hospitalization, and a subsequent 30-day follow-up period begins. Another readmission can be counted within subsequent 30-day periods.[54–56]

Independent Variable

The main independent variable (key predictor) is a binary indicator variable of whether a county falls into the high Medicare Advantage penetration rate (MAPR) category. The steps for creating the indicator are as follows. First, I calculate the yearly county-level MAPR for each of the 67 counties in Pennsylvania from 2011 to 2014. County-level MAPR is calculated as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county.[88] Next, I find the county-level MAPR quartiles (Table 3-1) to create two versions of the indicator variable. For version 1, the indicator takes value 1 if MAPR>34.06% (median) and value 0 if below. For version 2, the indicator takes value 1 if MAPR>51.22% (i.e., above the 75th percentile) and value 0 if below. I use these two versions in my analysis later to test if a higher threshold for MAPR would result in stronger spillover effects.

Table 3-1: County-level MAPR Quartiles (2011-2014)

	Quartiles
Q1 (25%)	27.61
Q2 (Median)	34.06
Q3 (75%)	51.22

Note. MAPR=Medicare Advantage Penetration Rate. County-level MAPR is calculated as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county. The median (Q2) indicates that 50% of the MAPRs are lower than 34.06%. The third quartile means 75% of the MAPR values are lower than 51.22%

Other Covariates

Other covariates used include age as a categorical variable with three categories: 65-74, 75-84, and 85+, race (Black, White, and Other), ethnicity (Hispanic and non-Hispanic), sex, year (to account for temporal trends), comorbidity level, and rurality. Below, I explain why I control for these variables and how the variables are defined.

Comorbidity

I control for the comorbidity level of the patients because research suggests that MA spillover effects on TM readmissions vary by the comorbidity burden of the beneficiary.[88] For example, Park et al. [88] did not find an overall association between FFS readmission rates and MA penetration, but when results were stratified by the number of chronic conditions, authors found a positive association between MA penetration and FFS readmissions. The comorbidity variable in this study is based on the Charlson Comorbidity Index. This index is based on a list of 19 conditions identified from diagnoses in hospital and physician data. Each condition is assigned a weight from 1 to 6. The index score is the sum of the weights for all identified conditions.[59] An index score of 0 indicates no comorbid conditions, while higher scores indicate a greater level of comorbidity. In this study, I define four comorbidity levels: no comorbidity (index score = 0), index score = 1, index score = 2, and index score 3 and above. Each level is defined as a binary variable (Appendix D).

Urban-Rural

Controlling for urban-rural differences is critical for a few reasons. First, research has shown that MA enrollment and rurality are correlated.[143,144] Many low MA penetration counties are in rural areas.[86] In addition, evidence suggests that there are widespread differences in clinical care between urban and rural MA enrollees. Compared with non-rural MA enrollees, rural MA enrollees experience worse clinical care.[145] For example, according to a 2018 Consumer Assessment of Healthcare Providers & Systems (CAHPS) survey, MA beneficiaries living in rural areas received worse clinical care than MA beneficiaries living in urban areas for 22 of 44 measures.[145,146] which raises the concern about rural differences driving differences in readmission independents of MA enrollment. Therefore, if we do not control for urban-rural differences, the analysis would reflect the rural differences in readmissions and not MA differences.

The urban-rural covariate is defined based on the U.S. Department of Agriculture Economic Research (USDA) definition for the Rural-Urban Continuum Codes (RUCC). The RUCC defined by the USDA[147] distinguishes metropolitan (metro) counties by the population size of their metro area and nonmetropolitan (nonmetro) counties by the degree of urbanization and adjacency to metro areas (Appendix E). To be consistent with previous research, finding differences in MA enrollment between large metropolitan counties and all other types of counties (small metropolitan, micropolitan, and noncore),[143] I use the UDSA rurality measure in my analysis.[143] As a result, I identified 37 urban counties (RUCC 1-3) and 30 rural counties (RUCC 4-9) in Pennsylvania.[147,148]

I also perform a sensitivity test to examine the robustness of the results by using an alternative measure for rurality defined by the Center for Rural Pennsylvania (CPR). Using the CPR definition resulted in identifying 48 rural counties and 19 urban counties in Pennsylvania. Performing this sensitivity analysis provides an opportunity to see if the level of detail for urban-rural classification would make a difference in the parameter estimates.

Statistical Analysis

I use a linear probability regression model to estimate the change in the probability of 30-day readmission, holding everything else constant. The regression takes the following form:

$$Y_{it} = \alpha + \beta_1 Post_t + \beta_2 High_i + \beta_3 Post_t * High_i + X_{it} \beta_5 + \varepsilon_{it} \qquad \text{(Equation 1)}$$

Where Y_{it} is a binary variable for 30-day readmission for patient i at time t, which takes value 1 if the patient is readmitted within 30 days of discharge from the hospital and 0 if not readmitted. The variable $Post_t$ is a binary variable that takes value 1 if the hospitalization was in 2013 or 2014 (post-HRRP period) and value 0 if in 2011 or 2012 (pre-HRRP period).

The variable $High_i$ is the main predictor, which is a binary variable taking value 1 if patient is in the high MAPR category and 0 if not. I estimate two versions of my model. For version 1, I estimate equation 1 with variable $High_i$ taking value 1 if MAPR>median and value 0 if below. For version 2, I estimate equation 1 with variable $High_i$ taking value 1 if MAPR>75th percentile and value 0 if below.

X represents the control variables, including age, race, ethnicity, sex, urban-rural, and comorbidity. Year fixed effects (defined as a dummy variable for each year) are also included in *X*. I test for differences in the socio-demographic characteristics of patients in high and low MAPR counties using a t-test. The coefficient for the interaction term $Post_t * High_i$ estimates whether the expected mean change in readmission from before to after the HRRP was different among Medicare FFS patients with heart failure, AMI, or pneumonia in high vs. low MAPR counties.

Results

Descriptive Statistics

A total of 131,766 Medicare FFS patients with heart failure (N=62,323), AMI (N=24,519), and pneumonia (45,555) were included in this study. Table 2 presents the characteristics of these patients hospitalized between 2011 and 2014 in Pennsylvania.

Comparing patients in high vs. low MAPR counties using the median MAPR as the cut-off, the differences in most characteristics, including age, sex, and ethnicity, were small. However, there were fewer white (86% vs. 95%) and more Black patients (12% vs. 3%) living in high MAPR counties. With respect to urban-rural residence, I observed significant differences based on which measure of rurality was used. When using the USDA definition of urban-rural, the proportion of patients living in a rural county was significantly higher for the low MAPR group compared to the low MAPR group (20% vs. 10.5%). However, when using the CRP definition of urban-rural, the proportions were more similar (36% vs. 31%).

Comparing patients in high vs. low MAPR counties using the 75th percentile of MAPR as the cut-off, the differences in most characteristics, including age, sex, and ethnicity, were small. We saw a larger proportion of white (94% vs. 91%) and smaller proportion Black (6% vs. 5%) patients in the high MAPR group compared to the low MAPR group. With respect to urban-rural residence, I observed significant differences based on which measure of rurality was used. When using the USDA definition of urban-rural, the proportion of patients living in a rural county was significantly higher for the high MAPR group compared to the low MAPR group (20% vs. 10.5%). Similar to using the median MAPR as the cut-off, the USDA measure of urban-rural shows 12% vs. 18% rural residence, while the CRP's measure shows 45% vs. 30% rural residence in high vs. low MAPR groups.

Table 3-2: Summary Statistics of the Study Sample

	Version 1 **High=Counties with MAPR>34.06%** **Low= Counties with MAPR<34.06%**			**Version 2** **High= Counties with MAPR>51.22%** **Low= Counties with MAPR<51.22%**		
	High	Low	p-value	High	Low	p-value
Age (average)	80.99	81.06	0.19	81.93	80.84	<0.0001
65-74 (%)	29.76%	28.59%	<0.0001	25.30%	29.82%	<0.0001
75-84 (%)	37.46%	40.06%	<0.0001	37.73%	39.37%	<0.0001
85+ (%)	39.75%	38.75%	<0.0001	44.13%	38.07%	<0.0001
Male (%)	44.07%	46.48%	<0.0001	43.46%	46.03%	<0.0001
Hispanic (%)	1.98%	1.99%	<0.0001	1.98%	1.99%	<0.0001
Race (%)						
White	85.68%	94.90%	<0.0001	93.67%	90.98%	<0.0001
Black	11.80%	2.69	<0.0001	5.31%	6.27%	<0.0001
Other	2.50%	2.38%	0.16	1.02%	2.74%	<0.0001
Comorbidity (Charlson Index)						
0 (No Comorbidity) (%)	5.67%	5.96%	0.03	5.88%	5.85%	0.87
1 (%)	21.40%	21.92%	0.02	22.44%	21.58%	0.004
2 (%)	22.39%	21.76%	0.008	22.74%	21.84%	0.002
3 (%)	50.33%	50.52%	0.51	48.92%	50.72%	<0.0001
Rural (%)						
Rural (RUCC Measure)	10.48%	20.27%	<0.0001	11.88%	17.62%	<0.0001
Rural (CRP Measure)	35.89%	31.32%	<0.0001	45.30%	30.43%	<0.0001
N	131,766					

Note. MAPR= County-level Medicare Advantage penetration rate calculated as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county; In version 1, the MAPR median (34.06%) is used as a threshold to create two categories: High MAPR counties (MAPR>34.06%) and low MAPR counties (MAPR<34.06%). In version 2, the MAPR third quartile (51.22%) is used as a threshold to create two categories: High MAPR counties (MAPR>51.22%) and low MAPR counties (MAPR<51.22%). RUCC= The urban-rural measure based on the U.S. Department of Agriculture Economic Research (USDA) definition for the Rural-Urban Continuum Codes (RUCC); CRP= The urban-rural measure based on the Center for Rural Pennsylvania's definition.

Figure 3-4 shows the distribution of county-level Medicare Advantage penetration rate in Pennsylvania between 2011 and 2014. The average county-level Medicare Advantage penetration rate (across the 67 counties in Pennsylvania) was 37.64 during 2011-2014, with a minimum of 4.72 for Bradford county in 2011 and a maximum of 65.80 for Beaver county in 2013. The median was 34.06, which means that half of the MAPR values were below 34.0%. The 75th percentile was 51.22% which means that two-thirds of the MAPR values were below 51.22%.

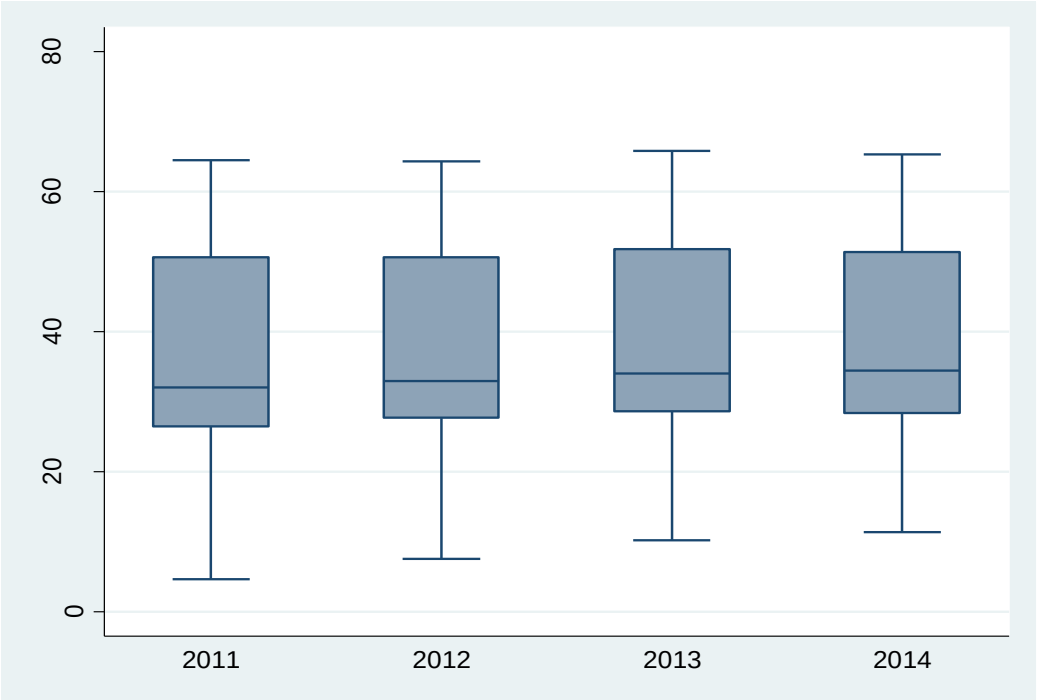


Figure 3-4: Distribution of County-Level Medicare Advantage Penetration Rate in Pennsylvania

Note. Within each box, horizontal lines denote median values; boxes extend from the 25th to the 75th percentile of each group's distribution of values; vertical extending lines denote adjacent values (i.e., the most extreme values within 1.5 interquartile range of the 25th and 75th percentile of each group); County-level Medicare Advantage Penetration Rate calculated as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county.

Figure 3-5 shows the overall urban-rural distribution of the study population (Medicare FFS patients with heart failure, AMI, or pneumonia) based on the USDA vs. CRP's measure of rurality, indicating that using either of these measures, the majority of the study population live in metropolitan areas with a population greater than 250,000. However, the USDA measure identifies a smaller proportion of patients with rural residence as opposed to the CRP's measure.

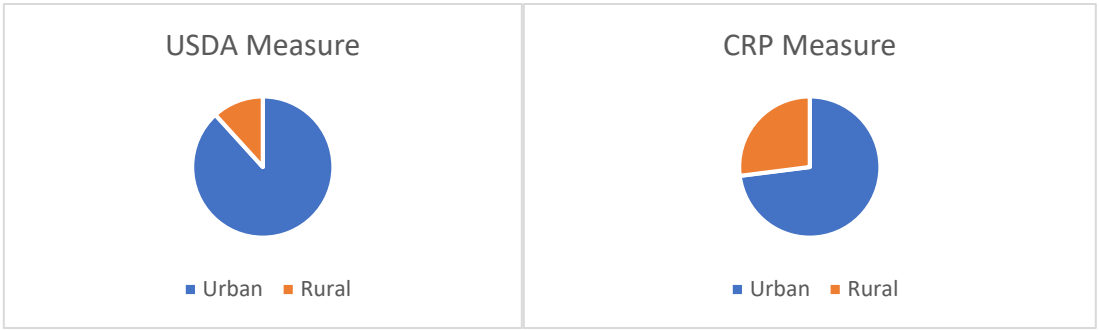


Figure 3-5: Distribution of Urban and Rural Population in Pennsylvania

Note. USDA = U.S. Department of Agriculture Economic Research; CPR = Center for Rural Pennsylvania

Readmission Trends

Figure 3-6 and Figure 3-7 show the readmission trends during 2011-2014. The vertical dashed line separates the pre-HRRP (2011-2012) and post-HRRP (2013-2014) periods.

Version 1

Figure 3-6 shows the readmission trend in version 1 for Medicare FFS patients with heart failure, AMI, or pneumonia during 2011-2014. High MAPR represents counties with a MA penetration rate above the median, and low MAPR represents counties with a Medicare Advantage penetration rate below the median. Overall, the counties in the high MAPR group have higher readmission rates compared to those in the low MAPR group. During 2011-2012 (pre-HRRP), we see a similar downward trend for readmissions in both groups. During 2013-2014 (post-HRRP), both high and low MAPR counties experienced a decline in readmissions. The magnitude of the decline in readmissions appears larger for the high MAPR group.

