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Abstract

My first chapter explores the relationship between readmission reduction efforts and hospital costs. A total hospital operating cost function is estimated using over 5,000 observations from 2,129 US hospitals from the period 2012 - 2017. Using these cost estimates, I estimate a hospitals marginal cost of a 1% readmission reduction for a single monitored disease. The average marginal cost of reducing risk-adjusted readmission rates for monitored diseases varies from $1,186,689 to $3,844,643. Significantly higher marginal cost are found for hospitals with the highest number of dual-eligible patients, with hospitals spending up to an extra $839,027 to reduce readmission rates. These results contribute to the growing literature on the burden of quality incentive programs on hospitals serving disproportionately low-income populations.

The second chapter adds to the growing literature on the Hospital Readmission Reduction Program by describing the financial incentives faced by hospitals, estimating their magnitude and distribution, and testing whether hospitals facing larger financial incentives are more likely to improve performance. I estimate the magnitude of the expected future penalty for one additional readmission across hospitals and procedures and find that on average hospitals can expect a penalty increase two periods in the future for one additional readmission today of: $27,906.74 for an additional AMI readmission, $39,161.94 for heart failure, and $30,574.30 for an additional pneumonia admission. I find evidence that hospitals improve their readmission rates over time for the monitored conditions for which they have the highest marginal incentives to improve. I also find evidence that approximately 30% of hospitals have no incentive to improve performance on any condition in a given year.

In the third chapter, I investigate the effect of observed hospital quality measures on patient demand for elective procedures. Using patient-level data from the state of Florida, I estimate a multinomial logit demand model using patient comorbidities and distance between patient zipcode and hospital zipcodes to identify the effect of a marginal decrease in Hip and Knee Replacement complication rates on hospital demand. Previous literature has investigated the impact of changes in readmission and mortality rates on hospital demand, but have not looked into complication rates. The findings indicate that patients have a significant willingness to travel for improved quality measures, including lower complication rates for elective hip and/or knee replacement, lower 30-day readmission rates and lower in-hospital mortality rates for patients with serious treatable conditions. Patient preference heterogeneity inputs older patients being less willing to travel further distances.

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Chapter 1

The marginal cost of readmission reduction - not equal among hospitals

1.1 Introduction

The Hospital Readmission Reduction Program, mandated by the 2010 Affordable Care act, is a program designed specifically to reduce payments to IPPS hospitals that exhibit excess readmission rates. The Centers for Medicare & Medicaid (CMS) are in charge of the implementation of the program, which was implemented for discharges beginning on October 1, 2012. [1] A hospital's excess readmission ratio is roughly a calculation of an individual hospital's performance compared to the national average for each monitored condition. An intrinsic part of the excess readmission ratio is the risk adjustment methods taken by CMS to adjust for clinically relevant patient factors. This risk adjustment is used to calculate the predicted readmission rate for each hospital, which directly determines their readmission adjustment factor. Therefore, any flaw in the risk adjustment methodology directly affects performance measures and, therefore, penalties to each hospital.

[1]The program consists solely of penalties to under-performing hospitals, with no chance of receiving additional benefits or money through performance. For fiscal years 2013 and 2014, the HRRP applies to 30 day readmission measures for Acute Myocardial Infarction (AMI), Heart Failure (HF) and Pneumonia (PN). In the fiscal year 2015, measures for chronic obstructive pulmonary disease (COPD), total hip arthroplasty (THA) and total knee arthroplasty (TKA) will be added to the previous measures. The penalties applied to an individual hospital will afect the base DRG payment for discharges and cannot exceed 1% of total Medicare payments in FY 2013, 2% in FY 2013 and 3% in FY 2015.

One noted criticism of the current risk adjustment methodology, as endorsed by the National Quality Forum (NQF), is the lack of consideration for patient and hospital socioeconomic factors. Since the implementation of the HRRP, the question of whether hospitals with a large population of poor patients are being unduly punished under the current penalty scheme. On examination of factors that influence the likelihood of readmission, Hu et al. (2014) find that patients living in high-poverty neighborhoods were 24 percent more likely to be readmitted after demographic characteristics and clinical conditions were adjusted for. Similarly, Nagasako et al. (2014) find that inclusion of tract-level socioeconomic factors in their models significantly reduced variation in the risk-adjusted performance among hospitals, suggesting that the inclusion of socioeconomic factors can lead to a better understanding of different contributors to adverse post-discharge outcomes. Their analysis compared the performance of models for hospital readmissions that incorporate socioeconomic data from the patient's census tract with standard risk-prediction models that do not include these factors.

A different approach is to directly analyze the characteristics of hospitals that have received penalties under the HRRP. Joynt and Jha (2013) take this approach and find that large hospitals, teaching hospitals and safety-net hospitals are disproportionately likely to be penalized than other hospitals. In fact, only 20% of all safety-net hospitals were not penalized in the first year of the program. They cite evidence that both case mix index and socioeconomic mix of the patient population may be responsible for the higher readmission rates in these hospitals (Joynt et al. (2011), Rathore et al. (2003)).

These studies provide evidence that the HRRP may be unduly punishing the hospitals that most need the resources provided by Medicare payments. Research on alternative risk-adjustment mechanisms is clearly needed as the effect of this undue punishment may cause these hospitals to "cherry-pick" their patients from high socioeconomic classes, reduce non-elderly discharges or even attempt to adjust their Case Mix Index (CMI) (White (2014), Liang (2014)).

All hospitals under the new HRRP are faced with the decision of whether or not to invest in technologies and services to reduce readmission rates in their hospital. Some possible investment choices are medication assistance programs, language services, electronic systems to remind patients to take medication, community health workers and care coordination programs that may involve skilled nursing facilities and assisted or independent living facilities. Alternatively, hospitals could adjust inpatient care procedures to include additional resources or lengthen the stays of patients of certain conditions. Faced with the wide variety of decisions possible for each hospital, perhaps the best approach is to attempt to estimate the cost of a reduced readmission of each hospital based on their quality measures, regulated payments and number of discharges.

The main objective of this paper is to identify the marginal cost of readmission reduction to hospitals and provide evidence that hospitals with high disproportionate share exhibit higher marginal costs. The first goal is to be able to quantify the burden placed on hospitals when they are asked to improve readmission rates. Secondly, we hope to investigate whether it is cost-effective for hospitals serving low income populations to invest in these readmission reduction technologies, because their marginal cost of reducing readmissions may be greater than hospitals serving wealthy populations.

The relevant literature on this topic will be discussed at length in Section 2, Section 3 describes the data used and section 4 provides reduced form evidence and motivation. Section 5 contains the empirical specification and estimation strategy. The estimation and results are discussed in Section 6, while Section 7 contains the conclusion and application of this model to future work.

1.2 Previous Literature

The Medicare readmission reduction program is currently in its second year of implementation. The program works by penalizing hospitals with readmission rates that are higher than the expected readmission rate for the hospital. Medicare defines a readmission as "an admission to a subsection(d) hospital within 30 days of a discharge from the same or another subsection(d) hospital" and has "established a methodology to calculate the excess readmission ratio for each applicable condition, which is used, in part, to calculate the readmission payment adjustment. . A hospital's excess readmission ratio for AMI, HF and PN is a measure of a hospital's readmission performance compared to the national average for the hospital's set of patients with that applicable condition". There is great contention over the calculation of these readmission payment adjustments as well as the effect of these penalties on hospital choices and quality. The existing literature provides more understanding of specific effects of the HRRP on hospital choices, cost functions and patient outcomes; it does not, however, address the overall effectiveness of the program, weighing the benefits to patients against the cost to hospitals and the government. This paper will rely on the previous research as a starting point into the investigation of the cost implications of the HRRP on different types of hospitals.

1.2.1 Unintended Consequences

There is some contention as to the nature of the program and possible unintended consequences for hospitals with a high percentage of low-income patients and evidence to this effect has been a hot topic of recent research papers. Two of the most relevant papers are Nagasako et al. (2014) and Hu et al. (2014). Nagasako et al. (2014) find that inclusion of tract-level socioeconomic factors in their models significantly reduced variation in the risk-adjusted performance among hospitals, suggesting that the inclusion of socioeconomic factors can lead to a better understanding of different contributors to adverse post-discharge outcomes. Their analysis compared the performance of models for hospital readmissions that incorporate socioeconomic data from the patient's census tract with standard risk-prediction models that do not include these factors. Similarly, Hu et al. (2014) examine how elements of individual characteristics and neighborhood socioeconomic status influenced the likelihood of readmission under a single fixed organizational and staffing structure. They find that patients living in high-poverty neighborhoods were 24 percent more likely to be readmitted, after demographic characteristics and clinical conditions were adjusted for. This is strong evidence to suggest that the Medicare risk-adjustment mechanism is not adequate. Laudicellaa et al. (2013) provides further evidence that due to imperfect observation of patient characteristics, hospitals with low mortality rates are likely to have served larger proportions of unobservably sick patients; these patients are at greater risk of readmission than can be estimated by an risk adjustment mechanism, therefore these hospitals will be seen as under-performing on readmission rates. These three papers call into question not only the specific mechanism used by CMS to risk adjust for patient characteristics, but also the entire idea of using only readmission rates as the desired measure of improvement. Though another method has yet to be suggested, it could possibly be a combination of patient and hospital characteristics compared to mortality and readmission rates.

Other papers have investigated the impact of the HRRP on different types of patient populations. Gu et al. (2014) use regression analysis and projections to estimate risk-adjusted readmission rates and penalties under the HRRP. They find that hospitals with high numbers of dual-eligible patients (eligible for both Medicare and Medicaid) were more likely to have excess readmissions than hospitals with low numbers of dual-eligible patients. They conclude that policies to reduce hospital readmissions must also balance the need to ensure access to quality care for vulnerable populations. Not only is the impact on elderly populations questionable, but the impact of Medicare payment systems on non-elderly populations has been called into question by White (2014) and White and Wu (2014). White (2014) investigates how changes in Medicare pricing mechanisms affect hospital treatment of non-elderly patients and find that Medicare price reductions are significantly correlated with reductions in capacity of non-elderly patients. Instead of changing the ratio of non-elderly to elderly patients, reductions in Medicare prices are associated with broad constraints on hospital operations, including reductions in non-elderly and elderly discharges. White and Wu (2014) estimated the effect of changes in Medicare prices on hospital revenue, expenses and other operating financial data. They find that hospitals make up for Medicare price changes by slowing their growth and adjusting operating expenses in the long run. Sood et al. (2013) and Liang (2014) similarly address the problem of hospitals "cherry picking" patients based on profitability levels due to changes in Medicare prices. This evidence is troubling because the HRRP was designed to incentivize hospitals to provide better care to patients rather than decrease patient access overall.

Another paper takes the approach of characterizing hospitals that have already been penalized under the HRRP. Joynt and Jha (2013) analyze the characteristics of hospitals that received penalties in the first year of the HRRP and find that large hospitals, teaching hospitals and safety-net hospitals are disproportionately likely to be penalized than other hospitals. In fact, only 20% of all safety-net hospitals were not penalized in the first year of the program. They cite evidence that both case mix index and socioeconomic mix of the patient population may be responsible for the higher readmission rates in these hospitals (Joynt et al. (2011), Rathore et al. (2003)).

While they do not look specifically at the HRRP program, Ryan and Damberg (2013) provide a review of evidence for the effectiveness of all pay for performance programs in Medicare. They assess to what extent the existing and planned Value-Based-Purchasing programs align with their identified criteria for best practices in pay for performance. They determine that HVBP (Hospital Value-Based-Purchasing) does not provide adequate financial incentives to hospitals. They show concern for the possibility that a certain class of providers and the patients they serve (low-income patients) will suffer under these incentives and hospitals may "cherry-pick" patients to increase the likelihood of obtaining the quality bonus payments. This paper is the first to suggest that hospitals are not being provided a strong enough incentive to change their behavior. This is particularly poignant for hospitals serving larger populations of patients in low income situations. In order for these hospitals to invest in readmission reduction technologies, they will need stronger financial disincentives towards their current behavior.

1.2.2 Cost Analysis

The evidence that hospitals serving poor populations may bear a larger financial burden due to the HRRP is strong. What has yet to be determined is if the overall cost of the program is being outweighed by the positive benefits to Medicare patients. Meacock et al. (2014a) answer this question for a similar program implemented in England. They propose a comprehensive framework to analyze the cost-effectiveness of the first pay-for-performance (P4P) scheme introduced for hospitals in England. They find that the Advancing Quality initiative generated approximately 5200 quality-adjusted life years (QUALYS) and 4.4m of savings in reduced length of stay. The program total cost was 13m, and overall the program was a cost-effective use of resources in its first 18 months.

What is available are a few investigations into the specific costs of different stages of the hospitalization process. Carey (2014) analyzes the relationship between length of stay and readmission within 30 days of discharge to determine the cost trade-off between an extra day of care and the expected cost of readmission. She finds that the cost of an additional day of stay would be offset by approximately 15% due to reduced chance of readmission. She suggests that hospitals receiving reimbursements under bundled payment mechanisms should be aware of the cost trade-off between longer lengths of stay and readmission. The study suggests that shorter lengths of stay are highly correlated with readmission rates. Gutacker et al. (2013) investigates the extent to which cost variation is associated with different patient outcomes and how accounting for health outcomes can change judgments about hospital cost performances. They do this using a new dataset of patient-reported outcome measures (PROMs) linked to inpatient records. They do not find that cost performances change when they account for outcomes.

The most direct approach to estimating the cost of quality improvement in hospitals comes from Romley and Goldman (2011). They attempt to analyze the cost of overall hospital improvement using a measure for 'revealed quality'. They infer this quality from patient choices and it is supposed to incorporate unobserved hospital attributes related to quality. They find that revealed quality is not significantly correlated with clinical quality but does differ among hospitals. Revealed quality itself is costly and increases with hospital productivity. They conclude that non-clinical aspects of the hospital experience, amenities and personal preferences, play important roles in hospital demand. This method may be a step in the right direction of discovering the real quality improvement in hospitals, unfortunately their measure of revealed quality has yet to be accepted as the standard and unobserved hospital amenities are ignored in the HRRP.

1.3 Data

1.3.1 Discharges and Medicare Payments

In this paper I use data from three primary sources: The Centers for Medicare & Medicaid Services (CMS), the American Hospital Directory (AHD) and the Health Resources and Services Administration's Area Health Resource File (AHRF). Data from these three sources were merged to create a full data set with control variables at the hospital and county level.

The "Medicare provider charge data: inpatient" is released yearly by CMS beginning in the spring of 2013b. I use this for my primary data supplemented with additional variates. The CMS data contain information for the 100 most commonly billed diagnoses categories for Medicare patients for 3,337 hospitals in the United States. For each hospital and each procedures performed by the hospital, the data set provides the average hospital charges, average Medicare payments to the hospital, and the total number of discharges in that diagnoses group (DRG) for that hospital. The hospitals in the sample perform between 1 and 100 of these most common diagnoses. For each hospital I calculate the number of procedures provided and use this as an control for the hospital's exposure to Medicare.

Each hospital during a calendar year creates a list of charges for each diagnosis group treated in the hospital. This "chargemaster" does not entail the prices actually paid by patients, but rather a general rubric for what is to be expected. The hospital then negotiates with each insurance provider as to how much of this "chargemaster" value it receives from the provider for each patient covered under their insurance. It then creates a list of per-diem rates for each diagnosis group and insurance provider. The charge sheet as well as the negotiated per-diem rates will differ across hospitals and diagnosis groups.

Medicare payments to hospitals, however, are viewed as being determined exogenously. Medicare uses a strict rubric to calculate the reimbursement rate for each DRG and hospital. When calculating the amount to be given to the hospital, Medicare considers six different categories and adjusts the price based on these categories. These categories take into account geographic and economic factors as well as the status of the hospital (teaching, for-profit) and the severity of the diagnosis. Other categories adjust for teaching expenses within the hospital as well as if the patient is considered as a full-length patient or a short length of stay patient because of a transfer. There is also another category for "outlier" patients that incur above average costs. For these patients the hospital receives an extra "outlier payment"(Medicare Payment Advisory Commission(2012)).

At the hospital level, the data provide the hospital name, unique identification number, address, city, state and zip code. Using this I find latitude and longitude coordinates for each hospital with a geo-coding process. I then calculate the linear distance between each hospital using the Haversine formula and use these distances to determine my market-areas. The identification number unique to the hospital is found in all but one of the secondary data sets and allowed for the compilation of data and variables.

1.3.2 Quality Measures

The second primary data set, also acquired from CMS , contains the relevant quality variables for my study.Centers for Medicare & Medicaid Services (2013a) From CMS I obtained a set of files that contain information for the set of Medicare affiliated hospitals. The Hospital_Outcome_Of_Care_Measures dataset contains a compiled set of the risk-adjusted 30-day readmission and mortality data per hospital for three different groups of diagnoses: pneumonia, AMI and heart failure. These measures were developed by clinical and statistical experts at Yale and Harvard universities. The CMS rates are calculated using Medicare claims. These rates adjust for patient characteristics that would make death or readmission more likely, including age, gender, past medical history and other medical factors upon arrival that would influence a person's chance of survival or readmission. This risk adjustment is necessary to control for the fact that more severely ill patients may be taken to higher quality hospitals and therefore those hospitals have higher mortality rates.