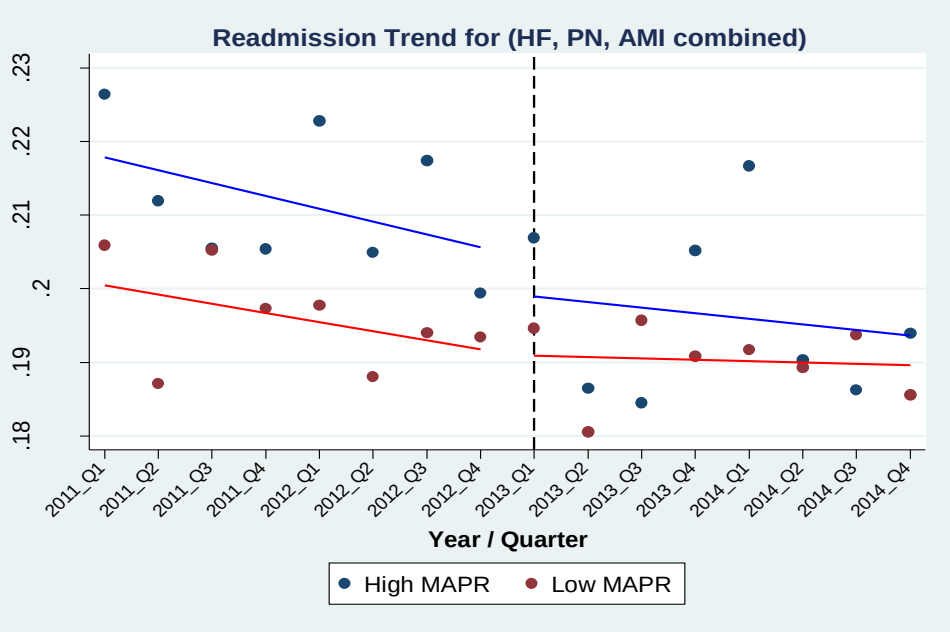


Figure 3-6: Readmission Trend in Pennsylvania (Version 1)

Note. MAPR= Medicare Advantage Penetration Rate, defined as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county. The MAPR median (34.06%) is used as a threshold to create two categories: High MAPR counties (MAPR>34.06%) and low MAPR counties (MAPR<34.06%). The Hospital Readmission Reduction Program (HRRP) started on October 1, 2012. 2011-2012 is the pre HRRP period, and 2013-2014 is the post HRRP period.

Version 2

Figure 3-6 shows the readmission trend in version 2 for Medicare FFS patients with heart failure, AMI, or pneumonia during 2011-2014. High MAPR represents counties with a Medicare Advantage penetration rate above the 75th percentile, and low MAPR represents counties with a Medicare Advantage penetration rate below the 75th percentile. Overall, the counties in the high MAPR group have higher readmission rates compared to those in the low MAPR group. During 2011-2012 (pre-HRRP), we see a downward trend for readmissions in both groups with a faster decline rate for the high MAPR group. During 2013-2014 (post-HRRP), both high and low MAPR counties experienced a decline in readmissions. The magnitude of the decline in readmissions seems to be larger for the high MAPR group.

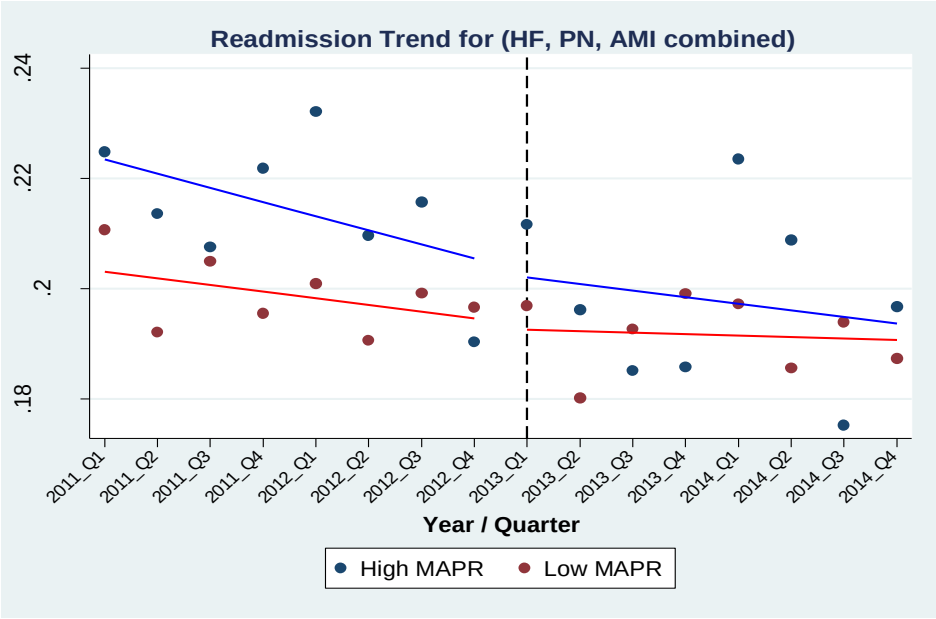


Figure 3-7: Readmission Trend in Pennsylvania (Version 2)

Note. MAPR= Medicare Advantage Penetration Rate, defined as the number of Medicare Advantage enrollees divided by the total number of Medicare beneficiaries within each county. The MAPR third quartile (51.22%) is used as a threshold to create two categories: High MAPR counties (MAPR>51.22%) and low MAPR counties (MAPR<51.22%). The Hospital Readmission Reduction Program (HRRP) started on October 1, 2012. 2011-2012 is the pre HRRP period, and 2013-2014 is the post HRRP period

Estimation Results

Table 3-3 shows the parameter estimates from equation 1 for Medicare FFS patients with heart failure, AMI, or pneumonia. Both version 1 and version 2 are estimated using equation 1.

Version 1

In version 1, counties with a Medicare Advantage enrollment rate above the median are grouped as high MAPR. The coefficient for the *High* variable has a positive sign and is statistically significant, which means, compared to patients living in a county with low Medicare Advantage penetration rate, those living in a high MAPR county have 1.38 percentage higher probability of having a 30-day readmission in the pre-HRRP period. The coefficient for *Post* is negative but not statistically significant, which means readmission rates decreased but not significantly after the implementation of the HRRP. The *Post*High* coefficient is also negative but not statistically significant, which suggests that readmissions decreased more in high MARP counties but not significantly so. The probability of having a 30-day readmission was 1.81 percentage points higher for Black patients relative to other races. As expected, patients with a higher comorbidity burden were more likely to have a 30-day readmission relative to patients with no comorbidity (reference group). The probability of readmission was 3.9, 6.6, and 12.6 percentage points higher for patients with Charlson score of 1, 2, and 3+ relative to patients with no comorbidity (reference group). There was no statistically significant difference in the probability of readmission with regard to different age groups, years, rural vs. urban residence, sex (male vs. female), and ethnicity (Hispanic vs. non-Hispanic). This result is consistent with the earlier studies.[88,139]

Version 2

In version 2, counties with a Medicare Advantage enrollment rate above the 75th percentile are grouped as high MAPR. The coefficient for the *High* variable has a positive sign and is statistically significant, which means, compared to patients living in a county with low Medicare Advantage penetration rate, those living in a high MAPR county have 1.69 percentage higher probability of having a 30-day readmission in the pre-HRRP period. Similar to version 1, the coefficient for Post is negative but not statistically significant. Also, the *Post*High* coefficient is negative but not statistically significant, which means the change in readmissions from before to after the HRRP was not significantly different between high and low Medicare Advantage penetration counties. The probability of having a 30-day readmission was 2.1 percentage points higher for Black patients relative to other races as the reference group. Similar

to version 1, patients with higher comorbidity burden were more likely to have a 30-day readmission relative to patients with no comorbidity (reference group). The probability of readmission was 3.9, 6.6, and 12.6 percentage points higher for patients with Charlson score of 1, 2, and 3+ relative to patients with no comorbidity (reference group). There was no statistically significant difference in the probability of readmission with regard to different age groups, years, rural vs. urban residence, sex (male vs. female), and ethnicity (Hispanic vs. non-Hispanic).

USDA vs. CRP Definition of Urban-Rural

As a sensitivity analysis, I examine the robustness of the results by using an alternative measure for rurality defined by the Center for Rural Pennsylvania (CPR). Using the CPR definition, I identified 48 rural counties and 19 urban counties in Pennsylvania. The results from table 3-3 show very similar coefficient estimates using either of the definitions. Therefore, although the urban/rural distribution is different using each of the two measures, the difference in the definitions does not seem to change the results very much.

Table 3-3: Differential Impact of HRRP on Readmission in High vs. Low MAPR Counties

	Version 1 N=131,766		**Version 2** N=131,766	
	USDA Measure	**CRP Measure**	**USDA Measure**	**CRP Measure**
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
High	0.0138*** (0.007 , 0.019)	0.0137*** (0.007 , 0.019)	0.0169*** (0.009 , 0.025)	0.0176*** (0.009 , 0.025)
Post	-0.0008 (-0.011 , 0.009)	-0.0008 (-0.011 , 0.009)	-0.0020 (-0.012 , 0.008)	-0.0020 (-0.012 , 0.008)
Post*High	-0.0080 (-0.017 , 0.001)	-0.0080 (-0.017 , 0.001)	-0.0071 (-0.018 , 0.004)	-0.0069 (-0.018 , 0.004)
Age				
65-74	0.0003 (-0.010 , 0.009)	0.0003 (-0.010 , 0.009)	0.0002 (-0.010 , 0.009)	0.0002 (-0.010 , 0.009)
75-84	0.0065 (-0.002 , 0.015)	0.0065 (-0.002 , 0.015)	0.0064 (-0.002 , 0.015)	0.0064 (-0.002 , 0.015)
85+	0.0028 (-0.006 , 0.012)	0.0026 (-0.006 , 0.011)	0.0024 (-0.006 , 0.012)	0.0026 (-0.006 , 0.012)

Rural	-0.0018 (-0.007 , 0.004)	-0.0036 (-0.008 , 0.001)	-0.0025 (-0.008 , 0.004)	-0.0040 (-0.008 , 0.0006)
Race				
White	-0.0021 (-017 , 0.013)	-0.0016 (-016 , 0.013)	-0.004 (-0.018 , 0.011)	-0.003 (-0.017 , 0.011)
Black	0.0181* (0.002 , 0.035)	0.0181* (0.002 , 0.035)	0.0210* (0.004 , 0.038)	0.0202* (0.003 , 0.037)
Other	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Hispanic	-0.0123 (-0.035 , 0.012)	-0.0116 (-0.049 , 0.012)	-0.0123 (-0.035 , 0.012)	-0.0116 (-0.049 , 0.012)
Male	-0.0006 (-0.005 , 0.004)	-0.0007 (-0.005 , 0.003)	-0.0007 (-0.005 , 0.004)	-0.0007 (-0.005 , 0.003)
Comorbidity (Charlson Index)				
0 (No Comorbidity)	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
1	0.0391*** (0.029 , 0.049)	0.0391*** (0.029 , 0.049)	0.0391*** (0.029 , 0.049)	0.0391*** (0.029 , 0.049)
2	0.0666*** (0.057 , 0.076)	0.0666*** (0.057 , 0.076)	0.0666*** (0.057 , 0.076)	0.0666*** (0.057 , 0.076)
3+	0.1263*** (0.117 , 0.135)	0.1261*** (0.116 , 0.135)	0.1263*** (0.117 , 0.135)	0.1261*** (0.116 , 0.135)

Note. The variable High is a binary variable for counties with high Medicare Advantage Penetration Rate (MAPR). In model1, variable High takes value 1 if a county has a MAPR above the median (34.06%%).In model 2, variable High takes value 1 if a county has a MAPR above the third quartile (51.22%). Variable Post denotes post HRRP period (2013-2014). Model has been adjusted for year fixed effects. *p<0.05. **p<0.01. ***p<0.0001

Discussion

The spillover effect of Medicare Advantage on TM readmission rates has not been well explored. The recent, rapid growth of MA plans has overlapped with the implementation of the HRRP, offering the opportunity to study the association between MA penetration and TM readmission rates within the context of a Medicare policy that aims to reduce TM readmissions. In this study, I explore the presence of MA to TM spillover effects by estimating whether there are differential patterns of readmission reductions in counties with high vs. low MA enrollment rates.

Using state-wide inpatient data from the PHC4 for the period 2011-2014, I found no evidence of MA to TM readmissions spillover effects. Contrary to my hypothesis, the present study demonstrated that changes in 30-day readmission rates following the HRRP were not significantly different between counties

with high and low MAPRs. The findings are in line with the previous literature reporting no overall association between MA penetration and FFS readmissions. One possible explanation for this finding can be the implementation of other CMS programs parallel to the HRRP. The study period (2011-2014) overlaps with the implementation of a few other CMS value-based programs (i.e., Accountable Care Organization Investment Model (ACO), Bundled Payments for Care Improvement (BPCI), Hospital Value-Based Purchasing Program (VBP), etc.), that have aimed to increase quality and care coordination. Therefore, hospitals have made efforts to improve patient care and outcomes using strategies similar to those used by MA, that may have directly or indirectly encouraged reducing readmissions. Another possible explanation, as indicated by recent studies, may be due to the limited impact of the HRRP on readmissions due to regression to the mean. Therefore, if the HRRP had little impact on readmissions, we would expect to see no difference in readmissions in high vs. low MA penetration counties. In addition, the analysis indicated that overall, the readmission rates among Medicare FFS patients are higher in counties with high Medicare Advantage enrollment rates.

Readmission risk factors, practice patterns, and readmission patterns may be different between heart failure, AMI, and pneumonia. For instance, a 2020 study published in JAMA[149] studying patients with heart failure, suggests Medicare Advantage plans may encourage greater uptake of process-based quality measures. This study assessed the differences in delivery of evidence-based treatments and outcomes in patients enrolled in Medicare Advantage plans vs. patients in Medicare FFS plans. Results showed MA beneficiaries received secondary prevention treatments more often than those in FFS plans. Those enrolled in MA plans also had greater odds of receiving guideline-recommended therapy for medications than FFS beneficiaries. Therefore, based on the conceptual framework for our study, HF patients in high MA penetration areas may also benefit from the MA practice patterns with a potential for reducing readmissions. Therefore, one potentially interesting area to explore in future research can be studying heart failure, AMI, and pneumonia separately to test whether the findings would vary between different conditions.

This study has important limitations to highlight. First, the analysis uses data from Pennsylvania and includes only three specific conditions; therefore, the results may not be generalizable to other states or conditions. Second, the analysis uses inpatient data only. Therefore, distinguishing elective readmissions from those through the emergency department was not possible. Third, some patients in our sample may have been readmitted to hospitals in nearby states, and those readmissions are not included in the analysis. Fourth, the study period is from 2011 to 2014, and although it covers two years before and after

the HRRP implementation, it does not include the years after which the additional conditions (i.e., COPD, CABG, TKA, and THA) have been targeted by the HRRP. Therefore, the findings may not be generalizable to other HRRP target conditions, nor may represent the most recent trends in readmissions. Fifth, due to the administrative nature of data, I had access to limited, de-identified information about hospitals. Therefore, a more detailed analysis based on hospital characteristics was not feasible.

Conclusion

This study examined the presence of MA to TM spillover effect by testing whether the traditional Medicare FFS readmissions respond differently to the HRRP in areas with high Medicare Advantage penetration. When comparing the pre- vs. Post-HRRP period, the findings do not suggest a differential change in FFS readmissions in high MA penetration areas. More research is needed to investigate the presence of MA to TM readmissions spillover effects for different HRRP target conditions (i.e., heart failure, AMI, or pneumonia.

Chapter 4
Utilization of Partial Nephrectomy and Perioperative Quality Indicators Pre- and Post- AUA Guidelines: An Analysis of National Cancer Database

Introduction

Kidney cancer is among the 10 most common cancers in both men and women in the United States, with the American Cancer Society's predicting nearly 76,000 new cases and 14,000 deaths for 2021.[150,151] The survival rate for individuals with kidney cancer varies significantly depending on the stage and how far cancer has spread.[152] For instance, the 5-year survival rate for individuals with stage I and II is nearly 93%. If kidney cancer has spread to surrounding tissues or organs and/or the regional lymph nodes, the 5-year survival rate is 70%, and if cancer has spread to a distant part of the body, the 5-year survival rate drops to 13%.[153]

The staging system commonly used for kidney cancer is the American Joint Committee on Cancer (AJCC) TNM system[154] which is based on 3 key pieces of information: Tumor size (T), spread to lymph nodes (N), and spread (or metastasis) to distant sites (M). According to the TNM system, in stage I, the tumor is <7cm and is only in the kidney (T1), with no spread to lymph nodes (N0) or distant organs (M0). In stage II, the tumor is >7cm and is only in the kidney (T2), with no spread to lymph nodes (N0) or distant organs (M0). In stages III and IV, the tumor is larger and/or has metastasized or spread to lymph nodes (see a more detailed explanation in Appendix F).

RCC therapy has historically been limited by lack of early detection and lack of effective cures for late-stage disease.[155] While there are currently no recommended screening guidelines for kidney cancer, there has been a significant increase in early detection of small asymptomatic kidney tumors, resulting in a shift toward stage l diagnosis.[156] Due to the widespread availability and utilization of imaging technologies such as computed tomography (CT) and magnetic resonance imaging (MRI), early detection has improved, partially due to abdominal scans conducted for other symptoms such as hematuria and flank pain.[157] Currently 48% to 66% of small asymptomatic renal masses are detected incidentally in the process of imaging for abdominal conditions unrelated to the kidney.[156,158] About 20% of these early detected asymptomatic small masses are benign, while 80% are malignant.[159–165]

The standard treatment for stage l and ll kidney cancer is surgery that removes the tumor. This can be done by just removing the tumor (and some of the surrounding tissue), known as partial nephrectomy

(PN), or by removing the whole kidney, known as radical nephrectomy (RN).[166] Historically, localized renal tumors have been treated aggressively, most often with radical nephrectomy.[167–171] However, this approach is associated with a higher mortality rate, the potential for a rapid decline in renal function leading to chronic kidney disease (CKD), and may increase the risk of cardiovascular events.[172–177] With the high survival rate for individuals with localized kidney cancer,[152,158] minimizing treatment-related morbidity is highly important. In an era when the prevalence of type 2 diabetes and CKD is increasing, renal preservation is key. Compared to RN, PN is an effective and less aggressive treatment, preserves the unaffected kidney tissue[178,179], and has the potential to maintain renal function.[175,178–181] In addition, multiple prospective and retrospective studies have shown that PN has equivalent oncological survival rates together with reduced risk of adverse outcomes related to treatment such as CKD.[170,175,178,181–186]

In 2009, due to a lack of clear guidelines and inconsistencies in the surgical treatment of stage I kidney tumors, the American Urological Association (AUA) assigned a panel to review the literature and provide guidelines for the management of stage I kidney cancer.[187] The panel's consensus was as follows: "Nephron-sparing surgery should be considered in all patients with a clinical T1 renal mass as an overriding principle, presuming adequate oncologic control can be achieved, based on compelling data demonstrating an increased risk of CKD associated with RN and a direct correlation between CKD and morbid cardiovascular events and mortality on a longitudinal basis."[187,188] The guidelines recommend that for all patients with a T1 (stage I) renal mass, regardless of tumor size, "physicians should counsel the patient about the potential advantages of a nephron-sparing treatment approach (e.g., partial nephrectomy, thermal ablation, and active surveillance) in the imperative and elective settings. These advantages include avoidance of the need for dialysis and a reduced risk of developing chronic kidney disease with the attendant morbidity and mortality."

Literature shows an increase in the use of PN for patients with stage l kidney cancer following the release of the AUA guidelines in 2009.[187,189–193] The focus of studies that have evaluated the 2009 guidelines has been on various topics. For example, variation in PN rates by patient and surgeon characteristics,[193] differences in PN use between teaching versus non-teaching hospitals,[189] overall PN trends before and after the guidelines controlling for CKD diagnosis,[190] utilization of PN versus RN, analysis of PN trends in patients with nondialysis dependent CKD before and after guidelines,[191] and socioeconomic disparities in receiving PN treatment, including comorbidity, race, and gender.[192] Recognizing that PN has become the preferred operative technique in the surgical management of stage I kidney cancer after 2009, evaluation of surgical quality indicators for kidney cancer patients is relevant

from a clinical and policy perspective. Yet, no study has evaluated the impact of 2009 guidelines on commonly used perioperative quality indicators.

The perioperative period is the timeframe surrounding the surgery, which includes three stages: preoperative, operative, and postoperative.[194] Complications occur frequently after surgeries and may lead to increased hospital length of stay, morbidity, and mortality, and are strongly associated with readmission.[195–198] Many studies have used readmission, length of stay (LOS), or mortality as perioperative quality indicators.[199,199–204] There are a variety of reasons why a surgical patient may be readmitted. Readmissions may be planned (i.e., scheduled admissions usually involving nonurgent procedures)[205] or unplanned but likely related to the surgery performed (i.e., post-surgery complications) (Appendix B). However, the potentially preventable readmissions are more likely to be unplanned and (directly or indirectly) related to events from the initial hospitalization.[206] The majority of surgical readmissions appear to be due to postoperative complications.[207] Therefore, readmissions after surgery may reflect the quality of care in the index hospitalization.[195] LOS has also been suggested as an outcome measure for quality improvement activities,[208] which can be a surrogate for complications, severity of illnesses, or healthcare resource utilization.[209–211] Similarly, perioperative mortality (i.e., in-hospital or 30-day) has been used as a quality measure for the initial postoperative period. In addition, some literature suggests that 30-day mortality may underestimate surgery-related mortality and morbidity,[212,213] and therefore, 90-day mortality may more accurately predict postoperative risk for high-risk operations.[213–217] In this paper, I particularly focus on LOS, 30-day readmission, and mortality (30-day and 90-day) as perioperative quality indicators.

Although partial nephrectomy was recommended as the preferred surgical treatment for stage I renal masses after 2009, the existing literature has not evaluated the trends in commonly used perioperative quality indicators before and after the 2009 guideline release. To address this gap, in this paper, I examine the change in the utilization of PN and changes in four perioperative quality indicators: unplanned 30-day readmissions, 30 and 90-day mortality, and length of surgical inpatient stay. I hypothesize an increase in the use of PN and a decrease in 30-day readmissions, 30 and 90-day mortality, and length of stay among stage I kidney cancer patients after the release of the 2009 AUA guidelines.

Prior Literature

A few studies have explored trends in utilization of PN before and after the 2009 guidelines release. Using the 2007-2010 Nationwide Inpatient Sample (NIS) data, Bjurlin et al. (2013)[190] evaluated the 1-year effect of the guidelines on the use of PN among patients older than 18 years with the diagnosis of renal neoplasm. This study found a 6 percentage points increase (27% to 33%) in the likelihood of PN use after the establishment of AUA guidelines (odds ratio [OR] of 1.20). Urban location, surgery at a teaching hospital, large hospital bed size, Northeast location, and Black race were positively associated with the use of PN. A major limitation of this study is the lack of clinical information regarding tumor characteristics, size, location, or stage in the NIS. Therefore, the authors were not able to focus on the group of patients that were most likely to be affected by the guidelines (i.e., with tumors smaller than 7 cm without metastasis or spread to lymph nodes).

Similarly, Liss et al. (2014)[191] analyzed national trends in PN utilization 2 years before and after the publication of the 2009 guidelines. The authors used 2007-2011 NIS data to identify all hospital admissions in patients older than 18 years who received either partial or radical nephrectomy. This study found a 6.4% increase in the proportion of PN among all patients receiving either PN or RN in the 2-year post-guidelines period. The authors also found higher odds of PN for obese patients and patients treated in high-volume hospitals for both PN and RN, which might indicate the availability of advanced medical technologies or having more experienced surgeons at high-volume hospitals. The authors suggest that the adoption of PN may be due, in part, to changes in technology during the same period, such as increasing use of laparoscopy and robotic surgery, which offers the potential benefits of improved perioperative outcomes and faster recovery compared with open PN.[218–220] Therefore the PN increase may not be due to the change in guidelines only. Similar to Bjurlin's study, due to data limitations, the authors were not able to specifically focus on patients with stage I tumors that were subject to the new guidelines.

Vigneswaran et al. (2016)[189] examined the differential change in PN and RN at teaching and non-teaching institutions from 2003 to 2012 using the Healthcare Cost and Utilization Project Nationwide Inpatient Sample. Patient selection was based on hospital ICD-9 diagnosis and procedure codes to identify patients undergoing PN or RN. The findings of this study showed that prior to the 2009 AUA guidelines, PN rates were 33% vs. 20% in urban teaching vs. urban non-teaching hospitals compared with post-guideline rates of 48% vs. 33% in urban teaching vs. urban non-teaching hospitals. conclude that the use of PN to treat small renal masses significantly increased in both teaching hospitals and in non-teaching

hospitals, with changes occurring at a slower rate in non-teaching hospitals. Similar to other studies that used NIS data, the authors were not able to identify patients based on tumor size and stage, which is critical for evaluating the AUA guidelines.

Sorokin et al. (2017)[193] used 2003-2014 data from the American Board of Urology (ABU) to evaluate patient, surgeon, and practice characteristics associated with PN in the pre-guideline and post-guideline periods. The authors examine the change in the proportion of PN cases (as a fraction of all nephrectomy cases), reporting increased utilization of PN in the post-guidelines era (39%) compared with pre-guidelines (25%). Further, the authors find a higher likelihood of undergoing PN with an open approach (through an incision created in the abdomen) as opposed to minimally invasive methods (i.e., laparoscopic or robotic-assisted). Similar to the other studies using NIS data, there is no stage information, so the study was unable to identify early-stage kidney cancers, which are the primary target of the guideline change.

Two studies have used data from the National Cancer Database (NCDB) to examine the impact of the 200 guidelines on PN use. A study by Miller et al. (2018)[221] analyzed 2004-2015 NCDB data to examine trends in the treatment of clinical T1 renal cell carcinoma with a specific focus on 80–89 years old age group (octogenarians) with clinical stage 1, tumor size ≤ 7 cm compared to a younger control arm of patients ≤ 70 years old. Although this study does not provide a pre-post guidelines analysis, the authors note that the results of their analysis reflect the impact of guidelines in the octogenarian study cohort. The authors report an increasing trend in the utilization of percutaneous ablative therapy (PAT) and PN and decreased utilization of RN for the management of stage 1 renal masses with octogenarians. Overall, this study highlights the impact of advanced age on treatment choice but does not examine the potential impact of the guidelines on any other variables beyond treatment choice.

The most recent study related to the trends in partial nephrectomy following the 2009 guideline release evaluated the underlying health disparities in PN utilization using 2004-2015 data from the National Cancer Database (NCDB). Consistent with the previous literature, May et al. (2019)[192] found a significant increase in PN use for small renal masses from 2004 to 2015. With a focus on identifying health disparities, this study found that despite the increase in the use of PN, Black, female, and low-income (measured as below median for the household), patients were still more likely to receive RN treatment even after guidelines were released. A noticeable limitation of this study is that while the 2009 AUA guidelines apply to all stage I renal masses (i.e., tumors smaller than 7 cm), this study only focused on T1a renal masses defined as ≤4.0 cm. The authors do not provide any reason for not including tumors larger

than 4 cm and smaller than 7cm. Similar to the rest of the literature, this study only focused on the trends in PN use only, with particular attention to disparities in treatment.

To summarize, most of the existing literature that evaluated the 2009 AUA guidelines from multiple perspectives only examined changes in PN use before and after the guidelines. The lack of information on stage and tumor size in the data sources used in the literature did not allow for clearly identifying the target population for the AUA guidelines, i.e., stage I defined as patients with a tumor smaller than 7 cm with no metastasis or spread to lymph nodes. The two studies that used NCDB data were able to identify patients based on stage and tumor size, however, they only examined trends in PN. Although the literature provides consistent evidence regarding the increase in PN use after 2009, none of the studies in the current literature have analyzed the potential impact of the AUA guidelines on perioperative quality indicators. To address this gap, in this paper, I examine the impact of 2009 guidelines on the PN use and the resulting changes in four perioperative quality indicators: unplanned 30-day readmissions, 30 and 90-day mortality, and LOS among stage I kidney cancer patients.

Methods

Data

This study uses 2004-2014 kidney cancer participant files from the National Cancer Database (NCDB). "The nationally recognized NCDB—jointly sponsored by the American College of Surgeons and the American Cancer Society—is a clinical oncology database sourced from hospital registry data that are collected from more than 1,500 Commission on Cancer (CoC)-accredited facilities. NCDB data are used to analyze and track patients with malignant neoplastic diseases, their treatments, and outcomes."[222] Data represent more than 70 percent of newly diagnosed cancer cases nationwide and represent a broad array of hospital environments.

The NCDB population consists of patients who received some element of their cancer care (treatment or diagnosis) at a cancer program that is accredited by the CoC. The NCDB data are abstracted from all available components of the medical record by certified tumor registrars. The reporting facility is also required to include elements of cancer care that take place outside of their facility (e.g., adjuvant chemotherapy at a different hospital or at a physician's office) even if the other facility is not accredited by the CoC.[200] NCDB data include sociodemographic characteristics, facility type and location, and detailed cancer identification information, such as stage, tumor size, primary site, laterality, histology, grade,

metastasis or spread to lymph nodes, surgical procedure, surgical approach, and site-specific surgery codes.

Study Sample

The steps for building the study sample are shown in Figure 4-1. To build the study sample, I use the NCDB kidney cancer participant file to identify all patients, between 18 and 90 years old, with kidney cancer diagnosed between 2004 to 2014. As the first step, I exclude patients if no mass or tumor was found or if the tumor size was unknown. The 2009 guidelines focus on stage I. In this study, in addition to examining the impact of the guidelines on stage I patients, I test whether the guidelines had a differential impact on stage I vs. stage II. Therefore, I keep stage I and stage II, and exclude stage III and stage IV or if the stage is unknown. Based on the TNM system, stage I is identified as patients with a tumor size <7cm, with no metastasis (M1) or spread to lymph nodes (N1), and stage II is identified as patients with a tumor size ≥7cm, with no metastasis or spread to lymph nodes.