Contained within each of these three groups are three related diagnoses from the inpatient database. To run accurate analysis, consolidation was required for hospitals that performed more than one of these diagnoses. For example, when a patient is admitted to a hospital, they are discharged under a specific AMI diagnosis (280, 281 or 282) depending on their individual condition. If this hospital discharged patients under diagnoses 280, 281 and 282, then the total discharged were summed and the average Medicare payments from each diagnosis were averaged to provide one AMI data point per each hospital in the sample.

This data, as well as the discharge and Medicare payment data is available for the years of 2011-2016.

1.3.3 Individual Hospital Characteristics

Hospital level information of bed capacity, gross patient profits, total hospital discharges and total patient days were also collected. These were obtained from Medicare fiscal year flatfiles as well as the Medicare cost reports. The flatfiles provide data points for case-mix index, number of beds, Medicare days %, readmission rates and readmission adjustment factor and hospital general information.

Each hospital provides data for the Medicare cost reports but fiscal years are unique to each hospital. To align hospital financial data with the readmission data, I average the relevant variables across years. Specifically, for variables that are flows, I take weighted sums over the cost reports, with the weights equal to the fraction of the cost report that fell into the Medicare fiscal year (July 1 - June 30).

Medicare also provides data on the share of Medicare patients each hospital treats who are also eligible for Medicaid. The eligibility requirements for Medicaid vary across states, but the national Medicaid minimum eligibility level is 133% of the federal poverty level. We use this term to control for the poverty of patients served in the hospital cost function. The average ”disproportionate share” for the sample is 26.9% as can be seen in the table 1.1 descriptive statistics.

1.3.4 County Demographics

County-level data was acquired through the Area Health Resource File (AHRF) access system. The AHRF is a free, downloadable database that contains information collected from over 50 sources, including but not limited to the Bureau of Labor Statistics, CMS, US Census Bureau and many national health databases. It is designed specifically for health care researchers with need for county and state level statistics. The AHRF program allows for the easy compilation of the researcher's choice of variables in various levels of detail. From this I pulled county-level information for Medicare penetration, HMO penetration, per capita and median income, the percent of persons in poverty along with other variables. These variables are particularly helpful in examining how living in an area with large populations of Medicare patients affects quality outcomes.

The demographics of the three samples under observation provide information about the types of hospitals and differences between procedure groups. The hospitals and counties represented in the pneumonia and heart failure samples show many similarities. Sample size, portions of non profit and government hospitals, number of beds and patient days indicate an almost complete overlapping between hospitals in these samples. A greater population density in the heart failure sample indicates that more rural hospitals are present in the sample area for pneumonia and absent from the heart failure sample. Hospitals in the heart failure sample are skewed more towards larger cities than hospitals performing pneumonia and AMI operations.

The sample for AMI hospitals is unique in that the hospitals are slightly larger, perform on average four more of the most common Medicare procedures and pull in larger revenues than the other two samples. These may be quirks of the data but the fact that Medicare payments for AMIs are on average $2,000.00 larger per patient is certainly important to our analysis. It is interesting to note that maximum and minimum Medicare payments are similar across the three diagnoses but are skewed more towards the maximum value for AMI procedures. Hospital charge sheets, while not an accurate method of price, provide some understanding of hospital charge structures. These charges show a difference in $7,000.00 between AMI and the other two diagnoses. The greater value and larger variance in AMI charges and Medicare payments indicate a different procedure dynamic than the other two samples; these differences appear again in the analysis of quality measures.

The nature of the different procedures is depicted in the differences between mortality and readmission rates. The mortality rates for pneumonia show the largest fluctuations across hospitals while the readmission rates are the most stable. For AMI and heart failure, readmission rates fluctuate more than mortality rates. These fluctuations indicate that quality and demographics more greatly affect mortality for pneumonia patients and readmission rates for AMI and heart failure patients. The mortality rate for AMI patients is much larger than that for the other two categories while the readmission rate for heart failure is larger than that for AMI. The higher mortality rate is explained in large part by the nature of AMI. Acute conditions have a rapid onset and a short duration while, pneumonia and heart failure are associated with a more gradual onset and a longer duration. The nature of heart failure, then, makes it more likely for patients to be readmitted to the hospital as many are terminally ill patients or those requiring a lifetime of observation.

1.4 Reduced Form Evidence

1.4.1 Socioeconomic Factors and Readmission Rates

One of the main purposes of this paper is to quantify the burden on hospitals of reducing readmission rates. Specifically, there has been reported evidence that socioeconomic factors negatively affect readmission rates; this suggests that hospitals with large populations of patients in poverty may have a higher marginal cost of readmission reduction. This section provides the motivation behind the need for a structural analysis of this market.

One of the main critiques of the Hospital Readmission Reduction Program is that the Medicare risk-adjusted mortality and readmission rates inadequately control for socioeconomic status. Specifically, there has been evidence suggesting that socioeconomic factors (income and poverty levels) directly affect the probability of readmission in a population. The result of this is that hospitals serving a disproportionate share of poor patients, or located in a poor community, have higher intrinsic readmission rates. Two papers that have investigated this phenomenon are Nagasako et al. (2014) and Hu et al. (2014). We also find evidence that suggests socioeconomic factors contribute to readmission rates, above and beyond what is considered in the CMS risk adjusted quality measures.

For all three of our diagnoses, we regress different socioeconomic variables on risk-adjusted mortality and readmission rates. As can be seen in table 1.3, two different indicators for poverty levels (the number of people eligible for Medicaid over 65 years old and the percent in poverty in the county) are both positively and significantly correlated with average readmission rates. These readmission rates are already risk-adjusted, and according to CMS these factors should not directly affect readmission rates. The significance of these variables in regressions in previous papers as well as in my own calls into question the risk-adjustment methods of CMS. The implications of a poor risk-adjustment mechanism, combined with the HRRP, could possibly be that for hospitals with high levels of dual-eligible (Medicare and Medicaid eligible) patients it may be too costly to implement readmission reduction programs because of their risky patient population.

As observed in my previous paper, an increased market concentration (HHI) negatively affects readmission rates but positive affects mortality rates. The HHI for each market is calculated as:

$$HHI_m = \sum_{j=1}^{J_m} \left(\frac{n_j}{n_1 + n_2 + .. + n_{J_m}} \right)^2$$

where n_j is the number of discharges for hospital j and $n_1, n_2, ..., n_{Jm}$ are the discharges from other hospitals within 20 miles of hospital j. Therefore a rural hospital with no other competitors within 20 miles will have a market concentration of 1. These results suggest that competition positively affects mortality rates while having an uncertain affect on readmission rates. This uncertain affect is due to the fact that a decrease in mortality rates necessarily implies an increase in readmission rates with the logic that the patients who are saved when mortality rates decrease tend to be more severely ill patients and therefore more likely to be readmitted to the hospital.

Another thing of note in table 1.4 is that an increase in median household income is negatively and positively correlated with mortality rates for all three procedures. This provides more evidence to the fact that income and poverty levels affect patient outcomes directly and should be accounted for in risk adjustment mechanisms. An interesting finding is that population density is negatively correlated with mortality rates while being positively correlated with readmission rates. This may be a result of the fact that larger densely populated cities tend to have better medical facilities than urban areas; it is also much easier to access hospitals (shorter distances to travel) in these areas.

Market Demand

To estimate market demand, we first have to tackle the problem of endogeneity of quality. Potential instruments for quality include productivity, average quality of nearby markets or quality of different procedures in the hospital. We do not have data on productivity of the hospital, so the two instruments available to us include average quality of markets within 50-100 miles of the hospital and quality of two other procedures from the hospital. These are ideal instruments because the first is correlated with hospital quality but should be unrelated to unperceived ability. The second set of instruments (quality of other procedures) are less ideal because they will limit the sample size as well as be potentially correlated with unobserved hospital characteristics. In this case, I instrument for hospital quality with the average and standard deviation of readmission and mortality rates from markets between 50 and 100 miles from the object hospital. The relevance of the selected instruments is proven in the first stage of the two-stage least squares instrumental variable regression.

Using our chosen instruments, we run a regression of quality and socioeconomic variables on the individual and total market demand of each hospital. The expected results of the demand estimation is that demand increases in hospital quality. Since mortality rates and readmission rates are necessarily correlated, this can be confounding when estimating the entire demand function. This is a probable reason why the literature has been moving towards using a logit model of patient choice of hospital, producing predicted patient flows Kessler and McClellan (2000). What we see from 1.5 is that individual hospital demand is significantly and positively correlated with a hospital's own readmission rate. The coefficients for own mortality and market readmission and mortality rates are not significant however, except in the case of the effect of the average market readmission rate on heart failure demand in 2011. This coefficient says that an increase in the readmission rate of other hospitals in the market by 1% will decrease hospital discharges by roughly 13 people. The lack of significance of the other quality measures here is concerning and may be due to a poor choice of hospital and socioeconomic controls. This is one thing that needs to be sorted out before I can properly parameterize the demand function for my GMM estimation.

The result of patient choices are evident in the fact that the number of procedures provided by the hospital increases the demand for the hospital. For each of the three procedures (AMI, heart failure and pneumonia), there are three different diagnoses that take into consideration varying degrees of sickness of the patient. Hospitals that provide care for all three types of patients (or hospitals that are more specialized in any of the three procedures), are of higher demand to the patient. This indicates that patients are aware of hospitals that perhaps have a reputation for a "heart failure" hospital or a "pnuemonia hospital". Non-profit hospitals also see significantly more patients than government-owned or other types of hospitals.

An interesting result is that hospitals in areas with higher per capita income have increased levels of demand for pneumonia and heart failure patients, but per capita income is not significantly correlated to demand for AMI procedures in a hospital. This can be explained by the fact that patients are more likely to search out better hospitals for pneumonia and heart failure procedures than AMI procedures because AMI is necessarily an "acute" disorder and patients are more often taken to the nearest hospital. It is possible that patients are choosing hospitals in higher income areas because of better reputation, amenities or perhaps because wealthier areas have better funded hospitals.

The estimation for total market demand follows more along the lines of something we would expect to see. Demand for the entire market is significantly and negatively correlated with average market mortality rates and positively correlated with market readmission rates. This suggests patient may choose hospitals based on mortality rates rather than readmission rates.

Market demand for Medicare services is decreasing in the number of Medicaid eligible patients over 65. Patients who are considered "dual-eligible", then, may be paid from the Medicaid program more frequently than from Medicare. This is a negative thing for the hospital because hospitals have a large loss margin for Medicaid patients as a whole. Total market demand is also increasing in per capita income and population density, perhaps owing to patients choosing hospitals in larger cities as opposed to rural areas.

1.5 Empirical Model

The literature contains a vast number of empirical models employing a variety of functional forms. The most common is the translog functional form in which the variables are logarithmically transformed, and the second power and interactions among variables are included as regressors. The main drawback of this form is the large number of coefficients to be estimated which leads to collinearity. Since the focus of this paper is marginal effects and I have limited input price variables, I follow the literature in using a log linear specification(Farsi and Filippini (2008), Carey and Burgess (1999), Carey (1997), Grannemann et al. (1986)). This is equivalent to the translog cost function where the coefficients of the second-order terms are restricted to zero.

My data is composed of a 5 year unbalanced panel containing observations on 2,129 hospitals. Exploratory analysis revealed low levels of within variation in many of the variables, leading to a choice of a random effects model. A fixed effects model would also require excluding all time-invariant variables (including teaching and profit status) which are strong predictors of hospital costs. To test the validity of the choice of a random-effects model, I implement a Breusch and Pagan Lagrange multiplier test. Under $H_0 : \sigma_v^2 = 0$. For each of my models the LM test statistic in large, which leads me to reject the null and assume that there does exist heterogeneity across hospitals and the choice of random effects model is justified. However, random effects models assume no correlation between observed variables and unobservable individual hospital effects, which may not be consistent in this model. I therefore use the generalized estimation equations (GEE) approach to address intra-cluster correlation in the data. I use GEE models using Stata xtgee to obtain robust standard errors and account for hospital level clustering.

Following Carey and Stefos (2010), I estimate my model using a log linear specification of the form:

$$C_{it} = P_{it} * exp^{f+e} \rightarrow lnC_{it} - lnP_{it} = f + e_{it} \tag{1.1}$$

where:

$$f = \alpha \sum_j \beta_{jit} lnY_{jit} + \sum_k \xi_{kit} X_{kit} \tag{1.2}$$

Where C_{it} is total operating costs of hospital i in year t, P_{it} represents input prices, X_{kit} are quality variables variables, and Y_{jit} are the outputs and fixed inputs. The parameters to be estimated are α, the β's and the ξ's. The variable P_{it} is the index of local area wage rates used by Medicare for reimbursing hospitals under the PPS.

1.6 Results

Table 1.7 reports the results of the regression estimates of equation (1). Model 1 is a benchmark analysis that does not include any readmission reduction measures. The key economic variables exhibited the expected signs with significant coefficients. Nonprofit hospitals had higher costs that for-profit hospitals (reference group) and hospitals with teaching programs also exhibited higher costs. System member hospitals displayed significantly higher costs than those not within a hospital system suggesting some amount of administrative costs to being within a hospital system.

Model 2 includes the predicted readmission rate variables for acute myocardial infarction, pneumonia and heart failure. These predicted readmission rates are equivalent to risk-adjusted 30-day readmission rates over the observation period. Model 3 includes raw readmission rates (without risk-adjustment), Model 4 includes the raw number of readmission per hospital per procedure and Model 5 includes the summed number of adverse events (AMI, PN & HF) per hospital.

Since an increase in readmission rate can be considered a fall in quality, the negative coefficient on the readmission rate variables is interpreted as a decrease in quality results in lower hospital costs. All coefficient estimates for both risk-adjusted and raw readmission rates are negative and statistically significant, the expected result.

In order to estimate the cost of reducing readmission rates in a hospital, I calculate the marginal cost of readmission rates, which take the form:

$$MC_{RR_k} = \frac{\partial C_{it}}{\partial RR_k} = \frac{\partial \ln C_{it}}{\partial RR_k} \cdot C_{it} = \xi_k \hat{C}_{it} \tag{1.3}$$

where RR_k is the readmission rate associated with measure k and ξ_k is the estimated coefficient on the measure in question.

Table 1.7 shows the average marginal costs for Models 2-4. As can be seen, the coefficients on the predicted (risk-adjusted) readmission rates show marginal costs of \$-2,206,040 for acute myocardial infarction, \$-1,186,689 for pneumonia and \$-3,844,643 for pneumonia. These estimates are interpreted as the cost to a hospital of increasing hospital-wide predicted readmission rates.

The estimated marginal cost of raw readmission rates are significantly lower than those for predicted readmission rates. This is due in part to the way in which CMS estimates predicted readmission rates (see Appendix C). Since these predicted rates are a function of patient comorbidities, hospitals with higher case-mix indexes are likely to have higher predicted than raw readmission rates and vice versa.

Appendix table A.2 details the average marginal costs based on a hospital's disproportionate share quartile. Hospitals in the highest quartile of disproportionate share are shown to have greater marginal costs for all measures of readmission rates. These pervasive differences provide additional evidence to support the hypothesis that hospitals with higher percentages of dual-eligible patients bear an undue financial burden in the efforts to reduce readmission rates. These results are robust to estimates from a first-stage model that excludes disproportionate share percentage from the independent variables.

1.7 Conclusion

This paper explores the relationship between readmission reduction efforts and hospital costs by estimating a translog cost function of total hospital operating costs as a function of hospital fixed inputs and outputs. Using observations from 2,129 US hospitals serving the Medicare patient population from fiscal year 2012 through fiscal year 2017, I find that the average marginal cost of reducing risk-adjusted readmission rates for monitored diseases by

1% varies from $1,186,689 to $3,844,643.

I then calculate the average marginal costs by quartiles of disproportionate share patient populations to identify the differences in cost reduction across different patient populations. I find significantly higher marginal cost for hospitals with the highest number of dual-eligible patients, with hospitals in this highest quartile spending up to an extra $839,027 to reduce readmission rates. This result contributes to the growing literature on the burden of quality incentive programs on hospitals serving a disproportionately large number of low-income patients.

Extensions of this paper include further investigations into the non-linearity of readmission reduction efforts. Hospitals that already have high quality (low readmission rates) may find it more costly to reduce their readmission rates even further. Some analysis into differences between high-quality and low-quality hospital costs of readmission reduction efforts could lend credence to the argument that there exists a natural floor on readmission rates.