Four out of five outcomes of interest for this study (i.e., unplanned 30-day readmission, 30 and 90-day mortality, and length of stay) are only recorded for surgical patients in NCDB (Appendices G,H,I). Therefore, to analyze these four outcomes, I need to limit the study sample to patients receiving surgical treatment only. Before excluding non-surgical patients, first I perform the first round of analysis on the 245,115 patients diagnosed with either stage I or stage II, to examine the change in PN after the guidelines. Next, I limit the sample to patients receiving surgical treatment. To do this, I exclude patients if there was no surgical procedure of primary site or if the patient record did not state whether a surgical procedure was performed. Then, I exclude procedures that are coded as a surgical event but may be considered as biopsy or therapies used in combination with a major surgery. Some examples of these procedures that account for 10% of all surgical events include local tumor destruction (i.e., photodynamic therapy, electrocautery, laser, thermal ablation), and local tumor excision (i.e., excisional biopsy, cryosurgery, laser ablation that. Finally, I limit the sample to those receiving either PN or RN. The final study sample includes stage I (86.6%) and stage II (13.4%).

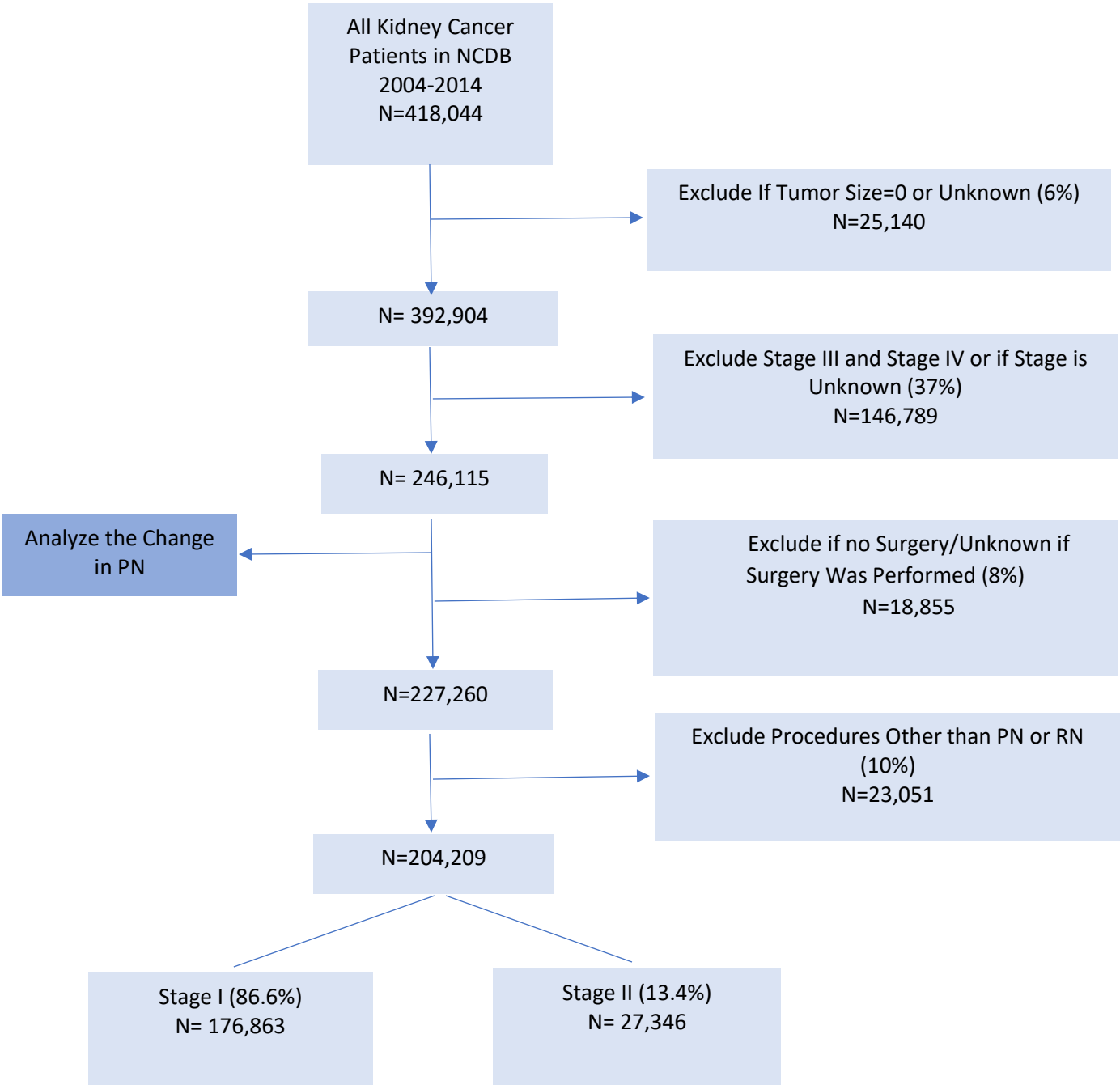


Figure 4-1: Steps for Building the Study Sample

Note. NCDB stands for the National Cancer Database. The staging system used for kidney cancer is the American Joint Committee on Cancer (AJCC) TNM system.[154] The TNM system is based on 3 key pieces of information: Tumor size (T), spread to lymph nodes (N), and spread (metastasis) to distant sites (M). Stage I is defined as T1N0M0, and stage II is defined as T2N0M0. In stage I, the tumor is 7 cm across or smaller and is only in the kidney (T1), with no spread to lymph nodes (N0) or distant organs (M0). In stage II, the tumor is equal to or larger than 7 cm across but is still only in the kidney (T2), with no spread to lymph nodes (N0) or distant organs (M0).

Outcome Variables

Five outcome variables are examined in this study: receipt of partial nephrectomy, unplanned 30-day readmission, 30-day mortality, 90-day mortality, and length of stay for the visit associated with the surgery. Below, I explain how each variable is defined based on the NCDB data dictionary definitions.[223]

NCDB codes planned and unplanned readmissions separately, which is determined based on the treatment plan. The data dictionary does not provide more details on how unplanned and planned readmissions are determined. Readmissions may be planned (i.e., scheduled part of the patient's plan of care) or unplanned, (i.e., acute clinical events experienced by a patient that require urgent hospital management).[224] Unplanned readmissions are likely related to the surgery performed (i.e., post-surgery complications). Based on the NCDB data dictionary, unplanned 30-day readmission refers to when the patient was surgically treated and was readmitted to the same hospital within 30 days of being discharged. Appendix G shows the 5 categories for the 30-day readmission in the NCDB.

I define 30 and 90-day mortality as death within 30 (or fewer) and 90 (or fewer) days of the primary site surgery (Appendices H and I). Surgical inpatient stay is defined as the number of days between the date the surgical procedure was performed and the date the patient was discharged following surgery. In this paper, I refer to surgical inpatient stay as length of stay (LOS).

Other Covariates

The NCDB includes an array of sociodemographic and clinical information. Patient covariates included in this study are age as a continuous variable (between 18 and 90), race (Black, white and other), sex, income status, insurance type (uninsured, private insurance, Medicaid, Medicare, other/unknown), urban/rural, and comorbidity.

The NCDB defines income status as the reported median household income for each patient's area of residence estimated by matching the zip code of the patient recorded at the time of diagnosis against files derived from the year 2000 US Census data. Household income is categorized as quartiles based on equally proportioned income ranges among all US zip codes. Four income categories are available in the data: less than $30,000, $30,000 - $34,999, $35,000 - $45,999, and $46,000 +.

Comorbidity is defined based on the Charlson comorbidity index and is coded within the NCDB using values of 0, 1, 2, or 3+. The NCDB data dictionary defines comorbid conditions described by Charlson/Deyo (1992),[225] mapped from as many as ten reported ICD-9-CM secondary diagnosis codes reported for cases diagnosed. The Charlson/Deyo value is a weighted score derived from the sum of the scores for each of the comorbid conditions listed in the Charlson Comorbidity Score Mapping Table in the NCDB data dictionary (Appendix Table D). The range for this value is between 0 and 25. Although individual comorbidities are captured using International Classification of Diseases 9th and 10th edition diagnosis codes, the data dictionary reports only a modified Charlson-Deyo comorbidity score (i.e., 0, 1, 2, or 3+). The scale is truncated at 3 or more, as only a small number of patients have a score of 3 or greater.

Urban vs. rural residence is based on the Rural-Urban Continuum Codes (RUCC), defined by the United States Department of Agriculture (USDA) Economic Research Service.[147] RUCCs form a classification scheme based on the population size and degree of urbanization. The NCDB data dictionary specifies three sub-groups for urban-rural residence: Metropolitan counties, urban, and rural counties (Appendix J).

In addition to patient data, facility type and location are also included in my analysis. Four facility type categories included are Community Cancer Program, Comprehensive Community Cancer Program, Academic/Research Program (includes NCI-designated comprehensive cancer centers), and Integrated Network Cancer Program. An academic-research hospital is associated with a medical school and participates in training residents, and is required to participate in clinical research. Facility location includes 9 regions: New England (CT, MA, ME, NH, RI, VT), Middle Atlantic (NJ, NY, PA), South Atlantic (DC, DE, FL, GA, MD, NC, SC, VA, WV), East North Central (IL, IN, MI, OH, WI), East South Central (AL, KY, MS, TN), West North Central (IA, KS, MN, MO, ND, NE, SD), West South Central (AR, LA, OK, TX), Mountain (AZ, CO, ID, MT, NM, NV, UT, WY), and Pacific (AK, CA, HI, OR, WA) (Appendix K).

Statistical Analysis

I estimate two separate models to examine the changes in five outcome variables after the 2009 guidelines release: PN, unplanned 30-day readmission, 30-day mortality, 90-day mortality, and LOS. For binary outcomes (PN, unplanned 30-day readmission, 30-day, and 90-day mortality), I estimate a linear probability regression, and for the continuous outcome (LOS), I estimate using linear regression. Although

logistic or Poisson regression models may be used as an alternative method of estimation for our data, I choose a linear probability regression for easier interpretation of the results.

Model 1

In model 1, the analysis is limited to stage I only, which is the target of the 2009 guidelines. The regression takes the following form:

$$Y_{it} = \alpha + \beta_1 Post_t + X_{it} \beta_3 + \varepsilon_{it} \qquad \text{(Equation 1)}$$

Where Y_{it} is the outcome variable for patient i at time t. I estimate equation 1 for each outcome variable separately. For PN, I include all patients diagnosed with stage I. PN, defined as a binary variable, takes value 1 if the patient received PN and 0 otherwise. For the four surgical outcomes, the study sample includes stage I patients receiving either PN or RN. Unplanned 30-day readmission, defined as a binary variable, takes value 1 if the patient is readmitted within 30 days after discharge and 0 if not. 30 and 90-day mortality are each defined as a binary variable that take value 1 if the patient died 30/90 or fewer days after surgery was performed and 0 if not. Length of stay is a continuous variable measured in days. The variable $Post_t$ is a binary variable that takes value 1 if the patient was treated between 2009 and 2014 (post-AUA guidelines release) and value 0 if the patient was treated between 2004 and 2008 (pre-AUA guidelines release). *X* includes the control variables, including age, race, ethnicity, sex, income status, urban-rural, comorbidity, and facility type, and facility location. Year fixed effects (defined as a dummy variable for each year) are included in the *X* variable.

Model 2

In model 2, I include both stage I and stage II with an interaction term to test whether the guidelines had a differential impact on stage I vs. stage II. The regression takes the following form:

$$Y_{it} = \alpha + \beta_1 Post_t + \beta_2 Stage1 + \beta_3 Post_t * Stage1 + X_{it} \beta_5 + \varepsilon_{it} \qquad \text{(Equation 2)}$$

Where Y_{it} is the outcome variable for patient i at time t. Similar to model 1, I estimate equation 2 for each outcome variable separately. For PN, I include all patients diagnosed with stage I or stage II. For the four surgical outcomes, the study sample includes stage I and stage II patients receiving either PN or RN. The variable $Post_t$ is a binary variable that takes value 1 if the patient was treated between 2009 and 2014 (post-AUA guidelines release) and value 0 if the patient was treated between 2004 and 2008 (pre-AUA

guidelines release). *X* includes the control variables, including age, race, ethnicity, sex, income status, urban-rural, comorbidity, and facility type, and facility location. Year fixed effects (defined as a dummy variable for each year) are included in the *X* variable. The variable *Stage1* is a binary variable taking value 1 if patient is at stage I and 0 if stage II. The coefficient for $Post_t$ * *stage1* shows whether the expected mean in the outcome from before to after the AUA guidelines release was different between stage I and stage II.

Results

Descriptive Statistics

The analysis resulted in 246,115 patients with stage I or stage II with 204,209 of those patients receiving either PN or RN during the 10-year study period (2004-2014). Table 4-1, shows the demographics of patients and the facilities, before and after the guidelines release. Overall, the differences between patient and facility characteristics before and after the guidelines were less than 2 percentage points which indicates that these characteristics did not change significantly over time. For stage I, I observed a slightly higher proportion of patients who were either Hispanic or Black, higher comorbidity burden, more uninsured patients, and more low-income patients in the post-guidelines period. With respect to facility type, the proportion of patients treated at a research /academic center was slightly lower in the post-guidelines period. For stage II, there is a higher proportion of male patients and patients were treated at a research or academic center post-guidelines period. Similar to stage I, differences in other patient or facility characteristics were small.

Trends in PN Over Time by Stage of Diagnosis

Figure 4-2 compares the nephrectomy trends among stage I and stage II patients who received either PN or RN during 2004-2014. For stage I, the utilization of PN has significantly increased over time (29.17% in 2004 to 58.28% in 2014), and the use of RN has declined (70.83% in 2004 to 41.72% in 2014). This trend has been confirmed by prior studies as well.[191,192] For Stage II, the rates of PN and RN have stayed nearly constant over time, except for the small decrease in RN and a small increase in PN after 2011.

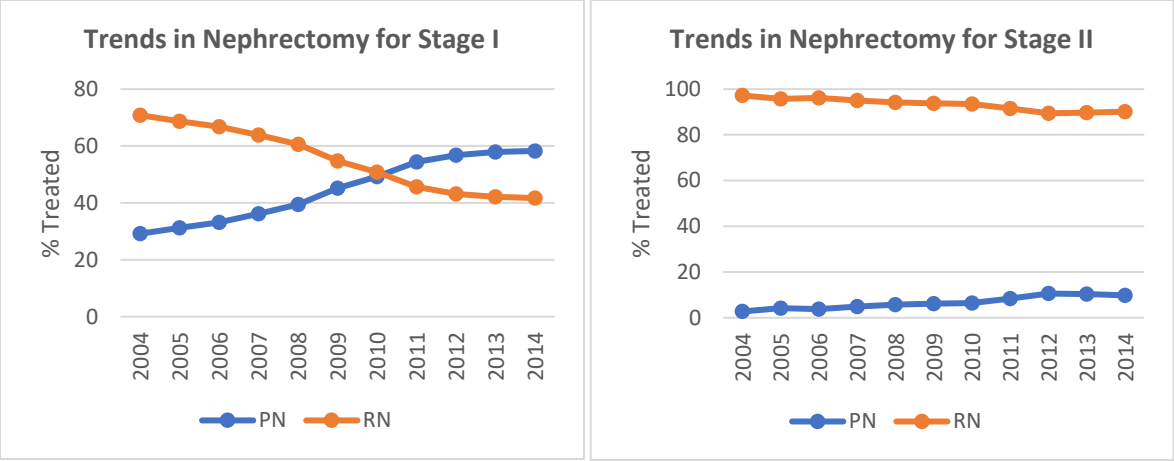


Figure 4-2: Trends in PN and RN for Stage I and Stage II

Figure 4-3 shows the trends of partial nephrectomy between 2004 and 2014. The graph shows a continued increase in the use of PN for stage I. Although the use of PN increased after 2009, the steady increase in the use of PN before 2009 suggests that the uptake of PN for stage I, began even before the AUA guidelines change. For stage II, we see a slightly increasing trend in the PN, but the average rate of RN is low (less than 7%).