Figures and tables

Table 1.1: Descriptive statistics

	Mean	**S.d.**
Total Costs ($1,000,000)	351.6	(380.2)
Discharges	14483.3	(11166.0)
Case-mix index	1.577	(0.229)
Beds	284.6	(202.6)
Herfindahl index of competition (HHI)	0.343	(0.398)
Inpatient-days	53571.0	(46517.1)
% Not for profit hospital	0.705	(0.456)
% Teaching hospital	0.489	(0.500)
Medicare days % of total inpatient	0.437	(0.123)
Disproportionate share %	0.269	(0.141)
Readmission adjustment factor	0.996	(0.00470)
Raw # number of adverse events	255.1	(155.5)
Observations	5713	

v

Table 1.2: Descriptive statistics: readmission measures

	Procedure	**Mean**	**S.d.**
Predicted readmission rate	AMI	17.68	(2.883)
	CABG	14.26	(1.764)
	COPD	19.68	(2.116)
	HF	21.92	(2.490)
	HIP/KNEE	4.999	(1.007)
	PN	16.96	(2.216)
Expected readmission rate	AMI	17.61	(2.360)
	CABG	14.23	(1.250)
	COPD	19.65	(1.563)
	HF	21.87	(1.428)
	HIP/KNEE	4.955	(0.642)
	PN	16.90	(1.468)
Raw readmission #	AMI	43.71	(37.12)
	CABG	25.11	(14.62)
	COPD	64.50	(52.45)
	HF	87.75	(79.92)
	HIP/KNEE	27.16	(19.22)
	PN	66.25	(54.85)
Raw number of adverse events		247.9	(164.7)
Observations	15625		

Table 1.3: Regression of Market-Level Readmission Rates on County Level Socioeconomic Factors

	Pneumonia		AMI		Heart Failure	
Variable	2011	2012	2011	2012	2011	2012
Eligible Medicaid Over 65 (000,000)	0.583	0.316	0.395	0.226	0.435	0.435
	(0.170)**	(0.154)*	(0.168)*	-0.123	(0.203)*	(0.203)*
Black Population (%)	0.017	0.013	0.018	0.012	0.014	0.014
	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**
In Poverty (%)	0.034	0.030	0.035	0.027	0.070	0.070
	(0.009)**	(0.008)**	(0.009)**	(0.007)**	(0.010)**	(0.010)**
Median Household Income (0,000)	0.087	0.064	0.130	0.120	0.165	0.165
	(0.038)*	-0.034	(0.037)**	(0.029)**	(0.045)**	(0.045)**
Population Density (000)	0.031	0.025	0.034	0.019	0.042	0.042
	(0.004)**	(0.004)**	(0.004)**	(0.003)**	(0.005)**	(0.005)**
HHI	-0.846	-0.912	-0.365	-0.124	-0.616	-0.616
	(0.129)**	(0.125)**	(0.094)**	-0.081	(0.155)**	(0.155)**
Census Population (00,000)	-0.024	-0.015	-0.016	-0.005	-0.015	-0.015
	(0.006)**	(0.006)**	(0.006)**	-0.004	(0.007)*	(0.007)*
_cons	18.527	16.251	18.565	18.106	24.372	21.549
	(0.311)**	(0.415)**	(0.287)**	(0.441)**	(0.366)**	(0.526)**
N	2,208	2,210	2,208	2,020	2,204	2,204

Coefficients
(s.e.)
* p<0.05; ** p<0.01

Table 1.4: Regression of Market-Level Mortality Rates on County Level Socioeconomic Factors

	Pneumonia		AMI		Heart Failure	
Variable	2011	2012	2011	2012	2011	2012
Eligible Medicaid Over 65	0.306	0.199	-0.110	-0.073	0.592	0.255
(000,000)	-0.184	-0.185	-0.140	-0.138	(0.156)**	-0.160
Black Population (%)	0.003	0.004	0.001	-0.002	-0.010	-0.012
	-0.002	(0.002)*	-0.002	-0.002	(0.002)**	(0.002)**
In Poverty (%)	0.002	-0.004	0.015	0.007	-0.025	-0.030
	-0.009	-0.009	-0.008	-0.008	(0.008)**	(0.008)**
Median Household Income	-0.140	-0.180	-0.163	-0.180	-0.130	-0.180
(0,000)	(0.041)**	(0.041)**	(0.032)**	(0.032)**	(0.035)**	(0.035)**
Population Density (000)	-0.002	-0.007	-0.010	-0.013	-0.014	-0.016
	-0.005	-0.005	(0.004)**	(0.004)**	(0.004)**	(0.004)**
HHI	0.701	0.495	0.382	0.170	0.763	0.628
	(0.140)**	(0.150)**	(0.089)**	(0.087)*	(0.115)**	(0.122)**
Census Population (00,000)	-0.024	-0.024	-0.005	-0.007	-0.038	-0.028
	(0.007)**	(0.007)**	-0.005	-0.005	(0.006)**	(0.006)**
_cons	12.446	12.729	15.956	15.965	12.656	13.194
	(0.343)**	(0.344)**	(0.270)**	(0.266)**	(0.291)**	(0.298)**
N	2,207	2,209	2,096	2,086	2,203	2,203

Coefficients
(s.e.)
* p<0.05; ** p<0.01

Table 1.5: IV Regression of Hospital Demand on County Level Quality and Socioeconomic Factors

	Pneumonia		AMI		Heart Failure	
Variable	2011	2012	2011	2012	2011	2012
Own Mortality Rate	0.048	0.091	-0.048	0.021	-0.127	0.212
	-0.101	-0.121	-0.068	-0.141	-0.193	-0.290
Own Readmission Rate	0.109	0.239	0.109	0.090	0.378	0.400
	-0.065	(0.090)**	(0.038)**	-0.063	(0.107)**	(0.160)*
Market Mortality Rate	-0.009	-0.012	0.001	-0.021	-0.052	-0.104
	-0.032	-0.035	-0.017	-0.030	-0.065	-0.082
Market Readmission Rate	0.017	-0.034	-0.041	-0.014	-0.131	-0.119
	-0.037	-0.043	-0.022	-0.028	(0.051)*	-0.067
Number of Procedures	0.839	0.721	0.410	0.424	1.162	0.952
	(0.044)**	(0.061)**	(0.023)**	(0.036)**	(0.074)**	(0.099)**
Government (Dummy)	0.142	0.167	0.048	0.000	0.367	0.283
	-0.081	(0.081)*	-0.042	-0.046	(0.127)**	(0.135)*
Non-Profit (Dummy)	0.353	0.350	0.074	0.075	0.586	0.624
	(0.055)**	(0.061)**	(0.038)*	-0.051	(0.094)**	(0.115)**
Eligible Medicaid Over 65	-0.162	-0.056	0.025	-0.040	-0.412	-0.566
(000,000)	-0.137	-0.144	-0.067	-0.068	-0.228	(0.247)*
Population Over 65 (0,000)	0.004	0.002	-0.001	0.001	0.009	0.021
	-0.005	-0.005	-0.002	-0.003	-0.008	(0.011)*
Per Capita Income (0,000)	0.077	0.099	0.014	-0.007	0.156	0.111
	(0.028)**	(0.035)**	-0.021	-0.033	(0.045)**	(0.053)*
Population Density (000)	-0.006	-0.002	-0.003	0.005	-0.024	0.009
	-0.006	-0.005	-0.003	-0.004	(0.010)*	-0.013
_cons	-3.859	-5.375	-1.052	-1.513	-5.138	-9.275
	(1.088)**	(1.509)**	-1.228	-2.342	-3.187	(4.420)*
Wald chi2(11)	644.21	620.53	975.82	973.76	474.67	394.64
N	1,999	2,067	1,484	1,458	1,988	2,045

Coefficients
(s.e.)
* p<0.05; ** p<0.01

Instrumented: Mortality Rate, Readmission Rate
Instruments: Av_50_100_Readmission, Av_50_100_Mortality, Std_50_100_Mortality, Std_50_100_Readmission

Table 1.6: Regression of Total Market Demand on County Level Quality and Socioeconomic Factors

	Pneumonia		AMI		Heart Failure	
Variable	2011	2012	2011	2012	2011	2012
Market Mortality Rate	-1.330	-1.283	-1.267	-1.319	-3.618	-3.618
	(0.238)**	(0.211)**	(0.172)**	(0.160)**	(0.471)**	(0.471)**
Market Readmission Rate	4.231	3.844	2.380	2.235	5.476	5.476
	(0.254)**	(0.246)**	(0.149)**	(0.177)**	(0.352)**	(0.352)**
Number of Procedures	-0.005	0.188	0.352	0.350	1.831	1.831
	-0.551	-0.441	-0.201	-0.180	-0.962	-0.962
Eligible Medicaid Over 65 (000,000)	-12.019	-10.276	-3.073	-3.326	-15.633	-15.633
	(1.803)**	(1.597)**	(0.921)**	(0.837)**	(2.980)**	(2.980)**
Population Over 65 (0,000)	0.658	0.580	0.159	0.164	0.896	0.896
	(0.056)**	(0.050)**	(0.029)**	(0.026)**	(0.094)**	(0.094)**
Per Capita Income (0,000)	2.662	2.464	0.582	0.797	3.293	3.293
	(0.342)**	(0.303)**	(0.181)**	(0.163)**	(0.562)**	(0.562)**
Population Density (000)	1.865	1.671	0.837	0.789	3.031	3.031
	(0.059)**	(0.052)**	(0.028)**	(0.026)**	(0.095)**	(0.095)**
_cons	-67.218	-57.230	-25.120	-22.404	-103.268	-103.268
	(5.764)**	(5.325)**	(4.114)**	(4.240)**	(11.682)**	(11.682)**
Wald chi2(11)	1140.95	1298.03	639.76	316.99	2191.61	1611.67
N	2,008	2,067	1,493	1,495	1,994	1,994

Coefficients
(s.e.)
* p<0.05; ** p<0.01

Instrumented: Mortality Rate, Readmission Rate
Instruments: Av_50_100_Readmission, Av_50_100_Mortality, Std_50_100_Mortality, Std_50_100_Readmission

Table 1.7: Regression Results and Coefficients

	(1)	(2)	(3)	(4)	(5)
Log of Discharges	0.527***	0.634***	0.649***	0.632***	0.605***
	(0.024)	(0.025)	(0.028)	(0.028)	(0.028)
Disproportionate Share	0.104*	0.215***	0.255***	0.220***	0.267***
	(0.045)	(0.050)	(0.051)	(0.052)	(0.052)
Log of number of beds	0.228***	0.151***	0.152***	0.142***	0.137***
	(0.040)	(0.036)	(0.039)	(0.038)	(0.037)
Inpatient case-mix index	0.576***	0.452***	0.527***	0.510***	0.564***
	(0.029)	(0.029)	(0.033)	(0.033)	(0.032)
Herfindahl index (HHI)	0.0320*	0.0774***	0.0959***	0.0787***	0.0908***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
System member indicator	0.0612	0.185***	0.182***	0.201***	0.204***
	(0.035)	(0.027)	(0.027)	(0.029)	(0.028)
Teaching hospital indicator	0.121***	0.117***	0.118***	0.107***	0.115***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Nonprofit hospital indicator	0.0590***	0.0981***	0.102***	0.101***	0.1000***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Pred readmission rate: PN		-0.00416*			
		(0.002)			
Pred readmission rate: AMI		-0.00773***			
		(0.002)			
Pred readmission rate: HF		-0.0135***			
		(0.001)			
Raw readmission rate: PN			-0.00226*		
			(0.001)		
Raw readmission rate: AMI			-0.00604***		
			(0.001)		
Raw readmission rate: HF			-0.00338***		
			(0.001)		
# Readmissions AMI				0.000651**	
				(0.000)	
# Readmissions HF				-0.000432***	
				(0.000)	
# Readmissions PN				0.000860***	
				(0.000)	
Total # of adverse events					0.000316***
					(0.000)
r2					
N	8752	6695	5713	5713	5713

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8: Mean values of marginal cost estimates

Model	**Quality Measure**	**Marginal Cost:** RR ($)	**Marginal Cost:** discharge ($)
Model 1 (benchmark)	None		12,509.83
Model 2 (predicted readmission rates)	Acute Myocardial Infarction	-2,206,040	14,378.59
	Pneumonia	-1,186,689	
	Heart Failure	-3,844,643	
Model 3 (raw readmission rates)	Acute Myocardial Infarction	-1,909,774	14,441.5
	Pneumonia	-715,125.4	
	Heart Failure	-1,067,481	
Model 4 (raw # of readmissions)	Acute Myocardial Infarction	204,903.2	14,045.35
	Pneumonia	270,736.6	
	Heart Failure	-135,843.3	
Model 5	Total # of readmissions summed	100,375.2	13,472.02

Chapter 2

Hospital Responses to Financial Incentives of the HRRP

2.1 Introduction

Outline

An intrinsic part of the Affordable Care Act (ACA) was the inclusion of a variety of programs with the goal of incentivizing hospitals to improve quality of patient care. These quality initiatives, including the hospital readmission reduction program and the hospital value based purchasing program were implemented with the goal of improving quality and reducing costs for the Centers for Medicare and Medicaid Services (CMS). The hospital readmission reduction program (HRRP) specifically focuses on readmission rates in hospitals. CMS estimates that 2,599 hospitals will be penalized in FY 2019 for a total sum of $566 million dollars.[1] In addition, preventable and non-preventable readmissions add to the total Medicare program costs, with estimates ranging from $12 to $24 billion annually.[2] While these estimates and magnitude depend on the type of readmission and year in which they were reported, the overall effect of readmissions on costs is not up for debate.

[1]The number of eligible hospitals was 3,062, meaning that 84.88% of hospitals were penalized with an average penalty as a share of payments of 0.67%. See https://www.govinfo.gov/content/pkg/FR-2018-08-17/html/2018-16766.htm

[2]$12bn MedPAC (2007) to $17.4bn Jencks et al. (2007) to, more recently, $24bn Hines et al. (2014).

All hospitals under the new HRRP are faced with the decision of whether or not to invest in technologies and services to reduce readmission rates in their hospital. Some possible investment choices are medication assistance programs, language services, electronic systems to remind patients to take medication, community health workers and care coordination programs that may involve skilled nursing facilities and assisted or independent living facilities (see Ahmad et al. (2013), McClintock et al. (2014)). Alternatively, hospitals could adjust inpatient care procedures to include additional resources or lengthen the stays of patients of certain conditions. While this is a plausible explanation for readmission reduction, Gupta (2017) finds no evidence of changes in patient composition or length of stay for HRRP patients. He does find evidence of an increase in the probability of having a doctor's visit within 15 days of discharge, suggesting additional coordination with primary care physicians in order to reduce readmissions.

Regardless of how they choose to go about readmission reduction, the HRRP introduces differential incentives to hospitals based on their current readmission rates, exposure to Medicare and patient populations. There is much evidence to suggest that patient populations have an impact on readmission rates above and beyond the risk adjustments made by CMS.[3] With the penalties from the HRRP easily reaching into the millions per hospital, it is of high importance to understand how the program differentially impacts decisions of hospitals serving vulnerable populations.

To measure the financial incentives created by the HRRP, I will first estimate the marginal expected future penalty (MFP) incurred due to an additional hospital readmission. This MFP term is composed of a hospital's expectation of penalty in time $t+2$ based on decisions in time t and is calculated as an expectation over the information set available to a hospital at the beginning of the current period.

Preliminary analysis reveals that patient income measures have a significant impact on expected future penalty. This calculated MFP term will be used as an indication of financial pressure placed on a hospital by the HRRP in regressions to estimate the impact this has on hospital decision making. Because this measure is based on observed readmission rate

[3] A paper by Barnett et al. (2015) shows that leaving out demographic characteristics (race and income) creates a quasi-permanent handicap for hospitals located in poor, higher minority neighborhoods.

in previous year, the potential bias in using this in an OLS regression must be addressed. The research approach uses predetermined hospital characteristics from an earlier period (subsequently omitted) to instrument for the hospitals belief of future penalty and savings due to current readmission reduction efforts. I use instruments for readmission rates before the passage of the ACA to implement this strategy and obtain consistent estimates.

In section 2.2 the HRRP and risk adjustment are discussed in detail. Section 2.3 details previous research in this area and section 2.4 lists the data used and variables of interest. Some preliminary results can be found in section 2.5. The main research design and discussion of the results of the investigation are found in sections 2.6 and 2.7 respectively. Concluding remarks are found in section 2.8.

2.2 Setting

2.2.1 Hospital Readmission Reduction Program

Included as one of the Affordable Care Act quality initiatives, The Hospital Readmission Reduction Program, is a program designed specifically to reduce payments to hospitals that exhibit high than average readmission rates across a variety of monitored diseases. The Centers for Medicare & Medicaid (CMS) are in charge of the implementation of the program, which was began for discharges beginning on October 1, 2012 and applies to all acute care hospitals that participate in the Inpatient Prospective Payment System[4]. In the first year, CMS calculated the predicted and expected readmission rates for each of three monitored diseases and then penalized a hospital if its' predicted rate was higher than the expected rate[5]. The penalties applied to an individual hospital will affect the base payment for discharges and cannot exceed 1% of total Medicare payments in FY 2013, 2% in FY 2013 and 3% in FY 2015 and onwards. CMS calculates the base payments for each procedure

[4]The program consists solely of penalties to under-performing hospitals, with no chance of receiving additional benefits or money through performance.

[5]For fiscal years 2013 and 2014, the HRRP applies to 30 day readmission measures for Acute Myocardial Infarction (AMI), Heart Failure (HF) and Pneumonia (PN). In FY 2015, CMS added measures for chronic obstructive pulmonary disease (COPD) and then total hip arthroplasty (THA), total knee arthroplasty (TKA) and CABG in FY 2017

through a reimbursement formula that considers wages, medical education and Medicaid patient percentage.

Beginning in FY 2013, CMS calculates an excess readmission ratio (ERR) as the fraction of predicted readmission rate to expected readmission rate for each hospital and monitored disease. For any hospital, h, predicted readmissions are the number of unplanned readmissions based on a hospital's observed performance and case-mix index. Expected readmissions are the number of unplanned readmissions CMS would expect for the average hospital with same case-mix index as hospital h. This is roughly a comparison of an individual hospital's performance compared to the national average for similar hospitals for each monitored condition[6]. Since the ERR is a ratio of these two terms, if a hospital performs better than the average hospital the ERR will be less than 1. If a hospital performs worse than average, the ERR will be greater than 1 and the hospital will incur a penalty for that measure.

An intrinsic part of the excess readmission ratio is the risk adjustment methods taken by CMS to adjust for clinically relevant patient factors. This risk adjustment is used to calculate the predicted readmission rate for each hospital, which directly determines their readmission adjustment factor[7]. Therefore, any flaw in the risk adjustment methodology directly affects performance measures and, by extension, penalties to each hospital.

This paper will focus on the impact of the three monitored diseases over the course of the program. As additional monitored diseases are included in the program, improvement on any one measure will have less impact on a hospital's future penalty.

2.2.2 Timing

The complex timing of the observation periods and penalty calculation complicates the estimation of hospital expectations. Figure 2.1 shows the timing of the HRRP implementation from the ACA being signed into law in 2010 to the latest addition of CABG as an observed measure in FY 2017.

The first penalty in FY 2013 was calculated from readmissions and discharges in the

[6] Technical details are available in appendix B.1

[7] Details on the risk-adjustment methodology can be found in appendix

observation period from July 1, 2008 - June 30, 2011, however the technicals details of the HRRP penalty were not made available until August 2011. Hospital administrators, then, were left to project how any changes to efforts to reduce readmission rates made in FY 2012 would impact their hospital's total penalty in FY 2014.

2.3 Previous Literature

Previous studies on the impacts of the hospital readmission reduction program have focused on hospital strategies to reduce readmission rates (Zuckerman et al. (2016), Gupta (2017)), the cost hospital readmissions and cost-effectiveness of quality improvement programs (Carey and Stefos (2015), Meacock et al. (2014b), Carey (2014)), as well the efficacy of readmission rates as a measure of quality (Axon and Williams (2011)).

Using a diff-in-diff research design, Gupta (2017) decomposes the readmission reduction attributed to the HRRP into two parts – quality improvement and change in patient admitting behavior and finds that quality improvement can explain 55-60% of the aggregate decrease in readmission rates. He also finds that use of observation status seems driven by the penalty since there is a decrease in admission rate for returning patients under monitored diseases but no effect for hospitals not monitored under the penalty, which leads to some evidence of harm to these patients. There is a negative and statistically significant impact between the probability of being penalized and the probability a patient is readmitted, given they return to the same hospital as an index admission.

Another study looking at the HRRP, by Mellor et al. (2017), uses triple difference estimation to identify effect on Virginia hospitals. They compare results for patients treated at hospitals at risk for penalties vs. not at risk for penalties and find that the HRRP significantly reduces readmission for AMI patients. They find no evidence that hospitals delay readmissions, treat patients with greater intensity, or alter discharge status in response to the HRRP. They also do not see any significant changes in the age, race/ethnicity, health status, or socioeconomic status of patients admitted for AMI.

Arifoglu et al. (2018) take a different approach and use a principle-agent model to show that: the HRRP over-penalizes hospitals with excess readmissions because of the multiplier and its effect can be substantial; having a penalty cap can curtail the effect of financial incentives and result in a no-equilibrium outcome when the cap is too low; not allowing bonus payments leads to many alternative symmetric equilibria, including one where hospitals exert no effort to reduce readmissions.

Most similar to this paper, Norton et al. (2016) study the Hospital Value-based Purchasing Program which reimburses hospitals for good performance on a variety of quality and spending measures. They estimate the magnitude of the marginal future reimbursement for individual patients across each type of quality and performance measure, describing how those incentives differ across hospitals, including integrated and safety-net hospitals. Their investigation finds some evidence that hospitals improved their performance over time in the areas where they have the highest marginal incentives to improve care.

These previous papers are all limited in the method in which they estimate hospital financial implications of the HRRP. Gupta (2017) and Mellor et al. (2017) investigate changes in hospital decisions based on expectations or realized penalties. More realistically, hospitals will identify which diseases they are at-risk for being penalized for and make effort decisions based on the comparison of the savings in future penalty verses the cost of readmission reduction effort today. There is little incentive for a hospital with an ERR < 1 for AMI to reduce AMI readmission rates, unless their ERR score is very close to 1.

2.4 Data sources & descriptive statistics

In this paper I use data from two primary sources: The Centers for Medicare & Medicaid Services (CMS) and the Health Care Utilization Project (HCUP). Data from these two sources were merged to create a full data set with control variables at the hospital and county level.

2.4.1 Discharges and Medicare Payments

The "Medicare provider charge data: inpatient" is released yearly by CMS beginning in the spring of 2013b. The CMS data contain information for all billed diagnoses categories for Medicare patients for 3,337 hospitals in the United States.[8] For each hospital and each procedures performed by the hospital, the data set provides the average hospital charges, average Medicare payments to the hospital, and the total number of discharges in that diagnoses group (DRG) for that hospital. From this data we can garner information about total Medicare revenue per hospital and fiscal year.

Medicare payments to hospitals are viewed as being determined exogenously because Medicare uses a strict rubric to calculate the reimbursement rate for each DRG and hospital. When calculating the amount to be given to the hospital, Medicare considers six different categories and adjusts the price based on these categories. These categories take into account geographic and economic factors as well as the status of the hospital (teaching, for-profit) and the severity of the diagnosis. Other categories adjust for teaching expenses within the hospital as well as if the patient is considered as a full-length patient or a short length of stay patient because of a transfer. There is also another category for "outlier" patients that incur above average costs. For these patients the hospital receives an extra "outlier payment"(Medicare Payment Advisory Commission(2012)).

At the hospital level, the data provide the hospital name, unique identification number, address, city, state and zip code. The identification number unique to the hospital is found in all but one of the secondary data sets and allowed for the compilation of data and variables.

2.4.2 Quality Measures

The Hospital_Outcome_Of_Care_Measures dataset contains a compiled set of the risk-adjusted 30-day readmission and mortality data per hospital for different groups of diagnoses including all diagnoses monitored by the HRRP. These measures were developed by clinical and statistical experts at Yale and Harvard universities.

[8]CMS published this data beginning in FY 2011, containing only information for the 100 most common diagnoses. This was expanded to include all Medicare diagnoses in FY 2013 and onwards.

The CMS rates are calculated using Medicare claims. These rates adjust for patient characteristics that would make death or readmission more likely, including age, gender, past medical history and other medical factors upon arrival that would influence a person's chance of survival or readmission. This risk adjustment is necessary to control for the fact that more severely ill patients may be taken to higher quality hospitals and therefore those hospitals have higher mortality rates.

Contained within each of these three groups are three related diagnoses from the inpatient database. To run accurate analysis, consolidation was required for hospitals that performed more than one of these diagnoses. For example, when a patient is admitted to a hospital, they are discharged under a specific AMI diagnosis (280, 281 or 282) depending on their individual condition. If this hospital discharged patients under diagnoses 280, 281 and 282, then the total discharged were summed and the average Medicare payments from each diagnosis were averaged to provide one AMI data point per each hospital in the sample.

This data, as well as the discharge and Medicare payment data is available for the years of 2011-2016.

2.4.3 Hospital-Level data

Hospital level information of bed capacity, gross patient profits, total hospital discharges and total patient days were also collected. These were obtained from Medicare fiscal year flatfiles as well as the Medicare cost reports. The flatfiles provide data points for case-mix index, number of beds, Medicare days %, readmission rates and readmission adjustment factor and hospital general information.

Each hospital provides data for the Medicare cost reports but fiscal years are unique to each hospital. To align hospital financial data with the readmission data, I average the relevant variables across years. Specifically, for variables that are flows, I take weighted sums over the cost reports, with the weights equal to the fraction of the cost report that fell into the Medicare fiscal year (July 1 - June 30).

Medicare also provides data on the share of Medicare patients each hospital treats who are also eligible for Medicaid. The eligibility requirements for Medicaid vary across states, but the national Medicaid minimum eligibility level is 133% of the federal poverty level. We use this term to control for the poverty of patients served in the hospital cost function. The average "disproportionate share" for the sample is 26.9% as can be seen in the descriptive statistics in table 2.8.

2.4.4 Disproportionate share

A hospital's disproportionate share percentage (DSHPCT) is calculated as the percentage of Medicare SSI days to total Medicare days plus the percentage of Medicaid (non-Medicare days) to total patient days[9]. A discharge is counted as SSI if the patient is eligible for both Medicare and Medicaid. SSI and DSHPCT are used as measures of hospital financial burden from Medicaid patients which reimburse only a small percentage of a hospital's cost of service[10]. Following (Chatterjee and Joynt (2014)), I characterize hospitals as safety-net if they are in the top quartile of DSH share for a given year.

A hospital's case mix index (CMI) represents the average diagnosis-related group (DRG) relative weight for that hospital and is used as a control for the severity of illness of a hospital's patient population. CMI is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges and are calculated using both transfer-adjusted cases and unadjusted cases.

This paper will also focus on differences between safety-net and non safety-net hospitals due to the preponderance of evidence that readmission rates are correlated with socioeconomic status. [11] Table 2.1 describes the data by safety-net status, with 3,093 non safety-net hospitals in the sample and 884 safety-net hospitals. Safety-net hospitals differ from non-safety hospitals in a variety of ways; safety-net hospitals are larger on average (385 beds vs. 257 beds) and are located in more highly competitive markets. Approximately 65% of safety-net hospitals have teaching affiliation compared with only 44% of non safety-net hospitals. Safety-net hospitals also have a higher percentage of disproportionate share patients as well as a higher case mix index.

[9]DSHPCT is calculated as: DSH Patient Percent = (Medicare SSI Days / Total Medicare Days) + (Medicaid, Non-Medicare Days / Total Patient Days)

[10]See The Kaiser Commission on Medicaid and the Uninsured.

[11]See Hu et al. (2014), Joynt et al. (2011), Kansagara et al. (2011)

2.4.5 State Inpatient Database

Some of the analysis requires having patient-level data. For this data, I turn to HCUP's state inpatient databases for the state of Florida. The data from HCUP contains inpatient discharges for all Florida hospitals in calendar year 2011 through 2015. Compared to the national sample, Florida hospitals ...

Following methodology used by CMS, I identify patients who are "tracked" under the HRRP and would increase a hospital's readmission rate if readmitted to any hospital within 30 days.[12]

Using the Visitlink variable provided in the SID, I can track patients across each year and calculate the number of days between admissions. To identify observation status usage, I look into the detailed charge sheet of each patient and identify charges associated with observation room stays.

2.5 Initial evidence

The first question to investigate is whether or not hospitals are actually responding to the incentives placed by the HRRP. To identify the answer to this question, I begin by estimating equations of the form:

$$\Delta\text{Readmission Rate}_{hk} = \beta_0 + \beta_1 \text{Penalty}_{hk} + X_h\beta + \varepsilon_{hk} \tag{2.1}$$

where ΔReadmission Rate$_{hk}$ is the change in hospital readmission rate from $t-1$ to t[13]. Other hospital characteristics that could impact readmission rates are included in X_h and "Penalty" is used to identify penalty burdens being placed on hospitals at time t. Estimates of these regressions are run using different "penalty" controls including readmission adjustment factor (RAF), excess readmission ratio (ERR) and dummy variables indicating hospitals that are receiving maximum penalties, at risk for a penalty, or no penalty.

[12]CMS excludes planned readmissions when identifying 30-day readmissions under the HRRP rules but allows very few reasons to identify a readmission as planned. These account for less than 5% of all readmissions.

[13]This variable is calculated as $RR_{t-1} - RR_t$, so a year-on-year improvement in readmission rate would result in a negative value in time t.

Readmission adjustment factor is the percentage by which the hospital's Medicare payments will be reduced in the current year. In FY 2013, the first year of the penalty, this is capped at 1% and increases to 2% in FY 2014 and 3% in FY 2015 and onward[14]. Excess readmission ratio is a procedure-specific ratio of a hospital's predicted readmission ratio to its expected readmission ratio and takes on values from between 0.666 to 1.441[15]. The maximum penalty and no penalty variables are dummies equaling 1 if the hospital is receiving either the max or no penalty and zero otherwise. The "High penalty" indicator variable is equal to 1 if a hospital is in the top quartile of penalty percentage. This variable will then include all hospitals receiving the maximum penalty as well as hospitals very close to the maximum penalty.

Table 1 and Table 2 detail the estimates of equation (1) where "penalty" is equal to either readmission adjustment factor or excess readmission ratio. Details of how these variables are calculated by CMS can be found in Appendix B.1.1. Increases in excess readmission ratio and RAF are both negatively and significantly correlated with year-on-year decreases in both raw and predicted readmission rates. An increase in disproportionate share is positively correlated with increases in readmission rates for some of the measures. This effect is expected given previous research on the impact of socioeconomic status on readmission rates (Hu et al. (2014), Nagasako et al. (2014), Barnett et al. (2015)). The fact that case mix index is positively correlated with increases in predicted readmission rate is in large part a function of how predicted readmission rates are calculated.

The "penalty" variable in Table 3 and Table 4 takes the form of the indicator variables discussed above. Hospitals receiving no penalty are significantly less likely to improve their readmission rate than those hospitals receiving either the maximum or close to the maximum penalty. In fact, the coefficients are highly significant and indicate that hospitals receiving no penalty may also worsen their readmission rates over time.

These results provide strong evidence that hospitals do respond to the HRRP penalties, however they are limited in two ways. The first way is that the independent variables (RAF,

[14]The RAF variable provided by CMS is formatted between 1 and 0.99. I have transformed this variable into a percentage to make the coefficient estimates more intuitive.

[15]Summary statistics can be seen in Table 2.8

ERR and the dummy variables) are at best imprecise estimates of penalty burden. These variables do not take into consideration total Medicare revenue, which changes the absolute penalty a hospital receives. Importantly, they also do not identify the importance of hospitals that are on the cusp of receiving a penalty. I try to estimate this impact by identifying hospitals that are not receiving a penalty but easily could in the next period and vice versa. These hospitals have in theory the most incentive to reduce their readmission rates, as small changes could save the hospital millions of dollars.

The second way these estimates are limited is that they are in reaction to penalties being implemented in the current period. When determining reduction effort-levels, hospital administrators are more likely to be forward-looking (i.e. how does a reduction in readmissions today save us money in the future?). Therefore, to more precisely estimate hospital responses, I should calculate a forward-looking estimate of penalty burden due to an increase/decrease in readmission rates in the current period. The methodology I use in calculating this forward-looking penalty burden estimate is described in detail in section 2.6.2.

Preliminary analysis shown in table 2.8 suggests that changes in raw readmission rate have more significant impacts on predicted readmission rate for hospitals with low predicted readmission rates. The results of fixed effects regressions of predicted readmission rate in time t on lagged raw readmission rate, case-mix-index, and disproportionate share percentage in time $t-2$ are shown in table 5. The independent variables are lagged by two years because that is the first year these discharges will affect the CMS penalty calculation. These are all calculated for FY 2015-2017 because HRRP penalties were first published for FY 2013.

The results indicate that an increase in raw readmission rate is positively correlated with a change in predicted readmission rate. These coefficients are around 0.3 because the predicted readmission rate is calculated as a three-year average. Hospital predicted readmission rate also differs significantly based on observed case-mix-index as well as observed disproportionate share.

2.6 Research Design

The main research question of this paper is "how do the financial incentives of the HRRP change behavior of hospitals?"

To estimate financial incentives created by the HRRP, I will first estimate the marginal expected future penalty (MFP) incurred due to an additional hospital readmission following the approach of Norton et al. (2016). This Marginal Future Penalty (MFP) is calculated as the expected increase in penalty incurred after one additional readmission to the hospital and takes the form:

$$\text{MFP}_h = \text{E}\left[\frac{\partial \text{Penalty}_h}{\partial RR_h}\right] \tag{2.2}$$

The marginal future penalty for one additional readmission is the full partial derivative of the relevant measure.

$$\text{MFP}_{kh} = \text{E}\left(\frac{d\text{Raw RR}_{kh}}{d1\text{readmission}_{kh}} \times \frac{d\text{ERR}_{kh}}{d\text{Raw RR}_{kh}} \times \frac{d\text{RAF}_h}{d\text{ERR}_{kh}} \times \frac{d\$_h}{d\%\text{RAF}_h}\right) \tag{2.3}$$

where ERR is excess readmission ratio and is calculated by dividing a hospital's predicted readmission rate by its expected readmission rate. Intuitively, we can think of the expected readmission rate as the average readmission rate for all other hospitals with the same patient case-mix. If it is the case that $ERR_{hk} > 1$ then this means that patients with disease k at hospital h were more likely to be readmitted than at other hospitals with identically sick patients. The way the penalty is formulated, if a hospital has $ERR_{hk} > 1$ for any disease k then the hospital will receive a penalty in the form of a percentage taken away from all Medicare payments for that fiscal year. Therefore the marginal future penalty (MFP) can be thought of as the additionally penalty incurred at time $t+2$ for one additional readmission in time t.

Because the conversion from RAF to total penalty dollars is independent of the specific measures, I can rearrange the formula by pulling out the last term. Additionally, the change in raw readmission rate due to one additional readmission is a precise measure and therefore the expectation term only matters for the second and third terms.

$$\text{MFP}_{kh} = \frac{d\text{Raw RR}_{kh}}{d\,1\text{readmission}_{kh}} \times \text{E}\left[\frac{d\text{ERR}_{kh}}{d\text{Raw RR}_{kh}} \times \frac{d\text{RAF}_h}{d\text{ERR}_{kh}}\right] \times \frac{d\$_h}{d\%\text{RAF}_h} \tag{2.4}$$

This measure of hospital belief of future penalty captures the margins of the penalty model. Hospitals receiving a current penalty, as well as hospitals not being penalized, but who are just under the current expected readmission rate, will all have strong incentives to improve their readmission rate performance.