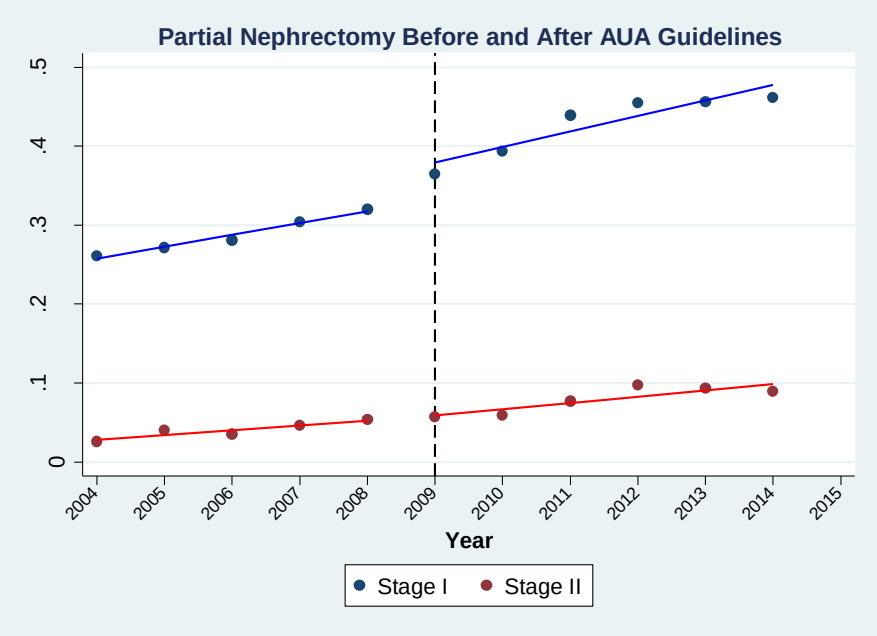


Figure 4-3: Partial Nephrectomy Rates by Stage 2004-2014
Note. The vertical line shows the year in which the AUA guidelines were released.

Table 4-1: Patient and Facility Characteristics with Pre-and Post-Guidelines for Stage I and Stage II

	Stage I N= 176,863			Stage II N= 27,346		
Variable	***Pre***	***Post***	***p-value***	***Pre***	***Post***	***p-value***
Age	60.99	60.48	<0.0001	61.66	61.64	0.91
Male	60.13%	61.03%	0.002	64.17%	66.51%	<0.0001
Hispanic	5.40%	6.46%	<0.0001	6.69%	6.45%	0.38
Race						
White	85.99%	83.72%	<0.0001	86.02%	84.69%	0.001
Black	10.16%	11.94%	<0.0001	9.89%	11.02%	0.001
Other	3.84%	4.32%	<0.0001	4.08%	4.27%	0.40
Comorbidity (Charlson Index)						
0	70.09%	68.10%	<0.0001	71.68%	70.44%	0.01
1	22.33%	23.77%	<0.0001	21.67%	22.51%	0.07
2	5.70%	5.89%	0.18	5.13%	5.26%	0.60
3+	1.86%	2.23%	<0.0001	1.49%	1.77%	0.06
Insurance Status						
Not Insured	2.10%	3.08%	<0.0001	3.51%	4.36%	<0.0001
Private Insurance or Managed Care	50.65%	47.70%	<0.0001	49.78%	46.74%	<0.0001
Medicaid	4.00%	5.66%	<0.0001	4.03%	5.59%	<0.0001
Medicare	41.32%	41.08%	0.41	39.75%	40.62%	0.11
Other/Unknown	1.90%	2.46%	<0.0001	2.91%	2.67%	0.18
Median Household Income						
Less than $30,000	16.43%	17.62%	0.0003	17.24%	17.60%	0.40
$30,000 $34,999	21.81%	23.01%	<0.0001	22.865	24.13%	0.008
$35,000 $45,999	26.24%	27.01%	0.004	27.23%	27.10%	0.80
$46,000 +	33.86%	32.34%	<0.0001	30.71%	30.76%	0.91
Urban / Rural						
Metropolitan	80.08%	79.42%	0.006	77.71%	77.56%	0.75
Urban	14.51%	16.03%	<0.0001	16.35%	17.56%	0.004
Rural	1.95%	2.06%	0.20	2.28%	2.33%	0.77
Facility Location						
New England	5.66%	5.10%	<0.0001	4.96%	4.76%	0.42
Middle Atlantic	16.99%	16.16%	0.0002	14.14%	13.80%	0.38
South Atlantic	18.03%	18.88%	0.0003	18.94%	20.58%	0.0003
East North Central	17.31%	17.88%	0.01	17.35%	17.67%	0.45
East South Central	7.15%	7.83%	<0.0001	7.02%	7.79%	0.01
West North Central	8.80%	7.35%	<0.0001	9.43%	8.45%	0.002
West South Central	7.65	7.29	<0.0001	9.13%	8.74%	0.22
Mountain	3.66%	3.73%	<0.0001	4.24%	4.23%	0.95
Pacific	3.66%	3.73	0.53	4.24%	4.23%	0.95
Facility Type						
Community Cancer Program	7.33%	5.96%	<0.0001	8.15%	7.20%	0.001
Comprehensive Community Cancer Program	38.68%	36.63%	<0.0001	42.12%	39.19%	<0.0001
Academic/Research*	39.01%	41.08%	<0.0001	36.25%	38.90%	<0.0001
Integrated Network Cancer Program	9.47%	10.53%	<0.0001	9.45%	10.74%	<0.0001

Note. *includes NCI-designated comprehensive cancer centers

Figure 4-4 shows the trends of unplanned 30-day readmission between 2004 and 2014 among stage I and stage II patients receiving either PN or RN. The graph shows a decline in the unplanned 30-day readmission after the 2009 guideline followed by an increase. For stage 2, we see a steady decreasing trend with no large changes from before to after 2009.

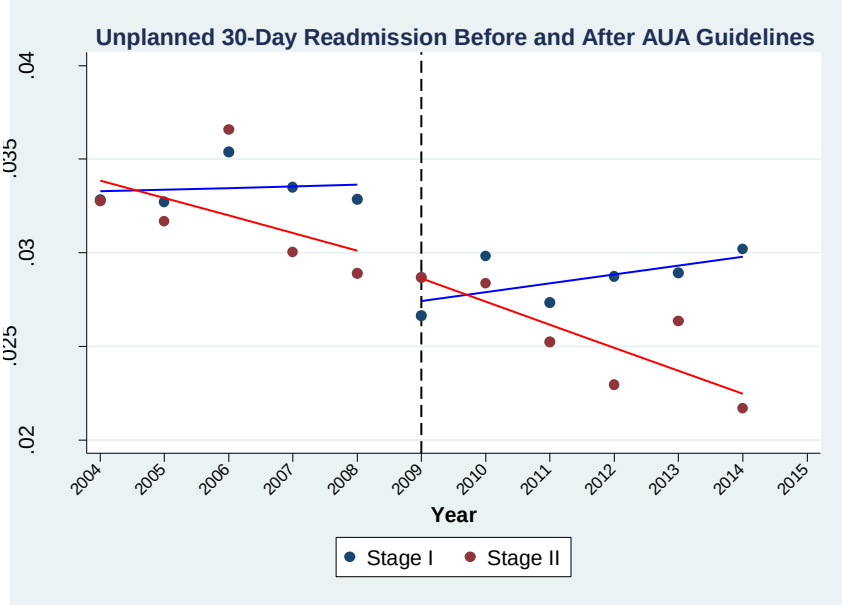


Figure 4-4: Unplanned 30-Day Readmission Rates by Stage 2004-2014

Figures 4-5 and 4-6 show the 30-day and 90-day mortality rate trend between 2004 and 2014 for stage I and stage II. There is a jump in mortality for stage II in 2008 and 2009 and then a decline and a consistent smooth decline for stage I. One explanation for the jump in stage II mortality rates may be the availability of new drugs that have shown to improve the survival rates for kidney cancer patients. Another potential reason may be the increase in early and incidental detection of stage I tumors and therefore treating the tumors before more aggressive treatments (i.e., RN) are necessary.

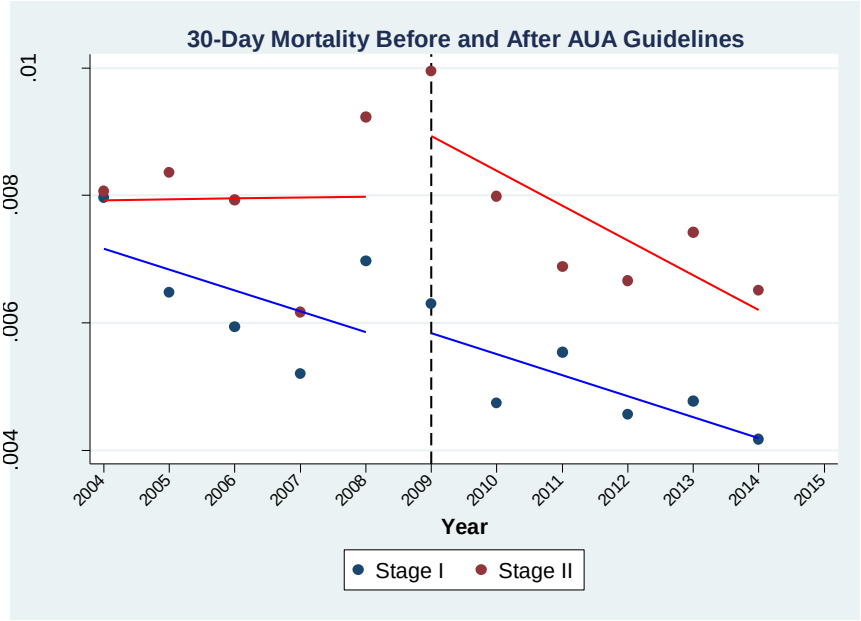


Figure 4-5: 30-Day Mortality Rates by Stage 2004-2014

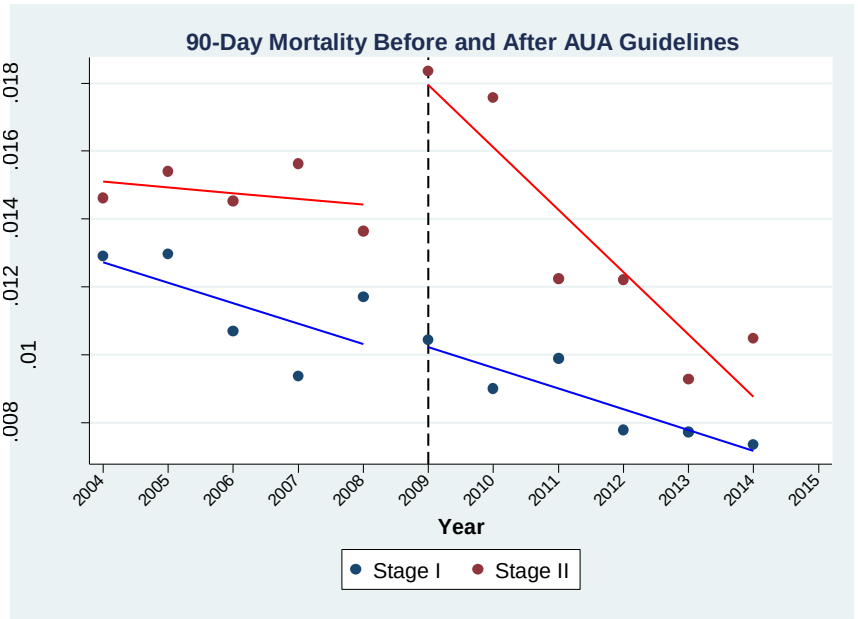


Figure 4-6: 90-Day Mortality Rates by Stage 2004-2014

Finally, Figure 4-7 shows the trends of LOS between 2004 and 2014 for stage I and stage II. The graph shows a decreasing trend in LOS for both stage I and stage II, which continues after 2009. This graph does not suggest a significant change in the trend after the guidelines were release.

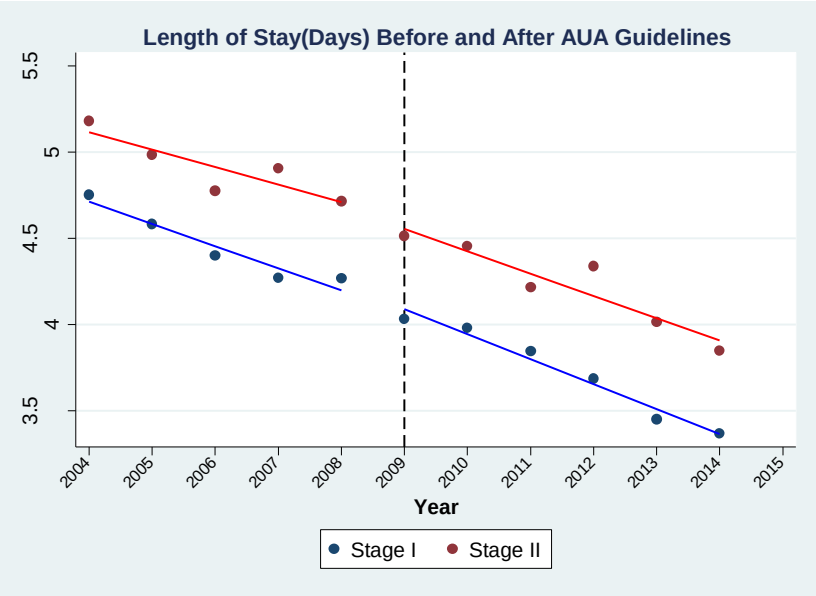


Figure 4-7: Average Length of Stay by Stage 2004-2014

Regression Results

Model 1

Table 4-2 shows model 1 estimates using equation 1, estimating the change in the outcomes after the 2009 guidelines release, among stage I patients only.

Results show a 14 percentage point (p-value<0.0001, CI, 0.13,0.14) higher probability of receiving partial nephrectomy after the release of the 2009 guidelines among stage I patients. The probability of an unplanned 30-day readmission, 30-day mortality, and 90-day mortality are 0.5 (p-value<0.0001, CI, -0.007,-0.003), 0.1 (p-value<0.0001, CI, -0.002,-0.0006), and 0.3 (p-value<0.0001, CI, -0.003,-0.001) percentage points lower after the guidelines release. The average length of stay was 0.71 days shorter (p-value<0.0001, CI, -0.75,-0.066) for stage I patients after the guidelines release.