The details of the calculation of MFP are discussed in length in section 2.6.2. With MFP estimates in hand, I can test the hypothesis that hospitals with higher expected penalties will be more encouraged to reduce readmission rates over time.[16] Specifically, I run a regression of the form:

$$\Delta\text{Readmission Rate}_{hk} = \alpha_h + \delta_t + \beta_k \text{MarginalFP}_{hk} + X_h\gamma + \varepsilon_{hk} \tag{2.5}$$

where ΔReadmission Rate$_{hk}$ is the change in readmission rate from the previous period for hospital h and disease k, MarginalFP$_{hk}$ is the expected marginal future penalty from one more readmission in time t, and X_h is a vector of hospital characteristics including the HRRP readmission adjustment factor, percent of Medicare days, teaching affiliation, number of beds, for-profit status and safety-net status. I identify hospitals as safety-net if they are in the top quartile of DSHPCT for a given year.

2.6.1 Endogeneity

The endogeneity concerns of estimating equation (2.5) via OLS is due to the fact that MFP_h is based on lagged readmission rate performance of hospital h, which is likely correlated with ε_{ht}.

$$MFP_{h,t} = \text{E}\left[\frac{\partial \text{Penalty}_{h,t+2}}{\partial RR_{h,t}}\right], \quad cov(\text{Penalty}_{h,t+2}, \varepsilon_{h,t}) \neq 0$$

[16]Details of the MFP calculation are found in section 2.6.2

An instrument is valid in this setting if $\mathrm{E}(\varepsilon_{ht}, \varepsilon hs) = 0$ for $t \neq s$. The literature on instrumental variable estimation of error-component models and their applications in applied settings is substantial. To obtain an unbiased estimate of β, one solution is to use lagged characteristics of hospital h as instruments for MFP_h (Amemiya and E MaCurdy (1986), Arellano and Bover (1995), Acemoglu and Finkelstein (2008)).[17]

The instrument of choice in this setting is predicted readmission rate for FY 2009. CMS published risk-adjusted readmission rates beginning with FY 2009. The FY 2009 measures are based on an observation period of 2005-2008, well before the implementation of the ACA. The identifying assumption here is then that without the enactment of the ACA, hospitals with low or high readmission rates would have progressed along parallel trends. The ACA was signed into law on March 20th, 2010, however the law did not specify the penalty rules for the HRRP and the announcement of the official details by CMS was not made until August 2011. It is therefore plausible to assume that hospitals did not begin to respond to the incentives imposed by the ACA until FY 2011 at the earliest. Various studies have also confirmed that hospital readmission rates did not begin declining until into 2012 (Carey and Lin (2015), Huckfeldt et al. (2014)).

2.6.2 Marginal future penalty

Term 1 details

To measure the effect of an additional readmission on expected hospital penalties, I estimate the increase in MFP due to one more patient being readmitted to the hospital. From the CMS yearly hospital flatfiles I know the number of patients who were treated for each monitored disease in a given measurement period. This same data also provides the number of these patients who were readmitted.

$$\frac{d\text{Raw RR}_{kh}}{d1\text{readmission}_{kh}}$$

[17] Gupta (2017) also uses a similar instrument to correct for mean reversion in his estimates using a dependent variable constructed with lagged readmission rates.

Calculation of the first term is straightforward. I re-calculate the raw hospital readmission rate for each observation period as if one more person had been readmitted to the hospital. Numbers on raw readmissions and discharges are published by CMS for every fiscal year beginning in 2012.

Terms 2 & 3 details

$$\mathrm{E}\left[\frac{d\mathrm{ERR}_{kh}}{d\mathrm{Raw\ RR}_{kh}} \times \frac{d\mathrm{RAF}_h}{d\mathrm{ERR}_{kh}}\right] \tag{2.6}$$

Next I must form an expectation for the change in readmission adjustment factor based on an increase in the raw readmission rate. ERR is excess readmission ratio and is calculated as a ratio of a hospital's predicted readmission rate to the expected readmission rate.[18]

Therefore, the key to identifying the first term of equation (2.6) is properly identifying a hospital's expectation of the effect of a change in raw readmission rate in time t on the change in excess readmission ratio in $t+2$. The excess readmission is composed of two components: the predicted readmission rate and the expected readmission rate. The expected readmission rate is a national average and follows a stable downward trend. The focus, then, will be on identifying the impact of raw readmission rate on predicted readmission rate, which is the hospital-specific risk adjusted readmission rate calculated by CMS.

Intuitively, we can think of the expected readmission rate as the average readmission rate for all other hospitals with the same patient case-mix. If it is the case that $ERR_{hk} > 1$ then this means that patients with disease k at hospital h were more likely to be readmitted than at other hospitals with identically sick patients. The way the penalty is formulated, if a hospital has $ERR_k > 1$ for any disease k then the hospital will receive a penalty in the form of a % taken away from all Medicare payments for that fiscal year.

As can be seen in table 5, the predicted readmission rate is highly correlated with raw readmission rate, CMI and disproportionate share. I use estimates of the marginal effects of raw readmission rate on predicted readmission rate at different points in the distribution, averaged over hospitals to identify the first term in the expectation. To avoid endogeneity

[18] Details on this calculation can be found in Appendix B.1.1

concerns, these estimates are calculated using only raw readmission rate, leaving out CMI and disproportionate share.

There must be an expectation around the entirety of terms 2 and 3 because the function takes on a piece-wise manner and the expectation is necessary to prevent zero derivatives. The second term will be equal to 0 if after an increase in ERR_k, the value of ERR_k remains less than 1 (hospitals receiving no penalty for disease k). This term will also be 0 if the hospital is already at the maximum penalty. Otherwise an increase in ERR_k for any given disease should lead to a decrease in RAF, pushing the hospital closer to the maximum penalty.

$$\text{RAF} = \max\left\{1 - \left(\frac{\sum_k SumBasePayments_k \times (ERR_k - 1)}{\sum_k SumBasePayments_k}\right), \text{Max Penalty}\right\} \tag{2.7}$$

where k represents all monitored diseases and Max Penalty = 0.99 in FY 2013, 0.98 in FY 2014 and 0.97 in FY 2015 and onwards.

As you can see in equation (2.7), the RAF is capped at the maximum penalty given the fiscal year. The HRRP payment adjustment penalty is capped at 1% for fiscal year 2013, 2% for fiscal year 2014 and 3% for all years starting in FY2015. In the first year of the penalty, I see 269 hospitals reach the maximum penalty (approximately 8% of hospitals) and 35% of hospital receive no penalty. Once the cap is increased to 2% and then further to 3%, I see less than 2% of hospitals in the sample reaching the maximum penalty while the number of hospitals receiving no penalty decreases to 21%. This increase in the total number of hospitals being penalized is driven by the inclusion of additional monitored diseases in 2015 (COPD and HIP/KNEE) and 2016 (CABG). This also creates a maximum allowance for the change in RAF due to changes in ERR. For many hospitals, an increase in readmission rate will push them to the maximum penalty or beyond. For these hospitals the expectation of $\frac{d\text{RAF}_h}{d\text{ERR}_{kh}}$ must allow for the fact that RAF cannot fall below 0.99, 0.98, etc.

For hospitals that do not reach the maximum penalty, the change in RAF is directly related to the percentage of disease-specific revenue compared to total Medicare revenue for each fiscal year, or:

$$\frac{d\text{RAF}_h}{d\text{ERR}_{kh}} = -\frac{BasePayments_{kh}}{\sum_k BasePayments_{kh}}$$

Term 4 details

$$\frac{d\$_h}{d\%\mathrm{RAF}_h} \tag{2.8}$$

The effect of the readmission adjustment factor on total HRRP penalty depends on total annual Medicare reimbursements, therefore it is roughly proportional to hospital size. The amount of the total penalty is:

$$\text{Total Penalty} = [1 - RAF] \times \text{Total Medicare Revenue} \tag{2.9}$$

The total Medicare payments will be relative to the number of Medicare patients and the average number of Medicare discharges for the sample is 2,145 and the average Medicare payments are \$1.25 million so a small change in RAF can lead to large changes in total penalty. Total Medicare revenue for a hospital is very highly correlated over time, allowing for accurate expectations in total penalty burden.

2.7 Results

Marginal future penalty for one more readmission

The marginal future penalty for one additional readmission varies greatly across hospitals in the sample. While the average MFP for all hospitals is $27,906 for AMI, $39,161 for HF and $30,574 for pneumonia, hospitals with different shares of dsh patients can expect very different changes in penalty due to a change in raw readmission rates. For heart failure readmission increases, hospitals in the lowest quartile of dsh share patients have an average MFP of $15,264 while hospitals in the fourth quartile have an average of $87,065. These differences in expected MFP across dsh quartiles lend more credence to the literature on the disproportionate effects of the HRRP on safety-net hospitals.[19]

Some of this variation is also due to the fact that the penalty is roughly proportional to hospital size, but the difference in MFP can be largely attributed to differences in excess readmission ratio at the start of the period. Figures 2.2 - 2.4 show the differences in change in RAF and MFP due to one more readmission during the observation period for AMI, HF and PN discharges. An increase in one readmission disproportionately impacts the future penalties of hospital already receiving a penalty ($ERR > 1$). Hospitals not receiving a penalty for a given monitored disease are also incentivized to keep their readmission rate in check, however, because a small increase could potentially push them over the threshold and be realized in huge increases in penalty burden.

Table 2.10 displays the results from the estimation of equation 2.5 using the specified instrument. An increase in marginal future penalty is negatively and significantly correlation with decreases in readmission rate. This effect is present for the AMI and heart failure cohorts, but lacks significance for the pneumonia cohort. Large, teaching and safety-net hospitals improve their readmission rates less across the sample than other hospitals.

[19]The literature on these negative impact of the HRRP on safety-net hospitals is extensive: see Gilman et al. (2014), Gu et al. (2014), Mohan et al. (2013).

Marginal future savings for one less readmission

An alternative approach to investigate hospital decisions between potential cost savings compared to extra spending to reduce readmission rates is to identify the marginal future savings (MFS) from improving readmission rates across years. In a similar way to the calculation of MFP, to identify this term, I calculate an expectation of savings on future HRRP penalties due to a decrease in one less readmission in an observation period. MFS is then calculated as:

$$\text{MFS}_{kh} = \text{E}\left(\frac{d\text{Raw RR}_{kh}}{d1 \text{ less readmission}_{kh}} \times \frac{d\text{ERR}_{kh}}{d\text{Raw RR}_{kh}} \times \frac{d\text{RAF}_{h}}{d\text{ERR}_{kh}} \times \frac{d\$_{h}}{d\%\text{RAF}_{h}}\right) \tag{2.10}$$

where the expectations around these terms are different from those of MFP because approximately 30% of hospitals are not receiving penalties in any given year of the HRRP.[20] The expected value of this term will be zero for any hospital in this situation, making the incentives created by MFS slightly different from those of MFP.

Table 2.11 shows the average savings across hospitals that can be garnered from one less readmission by quartile of disproportionate share. As can be seen here, potential marginal future savings for improving heart failure readmission rates are significantly higher than for that of AMI or pneumonia. This phenomenon is not unique to this paper and evidence has suggested that heart failure readmission rates are disproportionately correlated with penalty rates (Vidic et al. (2015)).

Another way to visualize these differences is through the change in RAF and total penalty burden depending on a hospital's initial excess readmission rate or readmission rate. As can be seen in figures 2.5 - 2.7, improving readmission rates has no impact on RAF or total penalty burden for many hospitals.[21] There are two reasons that hospitals would not benefit from a 1-person reduction in readmissions: either they are receiving no penalty and therefore do not need to reduce further, or even a small reduction in readmission rates for

[20] In FY 2013, the first year of the penalty, 1,234 hospitals received no penalty (approximately 35.7%). The percentage of hospitals being penalized has increased over the course of the HRRP as more diseases have been added to the list of "monitored diseases". In FY 2017, only 21.5% of hospitals escaped being penalized by the HRRP.

[21] In FY 2015, 62% of hospitals would see no change from an improvement in AMI readmission rate, 59% for heart failure measure improvement and 65% for pneumonia improvement.

one procedure would not reduce their overall penalty burden.

The results of the main specification estimation of an equation of the form:

$$\Delta\text{Readmission Rate}_{hk} = \alpha_h + \delta_t + \beta_k \text{MarginalFS}_{hk} + X_h\gamma + \varepsilon_{hk}$$

are shown in table 2.12. The impact of marginal future savings on readmission reduction is significant and positive. Since average MFS for all hospitals is \$-15,979 for AMI, \$-77,328 for HF and \$-12,205 for pneumonia, a positive correlation between readmission reduction and MFS implies that hospitals that could save more money in penalty burden exhibit higher reductions across readmission rate.

An alternative specification is to identify hospitals that need extreme amounts of readmission reduction effort before garnering any decreases in penalty from the HRRP. I identify these hospitals are those that would still be receiving the maximum penalty even with a reduction in readmission rates on a specific monitored disease. The results from an IV regression of change in readmission rate on ”no penalty change” status and other hospital characteristics are shown in table 2.13.

These hospitals on the extreme end of the penalty spectrum exhibit larger than average decreases in readmission rate. The average hospital reduced their AMI readmission rate after the implementation of the HRRP by 1.32% from FY 2013 - FY 2017. Hospitals that are identified as ”no penalty change” for a specific procedure reduce their readmission rates by 1.5% over the same period and monitored disease. The results of the regression shown in table 2.13 also confirm that this extreme status significantly impacts readmission reduction efforts.

2.8 Conclusion

In this paper I have identified and estimated a hospital-specific forward-looking expectation of change in HRRP penalty due to an increase or decrease in observed readmission rates. Hospitals have a wealth of information at the beginning of a fiscal year including their own previous and current readmission rates and penalty status, as well as the readmission rates and penalty status of all other IPPS hospitals. They can easily identify how previous changes in readmission rate have correlated to changes in penalty and also have information over their patient populations statistics (dsh share, income status, age, etc. are all shown to be correlated with readmission probability).[22]

I find that increases or decreases in individual readmissions have significant impacts on changes in future penalty burden. Just one more heart failure readmission can lead to average increases in penalty of $39,161, while hospitals can expect savings of $77,328 by a decrease of one heart failure readmission. These expected changes in future penalty are significantly related to year-on-year hospital improvements of readmission rates for these monitored diseases. Hospitals on the extreme end of the penalty burden (those receiving the maximum penalty by the HRRP) improve their readmission rates across periods by up to 6% more than hospitals not on the extensive end of the penalty.

These findings add to the breath of literature on the HRRP and its effects by estimating real-time vs. reactionary hospital responses to the financial incentives created by the HRRP. Previous work has estimated the impact of high penalties or expectations of any penalty on changes in hospital behavior; this same work has failed to account for the margins of the HRRP penalty, specifically the incentives faced on hospitals

An extension of this paper that is currently in progress is to use the MFP and MFS estimates to identify changes in observation rate usage and possible changes in patient-mix or length of stay due to the HRRP penalty incentives. Future lines of research include formulating expectations of changes in penalty due to a one-decile improvement in readmission rates. These decisions would be made more at the hospital-wide level and are an arguably better measurement of hospital effort compared to a decrease or increase in one individual readmission. Individual readmissions are dependent on distinct patient characteristics and therefore can be noisy measurements of effort, whereas a one-decile reduction could more realistically identify hospital administrative efforts.

[22]See Aggarwal and Gupta (2014)

Figures and tables

Figure 2.1: Timeline of HRRP rollout

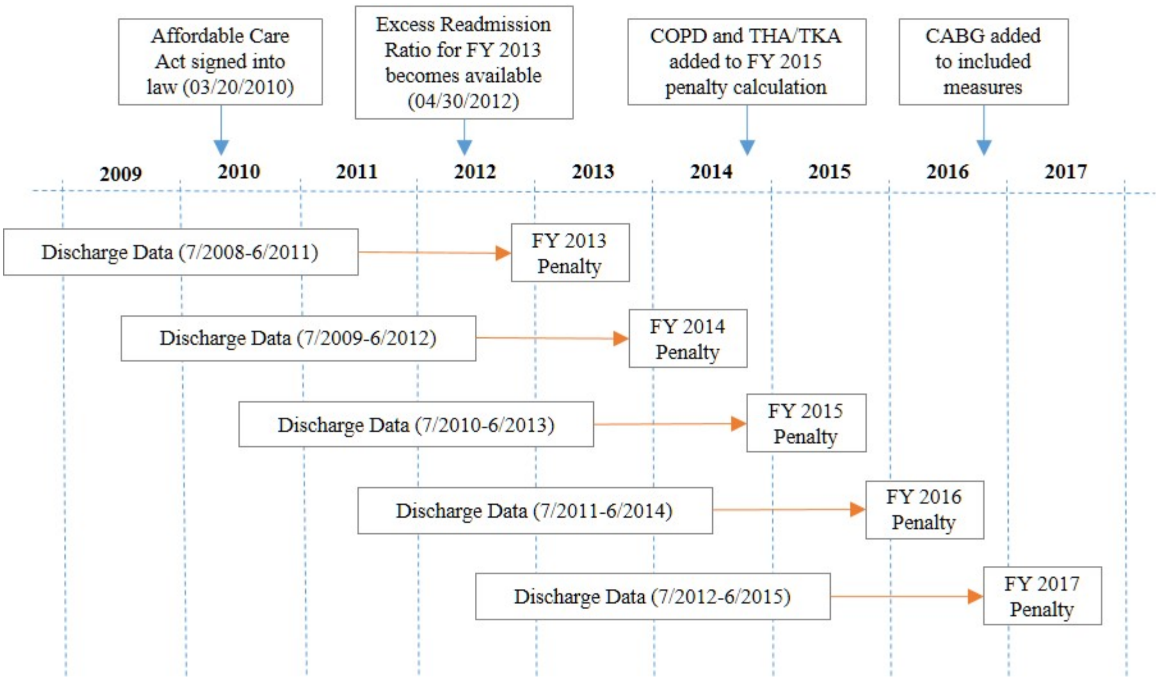


Table 2.1: Descriptive statistics by safety-net status

	Non safety-net	**Safety-Net**
Total Costs ($1,000,000)	314.0	492.8
	(326.4)	(512.2)
Discharges	13256.3	19088.3
	(9707.6)	(14567.9)
Case-mix index	1.563	1.631
	(.2174)	(.2601)
Beds	257.8	385.1
	(172.2)	(266.6)
Herfindahl index of competition (HHI)	.3667	.2563
	(.4041)	(.3616)
Inpatient-days	48292.16	73382.14
	(39296.73)	(63205.29)
% Not for profit hospital	.7424	.5641
	(.4374)	(.4961)
% Teaching hospital	.4442	.6564
	(.4970)	(.4751)
Medicare days % of total inpatient	.4598	.3500
	(.1132)	(.1178)
Disproportionate share %	.2130	.4808
	(.0775)	(.1250)
Readmission adjustment factor	.9960	.9953
	(.0046)	(.0050)
Raw # number of adverse events	258.8	242.0
	(152.7)	(164.3)
Marginal Future Penalty (AMI)	23390.14	41781.47
	(67838.99)	(108451.3)
Marginal Future Penalty (HF)	22425.66	87006.32
	(94806.9)	(332032.2)
Marginal Future Penalty (PN)	18594.08	64994.05
	(94471.9)	(276265)
Observations	3,093	884

Table 2.2: Descriptive statistics: readmission measures

	Procedure	**Mean**	**S.d.**
Predicted readmission rate	AMI	17.68	(2.883)
	CABG	14.26	(1.764)
	COPD	19.68	(2.116)
	HF	21.92	(2.490)
	HIP/KNEE	4.999	(1.007)
	PN	16.96	(2.216)
Expected readmission rate	AMI	17.61	(2.360)
	CABG	14.23	(1.250)
	COPD	19.65	(1.563)
	HF	21.87	(1.428)
	HIP/KNEE	4.955	(0.642)
	PN	16.90	(1.468)
Raw readmission #	AMI	43.71	(37.12)
	CABG	25.11	(14.62)
	COPD	64.50	(52.45)
	HF	87.75	(79.92)
	HIP/KNEE	27.16	(19.22)
	PN	66.25	(54.85)
Raw number of adverse events		247.9	(164.7)
Observations	15625		

Table 2.3: Descriptive statistics

	Mean	**S.d.**
Total Costs ($1,000,000)	351.6	(380.2)
Discharges	14483.3	(11166.0)
Case-mix index	1.577	(0.229)
Beds	284.6	(202.6)
Herfindahl index of competition (HHI)	0.343	(0.398)
Inpatient-days	53571.0	(46517.1)
% Not for profit hospital	0.705	(0.456)
% Teaching hospital	0.489	(0.500)
Medicare days % of total inpatient	0.437	(0.123)
Disproportionate share %	0.269	(0.141)
Readmission adjustment factor	0.996	(0.00470)
Raw # number of adverse events	255.1	(155.5)
Observations	5713	

Table 2.4: Estimates of change in predicted readmission rates on RAF/Excess readmission ratio

	AMI		Pneumonia		Heart Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag CMI	0.469***	0.466***	0.368***	0.122	0.269**	0.226**
	(0.101)	(0.0935)	(0.0944)	(0.0868)	(0.0820)	(0.0807)
Lag DSHPCT	0.152	0.278	-0.0178	0.324*	0.329*	0.400**
	(0.168)	(0.155)	(0.149)	(0.139)	(0.128)	(0.122)
Lag RAF	-0.700***		-0.789***		-0.286***	
	(0.0912)		(0.0819)		(0.0774)	
Lag ERR		-4.309***		-5.490***		-3.130***
		(0.305)		(0.304)		(0.288)
Constant	-1.066***	3.020***	-0.668***	4.863***	-0.557***	2.537***
	(0.168)	(0.343)	(0.153)	(0.355)	(0.131)	(0.322)
R-squared	0.255	0.280	0.296	0.330	0.259	0.277
N	4211	4134	5773	5762	5877	5862

Standard errors in parentheses; All models have SSA fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5: Estimates of change in raw readmission rates on RAF/Excess readmission ratio

	AMI		Pneumonia		Heart Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag CMI	0.405	0.318	0.260	-0.208	0.665***	0.467**
	(0.275)	(0.240)	(0.208)	(0.194)	(0.194)	(0.172)
Lag DSHPCT	1.085*	1.691***	-0.0512	0.594	0.573	0.835**
	(0.482)	(0.448)	(0.357)	(0.342)	(0.312)	(0.275)
Lag RAF	-1.628***		-1.433***		-0.880***	
	(0.229)		(0.169)		(0.162)	
Lag ERR		-11.21***		-9.806***		-10.30***
		(0.744)		(0.662)		(0.565)
Constant	-0.877	9.875***	-0.246	9.666***	-1.049***	9.248***
	(0.466)	(0.852)	(0.331)	(0.777)	(0.310)	(0.643)
R-squared	0.249	0.291	0.331	0.357	0.267	0.312
N	3281	3275	5347	5346	5311	5311

Standard errors in parentheses; All models have SSA fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Estimates of change in predicted readmission rates on penalty status dummy variables

	AMI		Pneumonia		Heart Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag CMI	0.488***	0.491***	0.247**	0.271***	0.397***	0.393***
	(0.101)	(0.102)	(0.0837)	(0.0820)	(0.0954)	(0.0945)
Lag DSHPCT	0.106	0.140	0.335**	0.353**	-0.0538	-0.0265
	(0.166)	(0.168)	(0.130)	(0.129)	(0.152)	(0.151)
No penalty	0.224***	0.193***	0.125**	0.124**	0.157**	0.105*
	(0.0568)	(0.0576)	(0.0453)	(0.0458)	(0.0490)	(0.0502)
Max penalty	-0.860***		-1.047***		-0.725***	
	(0.0984)		(0.0994)		(0.0999)	
High risk		-0.262***		-0.113*		-0.376***
		(0.0613)		(0.0507)		(0.0574)
Constant	-1.305***	-1.275***	-0.595***	-0.654***	-0.938***	-0.856***
	(0.164)	(0.167)	(0.132)	(0.130)	(0.149)	(0.151)
R-squared	0.260	0.247	0.285	0.259	0.290	0.288
N	4211	4211	5877	5877	5773	5773

Standard errors in parentheses; All models have SSA fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: Estimates of change in raw readmission rates on penalty status dummy variables

	AMI		Pneumonia		Heart Failure	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag CMI	0.473	0.448	0.632**	0.648***	0.330	0.295
	(0.272)	(0.273)	(0.197)	(0.194)	(0.210)	(0.208)
Lag DSHPCT	0.914	1.079*	0.630*	0.672*	-0.120	-0.0611
	(0.483)	(0.481)	(0.313)	(0.313)	(0.357)	(0.358)
No penalty	0.640***	0.551***	0.514***	0.476***	0.321**	0.220*
	(0.149)	(0.153)	(0.107)	(0.109)	(0.109)	(0.112)
Max penalty	-1.496***		-1.243***		-0.990***	
	(0.265)		(0.202)		(0.226)	
High risk		-0.660***		-0.324**		-0.680***
		(0.164)		(0.110)		(0.111)
Constant	-1.523***	-1.377**	-1.357***	-1.350***	-0.795*	-0.583
	(0.454)	(0.457)	(0.306)	(0.304)	(0.323)	(0.323)
R-squared	0.249	0.244	0.275	0.268	0.323	0.325
N	3281	3281	5311	5311	5347	5347

Standard errors in parentheses; All models have SSA fixed effects

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.8: Regression results: Predicted readmission rate on lagged raw RR, CMI and disproportionate share percentage

	AMI (1)	HF (2)	PN (3)
Lagged Raw Readmission Rate	0.222***	0.223***	0.232***
	(0.0131)	(0.0124)	(0.0111)
Lagged CMI	-1.242***	0.513***	1.558***
	(0.215)	(0.145)	(0.158)
Lagged disproportionate share	1.810***	1.700***	1.859***
	(0.363)	(0.284)	(0.249)
R^2	0.556	0.470	0.466
N	5492	8326	8306

Standard errors in parentheses
All models have SSA fixed effects
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Average marginal future penalty from one more readmission by disproportionate share quartile

Quartile	AMI	HF	PNEUMONIA
1	23475.71	15264.57	8379.806
	(65055.92)	(58202.72)	(30840.53)
2	22736.4	23435.26	17361.56
	(67445.58)	(89998.11)	(93777.63)
3	23976.46	25906.56	26029.29
	(69975)	(115316.8)	(117563.9)
4	41781.47	87065.23	64994.05
	(108451.3)	(332143.4)	(276265)
Total	27906.74	39161.94	30574.3
	(80125.73)	(189765.6)	(163487.7)

Standard errors in parentheses

Table 2.10: Impact of marginal future penalty on change in predicted readmission rate

	(1) AMI	(2) HEART FAILURE	(3) PNEUMONIA
Marginal Future Penalty	-0.342***	-0.0784***	-0.0799
	(0.0936)	(0.0176)	(0.0701)
Beds	0.0129	0.0775***	0.0421**
	(0.0208)	(0.0161)	(0.0140)
Safety-net	0.169	0.241***	0.130**
	(0.125)	(0.0714)	(0.0476)
Non-profit	-0.114	-0.167**	-0.0251
	(0.105)	(0.0559)	(0.0550)
Proprietary	-0.102	-0.0854	0.00122
	(0.121)	(0.0750)	(0.0562)
Teaching hospital	0.163*	0.111*	0.00629
	(0.0735)	(0.0516)	(0.0472)
R^2 overall	0.00190	0.00104	0.0105
N	5294	6729	5552

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.11: Average marginal future savings from one less readmission by disproportionate share quartile

Quartile	AMI	HF	PNEUMONIA
1	-10985.75	-26278.68	-7545.998
	(44899.59)	(88196.25)	(34607.03)
2	-11074.59	-45664.22	-10168.75
	(51501.26)	(164094.8)	(50744.74)
3	-13269.62	-51852.97	-11418.73
	(54405.36)	(192694.6)	(52213.71)
4	-28804.12	-184160.2	-19176.61
	(92076.71)	(534178.3)	(69640.54)
Total	-15979.69	-77328.52	-12205.58
	(63904.92)	(304288.7)	(54061.16)

Standard errors in parentheses

Table 2.12: Impact of marginal future savings on change in predicted readmission rate

	(1) AMI	(2) HF	(3) PNEUMONIA
Marginal future savings	0.142***	0.0230***	0.00705
	(0.0228)	(0.00314)	(0.00532)
Beds	0.0693***	0.0503***	0.0300**
	(0.0110)	(0.0104)	(0.0105)
Safety-net dummy	0.0559	0.116***	0.0684**
	(0.0463)	(0.0311)	(0.0218)
Non-profit	-0.00939	-0.0682	-0.0122
	(0.0338)	(0.0388)	(0.0306)
Proprietary	0.0821	-0.0426	0.0513
	(0.0455)	(0.0500)	(0.0346)
Teaching hospital	0.0775*	0.0603*	-0.00698
	(0.0379)	(0.0244)	(0.0162)
R^2 overall	0.0131	0.00901	0.0263
N	7993	9051	9058

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.13: Effect of ”no hope” status on change in predicted readmission rate

	(1) AMI	(2) HF	(3) PNEUMONIA
No penalty change	-2.359***	-6.795***	-0.607
	(0.366)	(1.481)	(0.525)
Safety-net dummy	0.0503	-0.0104	0.0824**
	(0.0331)	(0.0575)	(0.0284)
Beds	0.0138*	0.0190*	0.0173**
	(0.00648)	(0.00961)	(0.00596)
Nonprofit hospital dummy	0.0261	-0.0807	-0.00446
	(0.0414)	(0.0470)	(0.0268)
Proprietary hospital dummy	0.101*	0.00518	0.0734*
	(0.0475)	(0.0628)	(0.0334)
Teaching hospital Dummy	-0.0131	0.0567	-0.000820
	(0.0265)	(0.0413)	(0.0272)
R^2 overall	0.0505	0.0109	0.0452
N	7993	9051	9058

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.2: Change in RAF and Penalty due to one more AMI readmission, by initial excess readmission ratio

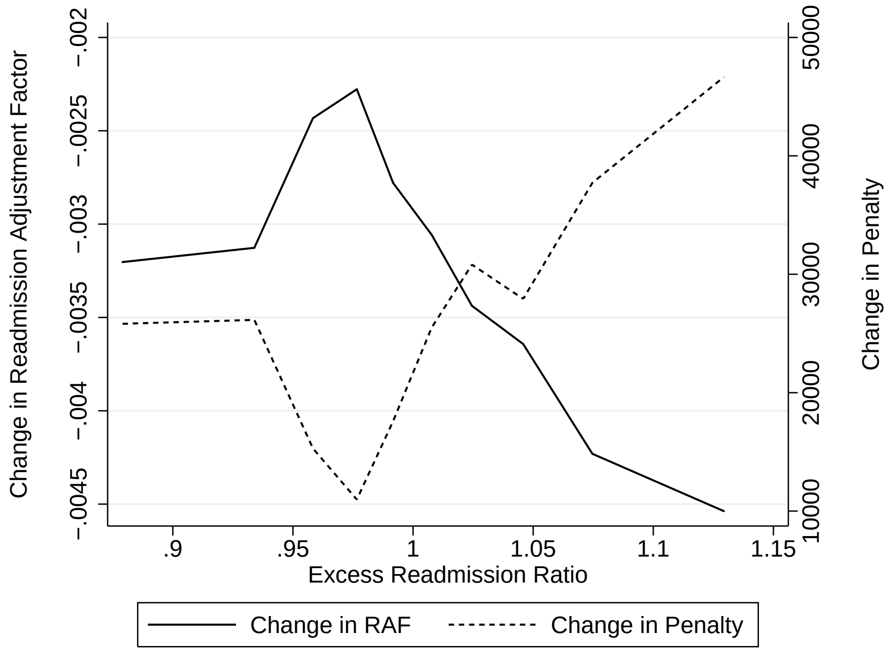


Figure 2.3: Change in RAF and Penalty due to one more heart failure readmission, by initial excess readmission ratio

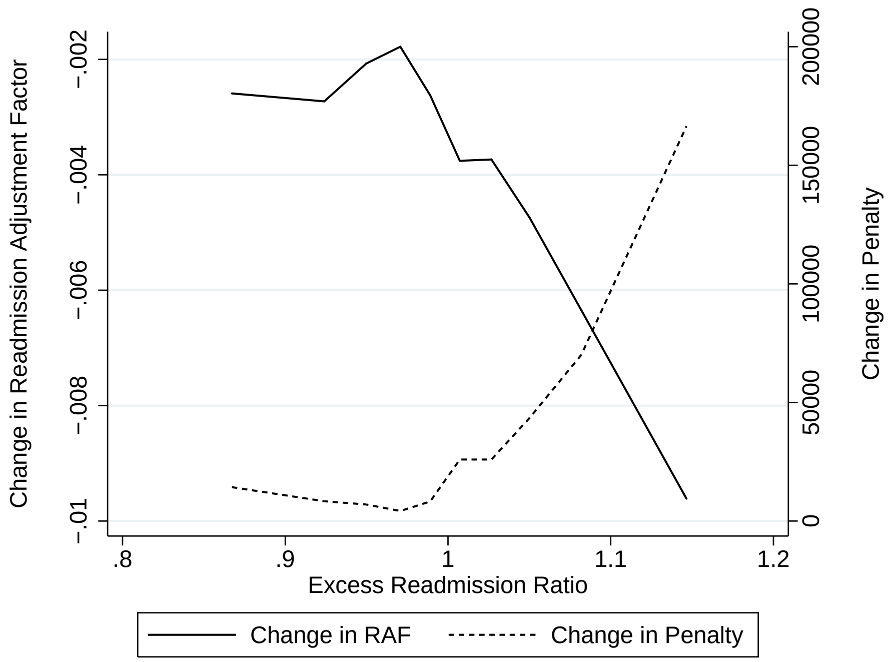


Figure 2.4: Change in RAF and Penalty due to one more pneumonia readmission, by initial excess readmission ratio

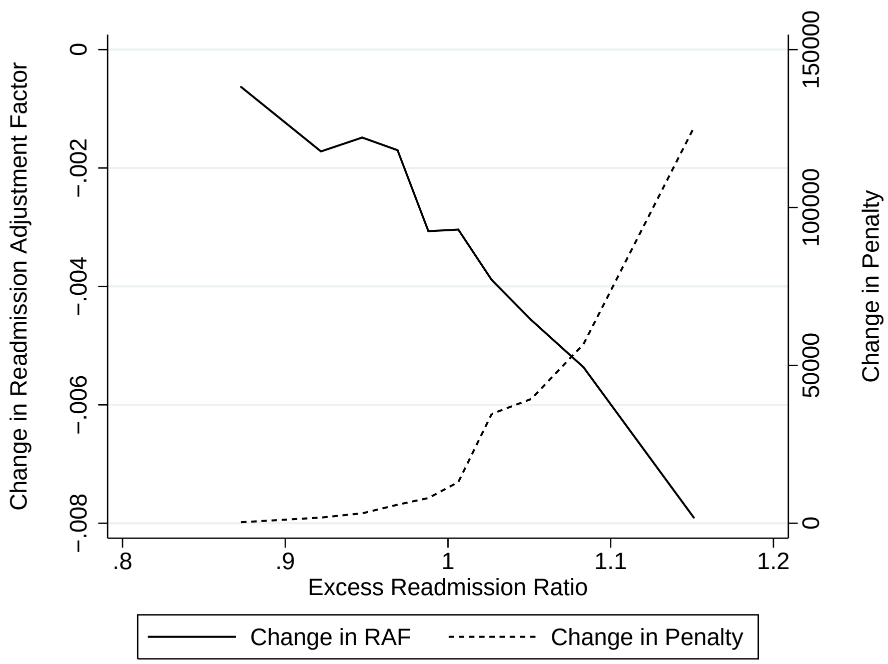


Figure 2.5: Change in RAF and Penalty due to one less AMI readmission, by initial excess readmission ratio