For PN, comparing before vs. after the guidelines release, age, receiving care at a non-academic/research hospital, and Hispanic ethnicity were negatively associated with the likelihood of receiving PN. Having lower comorbidity burden, receiving care at a research/academic hospital, and white race were positively associated with the probability of receiving PN. With respect to facility location, the likelihood of receiving PN in the Middle Atlantic and the South Atlantic regions was the highest and lowest,

relative to the Pacific region as the reference group. With respect to insurance type, privately insured patients had the highest probability of receiving PN (10.1 percentage points higher) compared to other insurance types. Higher household income (above $30,000) was associated with a higher probability of receiving PN.

For unplanned 30-day readmissions, patients with lower comorbidity burden, or those living in an urban area, were less likely to have unplanned 30-day readmission. With respect to facility location, the probability of having unplanned 30-day readmission was highest and lowest in East South Central and Mountain regions, respectively. With respect to insurance status, Medicaid patients were slightly more likely to have unplanned 30-day readmission. The probability of readmission did not vary significantly between different facility types. Income was not associated with the likelihood of unplanned 30-day readmission.

For 30- and 90-day mortality, the likelihood of death after surgery within 30 or 90 days was lower for patients with lower comorbidity burden and higher-income patients. Black patients were more likely to experience 30- and 90-day mortality. With respect to facility type, patients going to academic/research hospitals had a lower probability of 30- and 90-day mortality.

For LOS, patients with no comorbidity had LOS of nearly 1 day shorter, and patients with a Charlson score of 3+ had nearly 0.6 days longer LOS relative to those with a Charlson score of 2 as the reference group. With respect to facility location, the largest change was in LOS (1/4 day shorter) was in facilities located in the East South Central and Mountain regions, relative to the Pacific region as the reference group. With respect to facility type, academic/research hospitals had nearly 0.4 day shorter LOS. Black patients had nearly half a day longer LOS relative to other races as the reference group. Privately insured patients had nearly half a day shorter LOS relative to the other/unknown insurance group. The highest income group had nearly 0.6 days shorter LOS.

Table 4-2: Model 1 Estimates of the Change in PN and Perioperative Quality Indicators Among stage I Patients Only

	PN	Unplanned 30-Day Readmission	30-Day Mortality	90-Day Mortality	Length of Stay
	N= 216,470	N= 176,863	N=176,863	N=176,863	N=176,863
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
Post	0.140*** (0.136 , 0.144)	-0.005*** (-0.007 , -0.003)	-0.001*** (-0.002 , -0.001)	-0.003*** (-0.004 , -0.002)	-0.710*** (-0.752 , 0.668)
Age	-0.006*** (-0.007 , -0.006)	0.00005 (-0.00004 , -0.0001)	0.0002*** (0.0002 , 0.0002)	0.0004*** (0.0004 , 0.001)	0.030*** (0.028 , 0.033)
Comorbidity (Charlson Index)					
0	0.108*** (0.095 , 0.121)	-0.026*** (-0.032 , -0.021)	-0.013*** (-0.015 , -0.010)	-0.021*** (-0.024 , -0.018)	-0.908*** (0.-997 , -0.819)
1	0.122*** (0.109 , 0.136)	-0.022*** (-0.028 , -0.017)	-0.012*** (-0.015 , -0.010)	-0.018*** (-0.022 , -0.015)	-0.559*** (-0.654 , -0.464)
2	0.080*** (0.065 , 0.095)	-0.009** (-0.015 , -0.002)	-0.006*** (-0.009 , -0.003)	-0.009*** (-0.012 , -0.005)	Ref. Group
3+	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	0.580*** (0.416 , 0.744)
Facility Location					
New England	0.023** (0.014 , 0.033)	0.003 (-0.001 , 0.007)	-0.004*** (-0.005 , -0.002)	-0.005*** (-0.007 , -0.003)	0.118** (0.017 , 0.220)
Middle Atlantic	0.072*** (0.065 , 0.079)	0.005*** (0.003 , 0.008)	-0.002** (-0.003 , -0.001)	-0.003** (-0.005 , -0.001)	-0.042 (-0.115 , 0.031)
South Atlantic	0.002 (-0.005 , 0.008)	-0.002 (-0.005 , 0.001)	-0.002** (-0.003 , -0.001)	-0.002** (-0.004 , -0.001)	-0.163*** (-0.232 , -0.093)
East North Central	0.031*** (0.024 , 0.037)	0.002 (-0.001 , 0.004)	-0.001* (-0.003 , -0.0002)	-0.002* (-0.003 , -0.0002)	-0.061 (-0.132 , 0.009)
East South Central	0.041***	0.009***	-0.001	-0.002	-0.258***

	(0.032 , 0.049)	(0.005 , 0.013)	(-0.003 , -0.0002)	(-0.004 , 0.0004)	(-0.348 , -0.167)
West North Central	0.021*** (0.012 , 0.029)	0.001 (-0.002 , 0.005)	-0.002** (-0.004 , -0.001)	-0.003 (-0.005 , 0.0004)	0.171*** (0.083 , 0.258)
Mountain	0.023*** (0.012 , 0.034)	-0.005* (-0.009 , -0.0003)	-0.001 (-0.003 , -0.0002)	-0.003 (-0.005 , 0.0004)	-0.255*** (0.0371 , -0.138)
Pacific	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Facility Type					
Community Cancer Program	-0.110*** (-0.124 , -0.097)	-0.003 (-0.009 , 0.002)	0.000 (-0.002 , 0.002)	-0.001 (-0.004 , 0.002)	0.125 (-0.015 , 0.265)
Comprehensive Community Cancer Program	-0.055*** (-0.066 , -0.043)	-0.005** (-0.010 , -0.001)	-0.002 (-0.004 , 0.0003)	-0.005*** (-0.008 , -0.003)	-0.192** (-0.309 , -0.076)
Academic/research[#]	0.073*** (0.082 , 0.085)	-0.006** (-0.011 , -0.002)	-0.003* (-0.005 , -0.001)	-0.006*** (-0.009 , -0.004)	-0.372*** (-0.488 , -0.255)
Integrated Network Cancer Program	0.003 (-0.010 , 0.006)	-0.006* (-0.011 , -0.001)	-0.002 (-0.004 . 0.001)	-0.005*** (-0.008 , -0.002)	-0.100 (-0.488 , -0.255)
Male	0.002 (-0.002 , 0.006)	0.002 (-0.00008 , 0.003)	0.002*** (0.001 , 0.003)	0.003*** (0.002 , 0.004)	0.072*** (0.031 , 0.114)
Race					
White	0.047*** (0.040 , 0.053)	-0.002 (-0.006 , 0.002)	0.001 (-0.0003 , 0.003)	0.001 (-0.001 , 0.003)	0.101 (-0.002 , 0.203)
Black	*Ref. Group*	0.003 (-0.001 , 0.008)	0.005*** (0.003 , 0.007)	0.007*** (0.004 , 0.009)	0.464*** (0.346 , 0.583)
Other	0.055 (0.044 , 0.066)	*Ref. Group*	*Ref. Group*	*Ref. Group*	*Ref. Group*
Hispanic	-0.017*** (-0.026 , -0.009)	-0.003 (-0.006 , 0.001)	-0.001 (-0.002 , 0.001)	-0.001 (-0.003 , 0.0004)	-0.130*** (-0.218 , -0.042)
Insurance Status					
Uninsured	Ref. Group	Ref. Group	Ref. Group	Ref. Group	-0.283 (-0.460 , 0.105)

Private	0.101*** (0.089 , 0.113)	-0.003 (-0.008 , -0.002)	-0.002 (-0.004 , 0.00008)	-0.002 (-0.005 , 0.001)	-0.478** (-0.460 , -0.106)
Medicaid	0.033*** (0.018 , 0.047)	0.007* (0.001 , 0.013)	-0.0003 (-0.003 , 0.002)	0.002 (-0.001 , 0.006)	0.032*** (-0.125 , 0.189)
Medicare	0.044*** (0.032 , 0.057)	0.003 (-0.002 , 0.008)	0.001 (-0.001 , 0.003)	0.002 (-0.001 , 0.005)	-0.106 (-0.126 , 0.190)
Other/Unknown	0.029*** (0.012 , 0.045)	0.004 (-0.003 , 0.011)	0.001 (-0.002 , 0.004)	0.003 (-0.001 , 0.007)	Ref. Group
Urban/Rural					
Metropolitan	0.015 (0.002 , 0.025)	-0.002 (-0.007 , 0.003)	-0.001 (-0.004 , 0.001)	-0.001 (-0.004 , 0.002)	0.002 (-0.135 , 0.138)
Urban	0.017 (0.003 , 0.031)	-0.007* (-0.013 , -0.001)	-0.002 (-0.005 , 0.00002)	-0.002 (-0.005 , 0.001)	-0.110 (-0.256 , 0.036)
Rural	0.012 (-0.007 , 0.031)	-0.005 (-0.013 , 0.011)	-0.001 (-0.004 , 0.003)	0.001 (-0.003 , 0.005)	0.107 (-0.090 , 0.304)
Median Household Income					
Less than $30,000	0.008 (-0.017 , 0.032)	0.001 (-0.009 , 0.011)	-0.013*** (-0.017 , -0.008)	-0.017*** (-0.023 , -0.011)	-0.376*** (-0.631 , -0.121)
$30,000 $34,999	0.020 (0.004 , 0.044)	-0.004 (-0.014 , 0.006)	-0.013*** (-0.017 , -0.009)	-0.018*** (-0.022 , -0.012)	-0.469*** (-0.721 , -0.216)
$35,000 $45,999	0.028* (0.004 , 0.052)	-0.001 (-0.011 , 0.009)	-0.013*** (-0.018 , -0.009)	-0.019*** (-0.023 , -0.013)	-0.511*** (-0.889 , -0.386)
$46,000 +	0.054*** (0.030 , 0.078)	-0.004 (-0.013 , 0.006)	-0.014*** (-0.018 , -0.01)	-0.020*** (-0.026 , -0.014)	-0.637*** (-0.889 , -0.386)

Note. The study sample for PN includes all patients diagnosed with stage I between 2004 and 2014. The study sample for unplanned 30-day readmission, 30 and 90-day mortality and length of stay includes stage I patients receiving either PN or RN. #includes NCI-designated comprehensive cancer centers. *p<0.05. **p<0.01. ***p<0.

Model 2

Table 4-3 shows model 2 estimates from equation 1. The *stage I* coefficient describes differences in stage I (vs. II) in the baseline period. The *post* coefficient describes changes from pre to post for both stage I and II. The *stage I * Post* describes differential changes from pre to post for stage I vs II. The coefficients for PN are estimated for all patients with stage I or stage II kidney cancer. The coefficients for unplanned 30-day readmission, 30-day and 90-day mortality, and length of stay are estimated for stage I or stage II patients receiving nephrectomy (PN or RN) only.

Overall, the probability of receiving PN was 25.1 percentage points higher (p-value<0.001, CI, 0.243,0.260) for stage I compared to stage II prior to the guideline change. The probability of receiving PN was 4.1 percentage points higher (p-value<0.001, CI, 0.031,0.051) in the post-guidelines period compared to the pre-guidelines period for both patients with stage I and II disease. The change in the probability of having PN from before to after guidelines was a statistically significant 9.8 percentage points higher (p-value<0.001, CI, 0.087,0.109) for stage I patients compared to stage II.

Overall, the probability of having unplanned 30-day readmission was not statistically different between stage I and stage II at baseline. The probability of having an unplanned 30-day readmission was a statistically significant 0.7 percentage points lower (p-value<0.001, CI, -0.011,-0.003) in the post-guidelines period compared to the pre-guidelines period across both stage I and II patients.

Overall, the probability of dying within 30 days or 90 days of discharge after surgery was a statistically significant 0.2 (p-value<0.01, CI, -0.003,-0.0002) and 0.4 (p-value<0.001, CI, -0.006,-0.002) percentage points lower for stage I compared to stage II in the pre-guideline change period. The probability of dying within 30 days or 90 days of discharge after surgery did not significantly change in the post-guidelines period compared to the pre-guidelines period (i.e. the coefficient on the Post variable was not statistically significant). The change in the probability of dying within 30 days or 90 days of discharge after surgery from before to after guidelines was not significantly different between stage I and stage II.

Overall, length of stay was a statistically significant half a day shorter for stage I compared to stage II in the pre-guideline change period. Length of stay was a statistically significant 0.7 day shorter (p-value<0.001, CI, 0.796,0.582) in the post-guidelines period compared to the pre-guidelines period for both stage I and II patients. The change in length of stay from before to after guidelines was not significantly different between stage I and stage II.

Table 4-3: Model 2 Estimates of the Differential Impact of the 2009 AUA Guidelines on Stage I Compared to Stage II

	PN	Unplanned 30-Day Readmission	30-Day Mortality	90-Day Mortality	Length of Stay
	N= 246,115	N=204,209	N=204,209	N=204,209	N=204,209
Variable	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**	**Coef. (95% CI)**
Stage 1	0.251*** (0.243 , 0.260)	0.001 (-0.002 , 0.004)	-0.002** (-0.003 , -0.0002)	-0.004*** (-0.006 , -0.002)	-0.507*** (-0.595 , -0.419)
Post	0.041*** (0.031 , 0.051)	-0.007*** (-0.011 , -0.003)	-0.0004 (-0.002 , 0.001)	-0.002 (-0.004 , 0.001)	-0.689*** (-0.796 , 0.582)
Stage 1 * Post	0.098*** (0.087 , 0.109)	0.002 (-0.003 , 0.006)	-0.001 (-0.003 , 0.001)	-0.001 (-0.004 , 0.002)	-0.023 (-0.138 , 0.093)
Age	-0.006*** (-0.003 , -0.003)	0.00004** (0.000001 , 0.0001)	0.0003*** (0.0003 , 0.0003)	0.001*** (0.001 , 0.001)	0.031*** (0.029 , 0.033)
Comorbidity (Charlson Index)					
0	0.095*** (0.083 , 0.107)	-0.017*** (-0.021 , 0.006)	-0.006*** (-0.008 , -0.005)	-0.012*** (-0.012 , -0.014)	-1.505*** (-1.643 , -1.367)
1	0.109*** (0.097 , 0.122)	-0.013*** (-0.016 , -0.009)	-0.005*** (-0.007 , -0.004)	-0.009*** (-0.011 , -0.007)	-1.143*** (-1.285 , -1.001)
2	0.071*** (0.057 , 0.084)	*Ref. Group*	*Ref. Group*	*Ref. Group*	-0.546*** (-0.704 , -0.388)
3+	*Ref. Group*	0.010*** (0.004 , 0.016)	0.006*** (0.0004 , 0.0009)	0.010*** (0.006 , 0.013)	*Ref. Group*
Facility Location					
New England	0.021*** (0.012 , 0.030)	0.002 (-0.002 , 0.0006)	-0.004*** (-0.005 , -0.002)	-0.005*** (-0.007 , -0.003)	0.092 (-0.004 , 0.189)