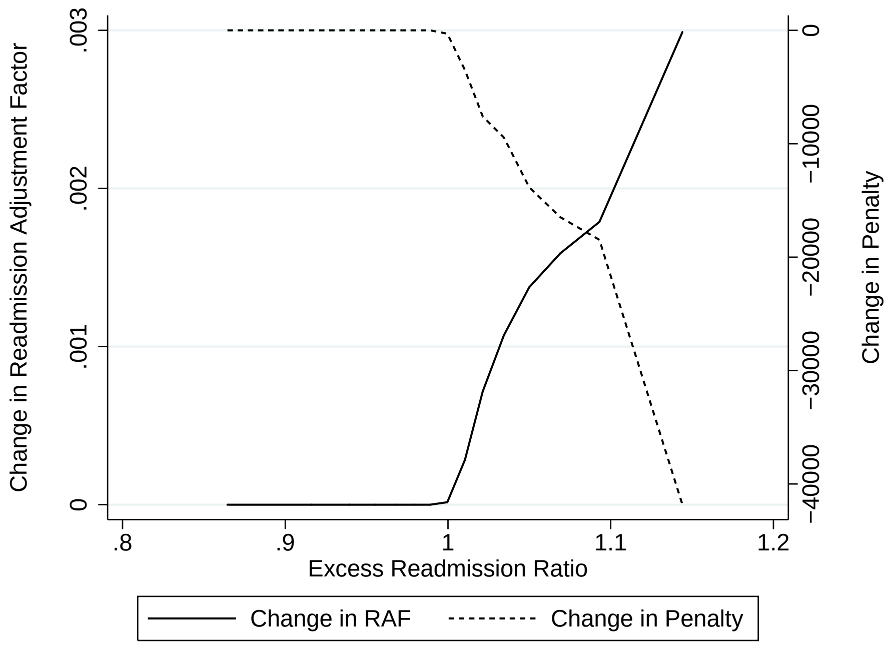


Figure 2.6: Change in RAF and Penalty due to one less heart failure readmission, by initial excess readmission ratio

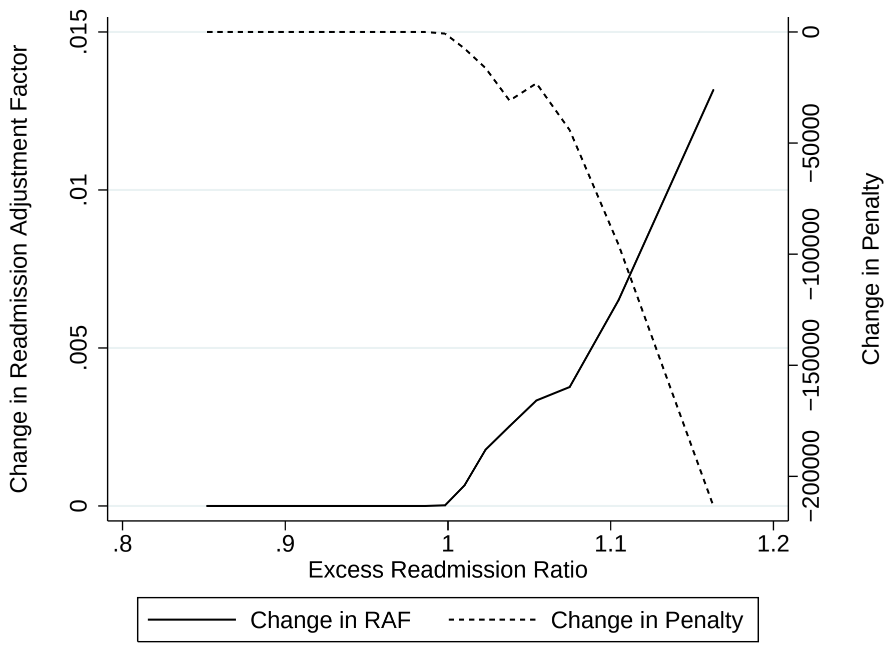
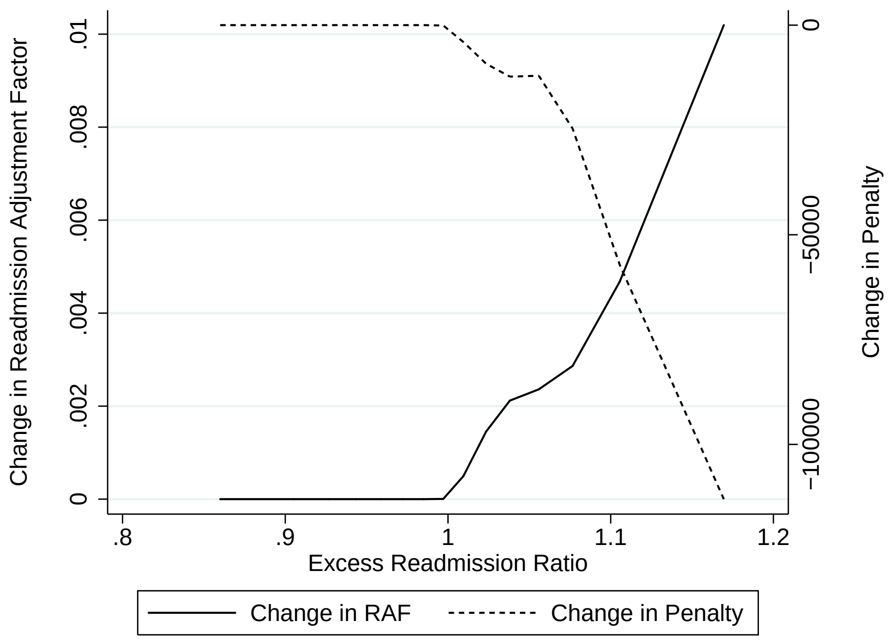


Figure 2.7: Change in RAF and Penalty due to one less pneumonia readmission, by initial excess readmission ratio



Chapter 3

Choice of hospital: Does quality reporting matter?

3.1 Introduction

The Hospital Inpatient Quality Reporting Program (IQR), mandated by Section 501(b) of the Medicare Prescription Drug, Improvement, and Modernization Act (MMA) of 2003, uses financial incentives to encourage hospitals and providers to improve the quality and cost of inpatient care.[1] Through this program the Centers for Medicare & Medicaid Services (CMS) collects quality data from hospitals paid through the Inpatient Prospective Payment System (IPPS). Hospitals that successfully report designated quality measures are paid a higher annual payment rate from CMS.

The IQR is just one of the quality initiatives implemented by CMS to adhere to their identified ”Meaningful Measures”. The ”Meaningful Measure” initiative assesses the main issues that are crucial to improving patient outcomes and providing high-quality of care and then identifies priorities for quality improvement and measurement. Drawing on work by multiple entities including the Health Care Payment Learning and Action Network, the National Quality Forum, and the National Academies of Medicine, the ”Meaningful Measure”

[1] *Data for selected measures are also used for paying a portion of hospitals based on the quality and efficiency of care, including the Hospital Value-Based Purchasing Program, Hospital-Acquired Condition Reduction Program, and Hospital Readmissions Reduction Program.*

initiative is responsible in part for the quality initiative programs implemented through the Affordable Care Act (ACA). Some of the ”Meaningful Measure” priorities identified by HHS include promotion of effective communication and coordination of care, promoting effective prevention and treatment of chronic disease and making care affordable. Measures associated with poor outcomes that are common in the Medicare population have been targeted by the IQR for public reporting, including the elective primary total hip arthroplasty (THA) and/or total knee arthroplasty (TKA) complication rates. This measure of complication rates after elective hip and knee replacement surgeries for Medicare patients is used in part to calculate hospital reimbursement or penalties through the Hospital Value Based Purchasing Program (HVBP).[2]

These quality reporting programs have multiple goals: driving quality improvement as well as improving transparency by publicly reporting quality data for hospitals. The data collected through the IQR are reported yearly and publicly available.[3] Using these quality measures reported through the IQR, I investigate the effect of observed hospital quality measures on patient demand for elective procedures. Using patient-level data from the state of Florida, I estimate a multinomial logit demand model using patient comorbidities and distance between patient zipcode and hospital zipcodes to identify the effect of a marginal decrease in Hip and Knee Replacement complication rates on hospital demand. Previous literature has investigated the impact of changes in readmission and mortality rates on hospital demand, but have not looked into complication rates. These estimates are restricted to patients in the Medicare population because these patients have the same deductible payment regardless of choice of hospital, therefore the results are not confounded by choice over price of procedure.

For the analysis I use individual discharge data from the state of Florida for the years 2013 - 2015. Using this data, I estimate a mixed logit model of patients hospital choices, controlling for demographic information in addition to hospital characteristics. The covari-

[2] The complication rates are discussed in detail in section 3.2.1. See https://www.cms.gov/medicare/quality-initiatives-patient-assessment-instruments/hospitalqualityinits/hospitalrhqdapu.html

[3] These quality measures are readily available at https://www.medicare.gov/hospitalcompare/search.html

ates of interest are distance from patient home and publicly reported quality information on complication rates after elective hip and/or knee replacement surgeries. I use the estimated coefficients to estimate changes in hospital demand caused by changes in reported quality ratings with a focus on the elective procedure complication rate. I also investigate questions of patient heterogeneity in preferences by including a full set of interactions between ”reference patient” characteristics and hospital covariates and identifying significant differences in coefficients. The issue of possible unobserved hospital heterogeneity is addressed through the specification of an alternative model which includes a full set of dummy variables identifying emergency admission patients.

Section 3.2 details the institutional background of the THA/TKA quality measures and previous work in this area. The data used for the estimation is described in section 3.3. Section 3.4 contains information on the empirical model and section 3.5 describes the summary statistics and contains a detailed discussion of the results. Section 3.6 contains concluding remarks.

3.2 Institutional background and previous literature

3.2.1 Institutional background

As mentioned in section 3.1, CMS publishes data on quality markers for a variety of measures in each fiscal year. Each fiscal year, IPPS hospitals have the choice to report their complication measure data for elective primary THA and/or TKA. CMS uses this data to publish their risk-standardized complication measures. The CMS measures capture results from eight possible complications, each assessed by a different clinical time period during which patient outcomes can be attributed to the treating hospital. One of the goal's CMS identified as a reason for the publication of these quality measures was to provide patients more information to help them choose at which hospital to have elective surgical procedures.[4] The 8 complications include: Heart attack, pneumonia, or sepsis/septicemia/shock

[4]See https://www.medicare.gov/hospitalcompare/Data/Surgical-Complications-Hip-Knee.html

during the index admission or within 7 days of admission; Surgical site bleeding, pulmonary embolism, or death during the index admission or within 30 days of admission; or Mechanical complications or periprosthetic joint infection/wound infection during the index admission or within 90 days of admission. Medicare chose to measure these complications within the specified times because complications over a longer period may be impacted by factors outside the hospitals control like other complicating illnesses, patients own behavior, or other care services patients received after they leave the hospital. The sample for the hip/knee complication rate includes only Medicare beneficiaries over the age of 65 who were electively admitted to an IPPS hospital. These patients must also have been enrolled in traditional fee-for-service Medicare for the entire 12 months prior to their hospital admission. Medicare advantage beneficiaries as well as emergency-admission patients are not included in the measure calculation.

Additional quality measures reports by CMS through the Hospital Value Based Purchasing (HVBP) program include the Patient Safety Indicators (PSIs). The PSI's are a set of indicators providing information on potential in hospital complications and adverse events following surgeries, procedures, and childbirth.[5] CMS intends hospitals to use these PSI's to help identify and assess the incidence of potentially adverse events and hospital complications.[6][7]"

One PSI of interest to this study is the safety indicator for in-hospital deaths per 1,000 surgical discharges, among patients ages 18 through 89 years or obstetric patients, with serious treatable complications including: deep vein thrombosis/ pulmonary embolism, pneumonia, sepsis, shock/cardiac arrest, or gastrointestinal hemorrhage/acute ulcer. This measure includes details on the number of discharges for each type of complication.[8]

Quality reporting required a delay in publication because of the time it takes for CMS to gather and clean the data and calculate the quality metrics. For example, quality metrics

[5] See https://www.ahrq.gov/sites/default/files/wysiwyg/professionals/systems/hospital/qitoolkit/combined/a1b_combo_psifactsheet.pdf

[6] The measures include indicators for complications occurring in hospital that may represent patient safety events; and, indicators also have area level analogs designed to detect patient safety events on a regional level.

[7] See https://www.qualityindicators.ahrq.gov/modules/psi_overview.aspx

[8] Patients transferred to an acute care facility or who were transferred from hospice care are excluded from the measure calculation.

for FY 2013 that become publicly available on hospital compare in December 2012, are based on data from previous fiscal years. The measure ”observation period” varies based on the quality metric, as can be seen in table 3.1. Table 3.1 details the observation periods for quality data released by CMS for FY 2013.

3.2.2 Literature review

This paper is related to a growing body of literature on the impacts of quality reporting and measures on changes in patient demand. With the implementation of the ACA, access to detailed information on quality measures for hospitals has become easier and more accurate for prospective patients (Marshall et al. (2003)). Previous to this new quality reporting, many studies had investigated the impact of observed quality on patient choice of hospital (Tay (2003), Gaynor et al. (2012), Gaynor et al. (2013), Dafny et al. (2013)).

A growing body of literature is investigating the impact of report cards on patient choice using panel data. Most of these studies find a positive effect. Varkevisser et al. (2012) find that patients are responsive to public reporting of quality data and tend to choose hospitals with good reputations and low readmission rates. They examine the relationship between hospital quality, as measured by publicly available quality ratings, in the market for angioplasty patients from a large health insurer in the Netherlands. Epstein (2010) find that the publication of coronary artery bypass graft (CABG) surgery report cards in 2002 in Pennsylvania did not have a large effect on patientsurgeon sorting. This finding is partially supported by Wang et al. (2011). Finding that public reporting of quality significantly affected patients choice of clinic, Bundorf et al. (2009) examine the effect of providing consumers with quality information in the context of fertility clinics. Other studies that have found evidence of patient selection over distance and quality variables include Sivey (2012), Goldman and Romley (2008), Dardanoni et al. (2018), Ho (2006) and Santos et al. (2017).

Some evidence of risk selection by providers due to the implementation of quality initiatives has been found by Dranove et al. (2003). They find that the implementation of mandatory CABG report cards in Pennsylvania and New York may encourage hospitals to ”game” the system by avoiding sick patients. They find evidence of substantial risk selection by hospitals. Similarly, Pope (2009) finds that annual published hospital rankings have a significant impact on patient choices. He estimates changes in patient volume and hospital revenues due to the publication of rankings created by the US News and World Report. He finds that for hospitals in his sample, year to year rank changes are responsible for 5% changes in patient volumes. Given the impact of public quality reporting on patient decisions, the methodology and availability of public quality data should be carefully inspected to avoid negative side-effects (Rothberg et al. (2008), Wang et al. (2011)).

Closest to this paper, Gutacker et al. (2016) investigate a similar question using a patient sample from England's NHS hospital system. Specifically, they ask if increases in patient gains as measured by patient surveys increase demand for services. They estimate a multinomial logit of hospital choice to test if hospital demand responds to observed changes in health gains of patients and find that a one standard deviation increase in average health gain increases demand by up to 10%. They model health gains on detailed patient reports of health status before and after treatment for hip-replacement patients in England's NHS between April 2010 and March 2013. Health gains are defined by questionnaires on health status and health-related quality of life given to patients immediately before admission as well as 6-months post-operative. These surveys are filled out by only 60% of patients in their sample.

3.3 Data

Hospital Data

At the hospital level, the Agency for Health Care Administration provides administrative data on hospitals in the state of Florida. The hospital general information dataset contains details on hospital name, unique identification number, address, city, state, zip code, profit status and hospital owner. Hospitals are identified as within a hospital system if there is one or more other hospital in the state of Florida with the same owner. The provided profit status variable identifies hospital as for-profit or not-for-profit. Using hospital zipcode, I find latitude and longitude coordinates for each hospital zipcode centroid using census data.

I do the same for patient zipcodes and then calculate the linear distance between hospitals and patients. Distance is calculated using the Haversine formula as implemented by the Stata command ”geodist”. Hospital level information of bed capacity, observed volume and Medicare percentage were also collected. These were obtained from Medicare fiscal year flatfiles, specifically the FY-specific impact files.