Middle Atlantic	0.067*** (0.061 , 0.074)	0.006*** (0.003 , 0.009)	-0.002*** (-0.003 , -0.001)	-0.003*** (-0.004 , -0.001)	-0.005 (-0.074 , 0.064)
South Atlantic	0.002 (-0.004 , 0.008)	-0.002 (-0.005 , 0.0002	-0.001** (-0.002 , 0.0002)	-0.002*** (-0.004 , -0.001)	-0.125*** (-0.190 , -0.059)
East North Central	0.027*** (0.021 , 0.033)	0.002 (-0.001 , 0.004)	-0.001 (-0.002 , 0.0004)	-0.001 (-0.002 , 0.001)	-0.039 (-0.315 , 0.144)
East South Central	0.036*** (0.028 , 0.044)	0.010 (0.007 , 0.013)	-0.001 (-0.002 , 0.0004)	-0.001 (-0.003 , 0.001)	-0.230*** (-0.315 , -0.144)
West North Central	0.019*** (0.012 , 0.027)	0.002 (-0.002 , 0.005)	-0.002** (-0.003 , -0.0001)	-0.002** (-0.004 , -0.001)	0.184*** (0.102 , 0,266)
Mountain	0.019 (-0.009 , 0.029)	-0.004** (-0.008 , 0.002)	-0.002** (-0.004 , -0.0001)	-0.004*** (-0.006 , -0.001)	-0.257*** (-0.367 , -0.147)
Pacific	*Ref. Group*	*Ref. Group*	Ref. Group	Ref. Group	Ref. Group
Facility Type					
Community Cancer Program	-0.102*** (-0.115 , -0.090)	-0.003 (-0.008 , 0.002)	-0.001 (-0.003 , 0.001)	-0.003** (-0.006 , 0.0004)	0.056 (-0.076 , 0.188)
Comprehensive Community Cancer Program	-0.054*** (-0.064 , -0.043)	-0.005** (-0.009 , -0.001)	-0.003*** (-0.005 , -0.001)	-0.007*** (-0.010 , -0.005)	-0.191*** (-0.302 , -0.081)
Academic/research#	0.066*** (0.056 , 0.076)	-0.007** (-0.011 , -0.002)	-0.003*** (-0.005 , -0.002)	-0.008*** (-0.011 , -0.006)	-0.371*** (-0.481 , -0.260)
Integrated Network Cancer Program	-0.002 (-0.013 , -0.010)	-0.005** (-0.010 , 0.0001)	-0.003*** (-0.005 , -0.001)	-0.007*** (-0.010 , -0.004)	-0.092 (-0.215 , 0.031)
Male	0.004*** (0.0001 , 0.007)	0.001 (-0.0003 , 0.003)	0.002*** (0.002 , 0.003)	0.003*** (0.002 , 0.004)	0.078*** (0.038 , 0.117)

Race					
White	0.040*** (0.034 , 0.045)	-0.005*** (-0.008 , -0.003)	-0.003*** (-0.004 , -0.002)	-0.005*** (-0.007 , -0.004)	-0.410*** (-0.473, -0.346)
Black	*Ref. Group*	*Ref. Group*	Ref. Group	Ref. Group	Ref. Group
Other	0.046*** (0.036 , 0.057)	-0.002 (-0.006 , 0.002)	-0.004*** (-0.006 , -0.002)	-0.006*** (-0.008 , -0.003)	-0.532*** (-0.644 , -0.420)
Hispanic	-0.017*** (-0.025 , -0.009)	-0.002 (-0.005 , 0.001)	-0.001 (-0.002 , 0.001)	-0.001 (-0.003 , 0.001)	-0.105** (-0.188 , -0.021)
Insurance Status					
Uninsured	*Ref. Group*	-0.004 (-0.011 , 0.002)	-0.002 (-0.005 , 0.001)	-0.003 (-0.006 , 0.001)	Ref. Group
Private	0.091*** (0.080 , 0.101)	-0.009*** (-0.013 , -0.004)	-0.004*** (-0.006 , -0.002)	-0.005*** (-0.008 , -0.002)	-0.203*** (-0.318 , -0.087)
Medicaid	0.029*** (0.016 , 0.042)	0.002 (-0.003 , 0.008)	-0.002 (-0.005 , 0.0005)	-0.001 (-0.004 , 0.003)	0.324*** (0.184 , 0.465)
Medicare	0.040 (0.029 , 0.052)	-0.003 (-0.007 , 0.002)	-0.001 (-0.003 , 0.001)	-0.001 (-0.004 , 0.002)	0.174*** (0.051 , 0.296)
Other/Unknown	0.026 (0.011 , 0.040)	Ref. Group	Ref. Group	Ref. Group	0.257*** (0.091 , 0.422)
Urban/Rural					
Metropolitan	0.013*** (0.001 , 0.025)	-0.003 (-0.008 , 0.002)	-0.001 (-0.003 , 0.001)	-0.001 (-0.004 , 0.002)	-0.039 (-0.169 , 0.090)
Urban	0.009*** (-0.006 , 0.023)	-0.008*** (-0.013 , -0.002)	-0.002 (-0.004 , 0.001)	-0.002 (-0.005 , 0.001)	-0.137 (-0.275 , 0.001)
Rural	0.011 (-0.006 , 0.027)	-0.008** (-0.016 , -0.001)	0.0003 (-0.003 , 0.003)	0.001 (-0.003 , 0.005)	0.036 (-0.151 , 0.222)
Median Household Income					

Less than $30,000	0.008 (-0.014 , 0.029)	0.003 (-0.007 , 0.012)	-0.013*** (-0.017 , -0.009)	-0.016*** (-0.022 , -0.011)	-0.361*** (-0.600 , 0.123)
$30,000 $34,999	0.020 (-0.001 , 0.042)	-0.002 (-0.0011 , 0.007)	-0.013*** (-0.017 , -0.009)	-0.017*** (-0.023 , -0.012)	-0.452*** (-0.688 , -0.215)
$35,000 $45,999	0.026** (0.005 , 0.048)	0.0002 (-0.009 , 0.009)	-0.014*** (-0.018 , -0.010)	-0.018*** (-0.023 , -0012)	-0.482*** (-0.718 , -0.361)
$46,000 +	0.050*** (0.029 , 0.071)	-0.002 (-0.011 , 0.007)	-0.014*** (-0.018 , -0.010)	-0.019*** (-0.023 , -0.031)	-0.596*** (-0.831 , -0.0361)

Note. The study sample for PN includes all patients diagnosed with stage I or stage II between 2004 and 2014. The study sample for unplanned 30-day readmission, 30 and 90-day mortality and length of stay includes stage I and stage II patients receiving either PN or RN. #includes NCI-designated comprehensive cancer centers. *p<0.05. **p<0.01. ***p<0.

Discussion

This study aimed to examine the impact of a change in the guidelines for the management of clinical T1 renal masses (stage I kidney cancer), released by the AUA in 2009, on the use of PN, and the resulting impact on four commonly used perioperative quality indicators: unplanned 30-day readmission, 30-day mortality, 90-day mortality, and length of stay. Focusing on stage I patients receiving either PN or RN, I found a significant increase in the use of PN after the AUA released guidelines in 2009. In line with the study hypothesis, the use of PN increased from 34.22% (2004-2008) to 53.93% (2009-2014). This finding is consistent with prior studies reporting an increase in PN after 2009[189–191,193] The analysis indicated that in the post-guidelines period (2009-2014), patients with stage I kidney cancer were 19.1 percentage points more likely to be treated with PN compared to the pre-guidelines period (2004-2008).

I observed an upward trend in PN use in the pre-guidelines period, which may be driven by the rapid increase in adoption of minimally invasive partial nephrectomy, including laparoscopic and robotic-assisted PN. As noted by other studies, the uptake of minimally invasive partial nephrectomy approaches may play a substantial role in the overall increase in the use of PN after 2009 besides the guidelines release. Procedure codes for robotic procedures were introduced in 2008. In the data used for this study, minimally invasive PN data is reported only after 2010; therefore, it was not possible to investigate the extent to which the increase in PN use may be attributable to the increase in the use of minimally invasive PN surgical approaches. One explanation for the impact of the guidelines on PN can be that prioritizing PN for the treatment of stage I, combined with the increase in minimally invasive partial nephrectomy, may have manifested as a steeper slope for the continuing increase in PN use after 2009.

Previous research has only focused on examining the trends in the use of PN before and after the 2009 guidelines. This study extends the evaluation of the AUA guidelines beyond examining the change in PN only. With the consistent evidence of an increase in PN as the standard surgical treatment for stage I kidney tumors, I provided an analysis of the impact of the guidelines on four perioperative quality indicators that have commonly been used in the literature: Unplanned 30-day readmission, 30-day and 90-day mortality, and length of stay. In line with the study hypotheses, a comparison of perioperative quality indicators before and after guidelines showed a decrease in unplanned 30-day readmission (3.34% to 2.86%), a decrease in 30-day mortality (0.75% to 0.49%), a decrease in 90-day mortality (1.32% to 0.86%), and a decrease in the average length of stay (4.2 to 3.7 days) among patients with stage I kidney

cancer. In addition, the analysis revealed that compared to the pre-guidelines period, the probability of having unplanned 30-day readmission, 30-day mortality, and 90-day mortality were 0.51, 0.13, and 0.25 percentage points lower among stage I patients after the guidelines release. Finally, the average length of stay was 0.71 days shorter for stage I patients after the guidelines release. While the improvement in the perioperative quality indicators may have been driven by the implementation of the new guidelines, there is a possibility that this improvement may partly be due to the increase in the use of laparoscopy and robotic surgery, which according to the literature, offers the potential benefits of improved perioperative outcomes and faster recovery compared with open PN.[218–220]

An analysis of the differential impact of the 2009 guidelines on stage I vs. stage II showed a higher probability of receiving PN after the guidelines for stage I patients. The guidelines did not differentially impact readmission, mortality, or length of stay across stage I and stage II. Stage I and stage II did not differ in readmissions prior to the guidelines release, which may explain no difference after the guidelines. Compared to stage II, stage I patients had lower mortality (30 and 90-day), and shorter LOS prior to the guidelines, however, the analysis did not show a differential change from pre to post for stage I vs II, which may suggest two possibilities. First, although guidelines targeted stage I patients, there might have been some positive spillover effect on the readmission, mortality and LOS for stage II patients. This positive spillover effect can improve the stage II patient outcomes and that's why we did not observe a differential impact of guidelines on stage I vs. stage II. Second, the availability of minimally invasive surgery techniques (i.e., laparoscopy or robotic surgery) in recent years may have contributed to enhancing quality of care and improving patient outcomes stage II, thus minimizing the difference in outcomes between stage I and stage II. In this case, the improvement in the quality indicators may be partially attributable to the use of new technologies rather than guidelines change.

The strength of this study is using data from the NCDB, which provided a large sample size with detailed information on tumor size and staging. Using NCDB enabled me to address a major data limitation in prior studies that were unable to identify stage I kidney cancer patients for the purpose of evaluating the 2009 guidelines. I used detailed information on tumor size and other TNM staging criteria to identify the target population for the AUA guidelines published in 2009, i.e., patients with tumor size of 7 cm or less with no metastasis or spread to lymph nodes. I was also able to include patients with stage II kidney cancer to test for any differential impact of the guidelines on stage I vs. stage II.

There are several important limitations of this study to highlight. While the NCDB is a large database, it represents 70 percent of newly diagnosed cancer cases nationwide. Therefore, the study cannot ensure that the database is representative of all stage I and stage II kidney cancer patients in the United States. The data used for this study only captures readmission to the same hospital, for the same illness, within 30 days of discharge following hospitalization for the surgery. Therefore, patients readmitted to a different hospital may not have been included in the analysis.

The use of a pooled data source limited my ability to assess the specifics for patient comorbidities, renal function of patients prior to treatment choice, and the decision-making process of patients and providers. The inclusion of comorbidity level in the analysis was based on Charlson comorbidity score (0, 1, 2, and 3+). Many of the conditions specified in the Charlson mapping table can directly or indirectly affect the treatment choice and risk of postoperative complications or even chance of mortality—e.g. those directly related to kidney function. However, I was not able to control for these specific comorbid conditions that can be associated with kidney cancer or postoperative complications. In the Charlson comorbidity score mapping table (Appendix D), for instance, diabetes, myocardial infarction, and congestive heart failure all have a score of 1, while diabetes with chronic complications and renal disease both have a score of 2. Although I controlled for comorbidity, I was not able to identify what specific condition a score of 2 represented for a patient, which might be important as some of these conditions may be directly related to the choice of treatment. In addition, some potentially important health-associated factors are not captured by the NCDB in its current form, e.g., weight, body mass index, smoking status, etc., many of which are associated with kidney cancer and the treatment options. Therefore, I was not able to control for such factors.

Patient preferences are a critical factor but are difficult to control for in health-related studies. The 2009 guidelines highlight the importance of counseling patients about the potential advantages of a nephron-sparing treatment approach. Despite the importance of patient preferences, I was not able to control for a particular treatment preference or perhaps a particular hospital or surgeon. In addition, because of the sensitive nature of reporting data on morbidity and mortality, there could be a potential for selection biases related to the preference for a specific hospital. Furthermore, due to data limitations, I was not able to control for the elective or imperative type of PN, which may also be related to patient preferences. Finally, the findings of this study represent the association between the 2009 guidelines and the outcomes of the study. The observed upward trend in PN use before the release of 2009 guidelines suggests the presence of factors driving the increase in PN pre-guidelines. Therefore, we could not make

causal inferences about the relationship between the guidelines and the outcomes of interest (i.e., PN use, readmission, mortality and LOS) because we could not rule out alternative explanations.

Conclusion

The evaluation of the 2009 American Urological Association guidelines for the management of stage I kidney tumors using 2004-2014 data from the National Cancer Database showed a significant increase in the utilization of partial nephrectomy among stage I kidney cancer patients in the post-guidelines period (2009-2014). The AUA guidelines were associated with a lower probability of having unplanned 30-day readmission, 30-day mortality, or 90-day mortality, and shorter length of stay among patients with stage I kidney cancer. The guidelines did not have a differential impact on stage I vs. stage II which suggests two possibilities. First, a spillover effect of the guidelines, which targeted stage I patients, on stage II patients. Second, stage II patients benefiting from the widespread use of minimally invasive treatments potentially improving their outcomes. With the rising incidence of early-detected renal masses and increasing use of partial nephrectomy—particularly minimally invasive approaches—it is critical to regularly evaluate the impact of guidelines on perioperative quality measures. As the US healthcare shifts from volume to value-based systems, evaluating quality indicators, especially for high-cost patient populations such as patients with cancer, ensures optimal care while minimizing healthcare costs.

Chapter 5 Summary

This dissertation aimed to better understand the relationship between health policies or interventions and patient outcomes in three different studies. Findings provided an evaluation of different health policies and their impact on patient outcomes which can help inform clinicians and policymakers about effective strategies to deliver appropriate care to patients and tailor policies to ensure patients receive high-value care.

In the first study, I examined the impact of skilled nursing facility care on readmissions focusing on a Medicare policy referred to as the 3-Day Rule. Studying Medicare patients over four years revealed that SNF discharge increases the probability of 30-day readmission. Interestingly, analyzing Medicare FFS and MA patients separately revealed that although most MA plans are not subject to the 3-Day rule for SNF coverage, MA enrollees have lower SNF discharge rates with similar (although statistically not significant) increase in readmission rates to FFS enrollees. This finding highlights three important policy improvement opportunities. First, the potential for reducing unnecessary SNF use, which is a costly and frequently used post-acute care setting. Second, hospitals need to carefully identify the appropriate post-acute care setting for their patients that is capable of meeting the patient's needs to avoid potentially avoidable readmissions. And third, the need to revisit Medicare's SNF coverage policies to ensure all Medicare beneficiaries receive comparable SNF care, regardless of how they participate in Medicare.

In the second study, I examined the association between MA growth and Medicare FFS readmission rates within the context of the HRRP. A comparison of the change in FFS readmission rates before and after the implementation of the HRRP showed the HRRP had no differential impact on FFS readmissions in areas with high MA enrollment rates. In other words, I did not find any evidence of MA penetration spillover effect on FFS readmissions. Findings provide insight to identify potential pathways that a national-level readmission reduction program may benefit from. Findings from this study contribute new and relevant information to the literature, as previous literature has not studied the relationship between MA and traditional Medicare FFS readmissions before and after the implementation of the HRRP.

Finally, in the third study, I evaluated the impact of a new treatment guideline on quality indicators. An evaluation of the impact of new cancer treatment guidelines on the perioperative quality indicators showed a decrease in readmission and mortality rates and a shorter length of stay in the post-guidelines period among patients with kidney tumors targeted by the new guidelines. In addition, the guidelines did

not differentially impact the quality indicators across stage I and stage II which suggests the presence of spillover effects of the new guidelines on stage II patients, or the overall positive impact of minimally invasive surgery techniques on stage I and stage II kidney cancer patients. Postoperative complications are frequent and are strongly associated with the risk of subsequent death, readmission, or length of hospital stay, all of which contribute to considerable costs of care and excess health care resource use. As the healthcare system shifts to value-based reimbursement models, achieving better quality in surgical care seems to be an essential part of the broader hospital quality improvement efforts.

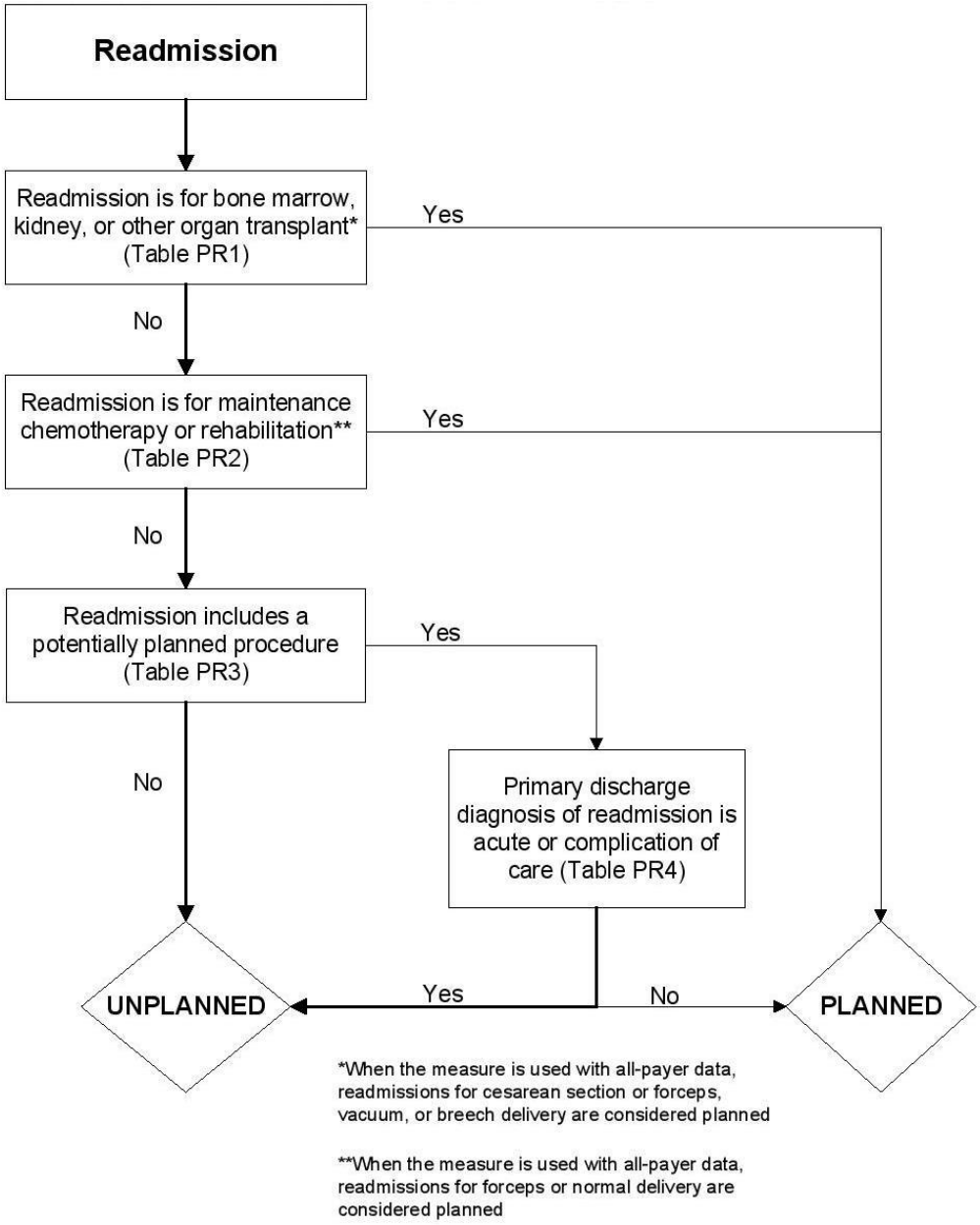
Appendix

Appendix A: Post-Acute Care Settings, Patient Requirements, and Services Offered by Each Provider

PROVIDER TYPE	Patient Requirements	Facility Requirements	Services
Home Health Agency (HHA)	Home-bound, need skilled nursing care on a part-time or intermittent basis	N/A	Skilled nursing care; physical, occupational, and speech therapy; medical social work; home health aide
Skilled Nursing Facility (SNF)	Need short-term skilled nursing or rehabilitation services on an inpatient basis after a hospital stay of at least three days	N/A	Skilled nursing care, rehabilitation services
Inpatient Rehabilitation Facility (IRF)	Must need intensive rehabilitation therapy and be able to tolerate and benefit from three hours or more of therapy a day	At least 60 percent of the facility's patients have one of several specific medical conditions that require inpatient therapy	Intensive inpatient physical, occupational, or speech rehabilitation services
Long-Term Care Hospital (LTCH)	Clinically complex problems	Average Medicare length of stay greater than 25 days	Acute care inpatient hospital services

Source: MedPAC, Report to the Congress: Medicare Payment Policy, *chapter 3, March 2010, available at* www.medpac.gov/documents/Mar10_EntireReport.pdf.

Appendix B: Planned Readmission Algorithm Version 2.1 – Flowchart



Note. Planned readmission algorithm version 2.1. Prepared by Yale New Haven Health Services Corporation Center for Outcomes Research & Evaluation (YNHHSC/CORE). Source: https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Measure-Methodology

Appendix C: Medicare Initiatives that Place Hospitals at Financial Risk for Readmissions from PAC[14]

	Initiative	Participation	Financial incentive to prevent readmissions
Inpatient hospital value-based purchasing program	VBP incentive that pays hospitals bonuses or imposes penalties based on their performance	Mandatory for all PPS hospitals	Payment determination is in part based on a measure of spending in the 30-day postdischarge period.
Hospital Readmissions Reduction Program	Penalty for hospitals that exceed expected rate of readmission for six conditions	Mandatory for all PPS hospitals	The program includes a financial penalty for hospitals with higher than expected readmissions.
Comprehensive Care for Joint Replacement	Creates an incentive that holds hospitals accountable for cost and quality of the inpatient acute care services and 90 days of postdischarge care for joint replacement patients	Mandatory for all hospitals in 67 selected urban areas (CMS intends to reduce to 34 areas in 2018)	Hospitals in the CCJR program can receive a bonus or penalty depending on their aggregate spending in the payment bundle. Lowering readmissions from PAC helps keep spending below target.
Bundled Payments for Care Improvement	Includes a model that allows hospitals to select a bundle that includes the inpatient stay plus PAC and all related services up to 90 days after discharge; the beneficiary's condition must be 1 or more of 48 diagnostic groups	Voluntary	Participants in the BPCI initiative can receive bonus payments if they keep spending below a target based on prior utilization.
Accountable care organizations (Next Generation or Medicare Shared Savings Program)	Hospitals can participate in ACOs with other stakeholders to share financial risk and collaborate to improve care; not all ACOs include a hospital	Voluntary	Incentives vary depending on the program. Hospitals that lower readmissions relative to their target will have lower spending and better quality, which will influence whether they receive penalties or bonuses.

Note: PAC (post-acute care), VBP (value-based purchasing), PPS (prospective payment system), CCJR (Comprehensive Care for Joint Replacement), BPCI (Bundled Payments for Care Improvement), ACO (accountable care organization).

Appendix D: Charlson Comorbidity Score Mapping Table

Reported ICD9 CM Codes	Condition	Charlson Score*
410 – 410.9	Myocardial Infarction	1
428 – 428.9	Congestive Heart Failure	1
433.9, 441 – 441.9, 785.4, V43.4	Peripheral Vascular Disease	1
430 – 438	Cerebrovascular Disease	1
290 – 290.9	Dementia	1
490 – 496, 500 – 505, 506.4	Chronic Pulmonary Disease	1
710.0, 710.1, 710.4, 714.0 – 714.2, 714.81, 725	Rheumatologic Disease	1
531 – 534.9	Peptic Ulcer Disease	1
571.2, 571.5, 571.6, 571.4 – 571.49	Mild Liver Disease	1
250 – 250.3, 250.7	Diabetes	1
250.4 – 250.6	Diabetes with Chronic Complications	2
344.1, 342 – 342.9	Hemiplegia or Paraplegia	2
582 – 582.9, 583 – 583.7, 585, 586, 588 – 588.9	Renal Disease	2
572.2 – 572.8	Moderate or Severe Liver Disease	3
042 – 044.9	AIDS	6

Note. *Individual Charlson scores are not provided in the PUF. Instead, the Charlson scores are summed for each patient and categorized by a value of 0, 1, and 2 or more. Charlson Comorbidity Index. Charlson index is based on a list of 19 conditions identified from diagnoses in hospital and physician data. Each condition is assigned a weight from 1 to 6. The index score is the sum of the weights for all identified conditions (Charlson et al., 1987).[226,59]
Source: The American College of Surgeons Participant User Files.[227]

Appendix E: The Rural-Urban Continuum Codes

Metropolitan Counties	**Description**
Code	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Nonmetropolitan Counties	
Code	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Note: The 2013 Rural-Urban Continuum Codes form a classification scheme that distinguishes metropolitan counties by the population size of their metro area and nonmetropolitan counties by degree of urbanization and adjacency to a metro area. Last updated on 12/10/2020. An update of the Rural-Urban Continuum Codes is planned for mid-2023.

Appendix F: The American Joint Committee on Cancer (AJCC) Staging System for Kidney Cancer

Stage	Grouping	Stage Description
I	T1, N0, M0	The tumor is 7 cm across or smaller and is only in the kidney (T1). There is no spread to lymph nodes (N0) or distant organs (M0).
II	T2, N0, M0	The tumor is larger than 7 cm across but is still only in the kidney (T2). There is no spread to lymph nodes (N0) or distant organs (M0).
III	T3, N0, M0	The tumor is growing into a major vein (like the renal vein or the vena cava) or into tissue around the kidney, but it is not growing into the adrenal gland or beyond Gerota's fascia (T3). There is no spread to lymph nodes (N0) or distant organs (M0).
	T1-T3 N1, M0	The main tumor can be any size and may be outside the kidney, but it has not spread beyond Gerota's fascia. The cancer has spread to nearby lymph nodes (N1) but has not spread to distant lymph nodes or other organs (M0).
IV	T4 Any N M0	The main tumor is growing beyond Gerota's fascia and may be growing into the adrenal gland on top of the kidney (T4). It may or may not have spread to nearby lymph nodes (any N). It has not spread to distant lymph nodes or other organs (M0).
	Any T Any N M1	The main tumor can be any size and may have grown outside the kidney (any T). It may or may not have spread to nearby lymph nodes (any N). It has spread to distant lymph nodes and/or other organs (M1).

Note. The American Joint Committee on Cancer (AJCC) staging system for kidney cancer, effective as of January 2018. The TNM system is based on 3 key pieces of information: Tumor size (T), spread to lymph nodes (N), and spread (metastasis) to distant sites (M). Stage I is defined as T1N0M0, and stage II is defined as T2N0M0. (source: https://www.cancer.org/cancer/kidney-cancer/detection-diagnosis-staging/staging.html)

Appendix G: NCDB Definition of Readmission Within 30 Days of Surgical Discharge

Code	Definition
0	No surgical procedure of the primary site was performed, or the patient was not readmitted to the same hospital within 30 days of discharge.
1	A patient was surgically treated and was readmitted to the same hospital within 30 days of being discharged. This readmission was unplanned.
2	A patient was surgically treated and was then readmitted to the same hospital within 30 days of being discharged. This readmission was planned (chemotherapy port insertion, revision of colostomy, etc.)
3	A patient was surgically treated and, within 30 days of being discharged, the patient had both a planned and an unplanned readmission to the same hospital.
9	It is unknown whether surgery of the primary site was recommended or performed. It is unknown whether the patient was readmitted to the same hospital within 30 days of discharge.

Note. NCDB=National Cancer Database. Source: The American College of Surgeons Participant User Files.[227]

Appendix H: NCDB Definition of 30-Day Mortality

Code	Definition
0	Patient alive, or died more than 30 days after surgery performed
1	Patient died 30 or fewer days after surgery performed
9	Patient alive with fewer than 30 days of follow-up, surgery date missing, or last contact date missing
blank	Not eligible; surgical resection unknown or not performed, or diagnosed in 2014

Note. NCDB=National Cancer Database. Source: The American College of Surgeons Participant User Files.[227]

Appendix I: NCDB Definition of 90-Day Mortality

Code	Definition
0	Patient alive, or died more than 90 days after surgery performed
1	Patient died 90 or fewer days after surgery performed
9	Patient alive with fewer than 90 days of follow-up, surgery date missing, or last contact date missing
blank	Not eligible; surgical resection unknown or not performed, or diagnosed in 2014

Note. NCDB=National Cancer Database. Source: The American College of Surgeons Participant User Files.[227]

Appendix J: The Rural-Urban Continuum Codes

Metropolitan Counties	**Description**
Code	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Urban Counties	
Code	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
Rural Counties	
Code	
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Note: The 2013 Rural-Urban Continuum Codes form a classification scheme that distinguishes metropolitan counties by the population size of their metro area and nonmetropolitan counties by degree of urbanization and adjacency to a metro area. Last updated on 12/10/2020. An update of the Rural-Urban Continuum Codes is planned for mid-2023.[147]

Appendix K: Facility Locations Defined in the NCDB Data Dictionary

Code	Label	State Grouping
1	New England	CT, MA, ME, NH, RI, VT
2	Middle Atlantic	NJ, NY, PA
3	South Atlantic	DC, DE, FL, GA, MD, NC, SC, VA, WV
4	East North Central	IL, IN, MI, OH, WI
5	East South Central	AL, KY, MS, TN
6	West North Central	IA, KS, MN, MO, ND, NE, SD
7	West South Central	AR, LA, OK, TX
8	Mountain	AZ, CO, ID, MT, NM, NV, UT, WY
9	Pacific	AK, CA, HI, OR, WA
0	Out of US	All other values

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