Quality Data

The second primary data set, also acquired from CMS, contains the relevant quality variables for my study. From CMS I obtained a set of files that contain information for the set of Medicare affiliated hospitals found in the Florida SID database. Included in the CMS annual hospital flatfiles are the IQR quality measures for the complication and readmission rates following elective primary total hip arthroplasty (THA) and/or total knee arthroplasty (TKA). In this study we use the complication rate for THA/TKA; hospitals in the sample have an average complication rate of 3.1%. Also included in the readmission and complication data provided by CMS are 30-day hospital wide readmission rates and complication rates for PSI variables. These variables are calculated using controls for patient risk factors. Complication rates and readmission rates calculations, as well as patient samples, vary by PSI and readmission measures (Krumholz et al. (2006)). From these I extract the data on PSI 04 - ”In-hospital deaths per 1,000 surgical discharges, among patients ages 18 through 89 years or obstetric patients, with serious treatable complications.[9] The average readmission rate in the sample is 15.8% and the average PSI 04 death rate in 1,000 patients is 114.5. The publicly reported quality data, as well as the discharge data is available for the years of 2013-2015.

[9]Complications include deep vein thrombosis/ pulmonary embolism, pneumonia, sepsis, shock/cardiac arrest, and gastrointestinal hemorrhage/acute ulcer. The measure excludes cases transferred to an acute care facility and cases in hospice care at admission. See https://www.qualityindicators.ahrq.gov/Downloads/Modules/PSI/V2018/TechSpecs/PSI_04_Death_Rate_among_Surgical_Inpatients_with_Serious_Treatable_Conditions.pdf

Discharge Data

The study using patient-level discharge data for the years 2013 to 2015 from Florida, State Inpatient Databases (SID), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality . The SID contains rich information on patients' demographic and medical characteristics, as well as on the hospital stay, including diagnoses, comorbidities, procedures and hospital charges.

I derive patient characteristics for age, gender, number of chronic conditions and length of stay. Additionally, using the user-written Stata command elixhauser and the input ICD-10 diagnostic codes provided by the SID, I calculate the total number of elixhauser comorbidity categories associated with each patient and discharge Stagg (2015). Using the same ICD-10 codes, I also calculate a Charlson score for each patient using the Stata command charlson Stagg (2006).[10] These two measures provide an indication of patient severity of illness. I use the elixhauser covariate in the main specification, but results are robust to substitution of the Charlson index variable.

3.4 Empirical Model

Beginning with fiscal year 2013, CMS has been reporting mortality, readmission and complication rates for patients receiving elective hip or knee surgery (THA/TKA) in US hospitals. The main research goal of this paper is to investigate whether hospital demand responds to differences or improvement in these quality measures. I specify a random utility choice model of hospital choice based on characteristics of the patient and hospital (McFadden (1974), McFadden and Train (2000)). The utility that patient i receives from being admitted to hospital j at time t is given by:

$$\begin{aligned} U_{ijt} &= V_{ijt} + v_{ijt} \\ &= D'_{ij}\beta_{d,i} + D^{2\prime}_{ij}\beta_{d^2,i} + D^{3\prime}_{ij}\beta_{d^3,i} + Q'_{jt-1}\beta_q, i + Z'_j\beta_{z,i} + v_{jit} \end{aligned} \tag{3.1}$$

[10]Based on a SAS program written by Dr. Hude Quan, the command calculates the Charlson index of comorbidity from data containing ICD-9-CM, ICD-10 or Enhanced ICD-9-CM comorbidity diagnoses codes. The Charlson score reflects the cumulative increase in likelihood of one-year mortality due to the severity of the effect of comorbidities Quan (2005).

where Z_j is a vector of time-invariant hospital characteristics, D_{ij} represents distance between the patient's zipcode and the hospital and Q_{jt-1} are hospital-level quality measures reported in the previous year. These β_q coefficients are the variables of interest in my investigation.

Preferences vary across patients based on their individual characteristics X_i which include age, gender, previous emergency admission, Charlson score and Elixhauser comorbid conditions. The marginal utility of quality of patient i is then:

$$\beta_{q,i} = \beta_q + X_i' \delta_q \tag{3.2}$$

Included in this patient vector is a measure of patient income defined by the average median income for the patient's own zipcode. Including interaction effects between distance and patient income quartile dummies identifies whether patients of low socioeconomic status have less mobility options to "choose" their hospital and are more influenced by proximity of hospital than wealthier patients. All covariates in X_i are mean-centered, therefore the vector of coefficients reflect the preferences of the reference patient.

If I assume that e_{ijt} is iid extreme value, then this yields the *multinomial logit* in which the probability that patient i chooses hospital j for procedure k at time t is:

$$P_{ijt} = \frac{\exp(V_{ijt})}{\sum_{j'=1}^{J} \exp(V_{ij^{prime}t})} \tag{3.3}$$

I run this model using my discharge-level patient data from 2014 - 2015. Fiscal year 2013 is the first year the hip and knee complication rates are published, and while these measures are published at the start of the fiscal year, patients may not have been aware of the measures.

Additional quality measures that can be included in this investigation are published yearly by CMS through their HVBP (Hospital Value Based Purchasing)Program and the HAC (Hospital Acquired Conditions) Reduction Program.[11] These other quality measures can be included as hospital-level controls in the patient-choice model. Of specific inter-

[11] See https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/downloads/Hospital_VBPurchasing_Fact_Sheet_ICN907664.pdf

est will be the patient safety indicator (from HVBP) that corresponds to in-hospital deaths among patients with serious treatable complications (deep vein thrombosis/ pulmonary embolism, pneumonia, sepsis, shock/cardiac arrest, or gastrointestinal hemorrhage/acute ulcer. All estimates are executed using the clogit command in Stata.

3.4.1 Endogeneity

The first possible source of endogeneity is that sicker patients may choose higher quality hospitals or hospitals may discourage or change admission behavior for patients with characteristics that indicate they are more likely to confound the quality metrics. If this type of selection is not controlled for in the calculation of the quality metrics, then the scores would be determined by hospital selection or patients' choices. The CMS THA/TKA complication rate scores are calculated with an adjustment for a robust set of demographic patient characteristics, reducing the probability that unobserved patient selection is likely to bias the quality scores significantly.[12]

A second, and more problematic source of endogeneity is the possibility of unobserved hospital characteristics. specifically, the error term in (3.1) may be the sum of unobserved hospital characteristics ξ_{ht} and an iid random patient utility, i.e. $v_{iht} = \xi_{ht} + \varepsilon_{iht}$ where the ξ_{ht} are correlated with unobserved variables and therefore affect demand (Ho (2006)). The use of quality information from previous periods when patients choose hospitals does not remove the possible omitted variable bias in this case.

To address this source of endogeneity, I follow Pope (2009) and Gaynor et al. (2012) and use a control group of emergency admission patients to assess the possible impact of unobserved hospital heterogeneity. These emergency patients have less choice over provider and do not have the time provided to elective patients to research and compare provider quality. I expect elective patients to respond more to quality that emergency patients, because elective patients have time to gather quality data, consult family doctors and relatives, etc. before making their decision on choice of hospital. I specify an alternative specification of equation 3.1 including patients who are emergency admissions. The specification includes a full set

[12] See the 2014 Measure Information and Instructions Report (MIIR) at https://www.qualitynet.org

of interactions with the dummy variable for emergency admissions.

3.5 Results

3.5.1 Descriptive Statistics

The main sample consists of 22,599 elective hip and knee replacement patients treated by 136 hospitals in Florida during the period of July 2013 - December 2015. The average age is 74.2 years old and 63.1 % are female (see table 3.2). The average length of stay is 2.9 days and patients have on average 5.2 chronic conditions with an elixsum score of 2.2.[13] The average zipcode-specific median income is $44,700.

Patients have, on average, 1.9 hospitals within a 10 mile radius, 6.5 within a 20 mile radius and 20.7 within 50 miles. The average distance traveled to a hospital is 16.6 miles, and patients choose to travel 10 miles further than their closest option. Patients who choose a hospital outside of 50 miles are dropped from the sample. Figure 3.1 shows that 29.1 % of the sample choose to be treated at the nearest hospital, while 7.9 % of patients are treated at a hospital of the 10th or more greatest distance from their home.

The 126 hospitals in the sample have on average 296.6 beds and a Medicare patient percentage of 42.4%. The average hip and knee complication rate is 3.1%, the 30-day hospital-wide readmission rate is 15.8% and the average number of deaths falling under the category of PSI 4 is 114 in 1000. Hospitals within a hospital system (defined as a hospital with one or more other hospital with the same owner) comprise 39.7% of the sample and 48.3% maintain a non-profit status.

3.5.2 Regression results

3.5.2.1 Main effects

Table 3.3 is the baseline specification with distance, hip-knee complication rate, 30-day all hospital readmission rate, and indicators for the type of hospital. The specification also

[13] Details on the calculation of the elixsum score are included in 3.3

includes interactions with patient age, gender, income, and number of elixhauser comorbidity characteristics. The main effects are the estimated marginal utilities for the reference patient. This reference patient prefers shorter distances, lower 30-day readmission rates and hospitals that improve upon previous year's hip-knee complication rates. Of interest, this patient also prefers hospitals that are not within a hospital system, after accounting for bed size and non-profit status. These results are robust to the inclusion of hip-knee complication rate rather than change in rate over time. Results from tables 3.4 and 3.3 show that patients have a significant willingness to travel for hospitals with lower complication rates (table 3.4) as well as hospitals that improve their complication rates across years (table 3.3).

3.5.2.2 Patient heterogeneity

Results from tables 3.4 and 3.3 also show differences in patient preferences over quality characteristics of hospitals. The coefficients on the interaction terms suggest that older patients dislike distance more, a similar result to that which has been found in a number of other studies (Sivey (2012), Goldman and Romley (2008)). These older patients also care more about improvements in hip-knee complication rates. Male and female patients do not show any significant differences across their preferences, and there is some evidence that higher income patients care more about increases in 30-day readmission rate. Differences in preferences over patients with different income status include high utility levels for travel associated with higher quality of care or less waiting times (Moscelli et al. (2018)).

There is much patient heterogeneity in preferences over increases in the PSI 04 death rate. Older patients, patients with higher incomes, and patients identified as having a greater number of elixhauser comorbidities all respond negatively to increases in the PSI 04 death rate. These results are shown from the expanded specification in table 3.5.

3.5.2.3 Responsiveness to other quality information

An alternative way to identify patient understanding and responsiveness to publicly-reported quality information is to test whether patient choice of hospital is influenced by other, periphery, quality metrics. One alternative quality metric that I include in a separate specification is the PSI 04 mortality rate, the in-hospital death rate per 1,000 surgical discharges, among patients ages 18 through 89 years or obstetric patients, with serious treatable complications (the included complications are described in detail in section 3.3). The inclusion of this additional publicly reported quality metric lends some evidence to the overall level of patient responsiveness to public reporting of quality data.

The sample is reduced from 79,977 to 69,409 because not all hospitals report PSI 04 metrics in each year. I find a negative and statistically significant effect of increase in PSI 04 death rate on hospital demand of -3.097 (SE = 1.172). The coefficient on change in hip-knee complication rate decreases from -0.410 (SE = 0.0581) to -0.264 (SE = 0.0586), perhaps due in fact to the correlation between the two metrics.

3.5.2.4 Testing for unobserved hospital heterogeneity

I also explore the possible impact of omitted hospital characteristics on our estimates of marginal utility for quality and other hospital characteristics. I compare the estimated marginal utilities of emergency and elective patients by estimating pooled choice model with a full set of interactions between the explanatory variables and a dummy variable of emergency status.[14] Emergency patients have a choice set of all hospitals within 50 miles who treated at least 25 emergency patients in the current year. This rules out hospitals that are more specialized and only treated elective procedure patients.

There are 3,289 emergency patients in my sample, 44.89% of which are treated at the nearest hospital as can be seen in appendix figure **??**; additionally 24.97% of the sample are treated at the second closest hospital to their home. Descriptive statistics for the emergency sample can be found in appendix table **??**. Emergency patients are older on average by 8.9 years with higher numbers of chronic conditions (6.3 vs. 5.2) and elixhauser comorbidities (3.5 vs. 2.2). Their hospital stays are longer on average by 3 days and they are also more likely to be female.

The results of the pooled choice model can be seen in table 3.6. This model specification suggests that change in hip/knee complication rate, readmission rate quality scores and also

[14] The detailed reasoning behind this choice of specification can be found in section 3.4.1.

mortality rates as measured by PSI 4 have less influence on the hospital used by emergency patients than for elective patients. Elective procedure patients are far more likely to be treated at a non-profit hospital.

3.6 Conclusion

In this paper, I use individual discharge data from the state of Florida for the years 2013 - 2015 to estimate a mixed logit model of patients hospital choices, controlling for demographic information in addition to hospital characteristics. The covariates of interest are distance from patient home and publicly reported quality information on complication rates after elective hip and/or knee replacement surgeries. I use the estimated coefficients to estimate changes in hospital demand caused by changes in reported quality ratings with a focus on the elective procedure complication rate. I also investigate questions of patient heterogeneity in preferences by including a full set of interactions between ”reference patient” characteristics and hospital covariates and identifying significant differences in coefficients. The issue of possible unobserved hospital heterogeneity is addressed through the specification of an alternative model which includes a full set of dummy variables identifying emergency admission patients.

The main findings indicate that patients have a significant willingness to travel for improved quality measures, including lower complication rates for elective hip and/or knee replacement, lower 30-day readmission rates and lower in-hospital mortality rates for patients with serious treatable conditions. Patient preference heterogeneity includes older patients being less willing to travel further distances. Older patients, higher income patients and patients with higher numbers of elixhauser comorbidities also show increased utility from lower in-hospital mortality rates. Higher income patients are also more responsive to differences in 30-day readmission rates.

Future work would include investigating how the inclusion of additional PSI and quality variables, as well as identification of differences in elasticities of demand are correlated with patient demand for quality.

Figures and tables

Table 3.1: Measure Dates for FY 2013 HVBP Measures

Measure	Measure Start Date	Measure End Date
30-Day Hospital-Wide All-Cause Unplanned Readmission Rate	7/1/2011	6/30/2012
30-Day Readmission Rate Following Elective Primary Total Hip Arthroplasty (THA) and/or Total Knee Arthroplasty (TKA)	7/1/2009	6/30/2012
Complication Rate Following Elective Primary Total Hip Arthroplasty (THA) and/or Total Knee Arthroplasty (TKA)	7/1/2009	3/31/2012

Figure 3.1: Percentage of elective patients who went to the Nth nearest hospital

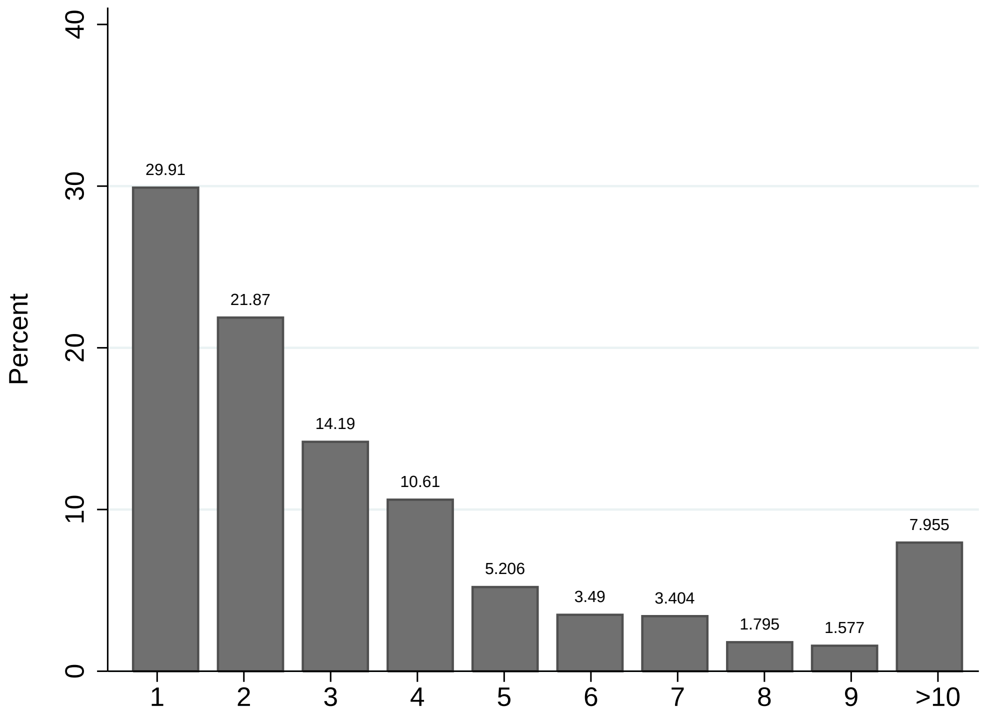


Table 3.2: Descriptive statistics - elective sample

	Obs	Mean	SD
Patient characteristics			
Distance traveled (in miles)	22,599	16.6	(10.6)
Distance traveled past closest hospital	22,599	10.1	(8.8)
Number of providers in 10 mile radius	22,599	1.9	(2.4)
Number of providers in 20 mile radius	22,599	6.5	(5.8)
Number of providers in 50 mile radius	22,599	20.7	(13.6)
Age	22,599	74.2	(6.5)
Female (%)	22,599	63.1	(48.3)
Number of chronic conditions	22,599	5.2	(2.6)
Elixsum	22,599	2.2	(1.6)
Charlson Score	22,599	0.62	(1.1)
Length of stay	22,599	2.9	(1.5)
Median income (zipcode)	22,599	44.7	(18.4)
Provider characteristics			
Observed volume	136	2051.6	(1252.6)
Beds	136	296.6	(262.6)
Medicare percentage	136	42.4	(13.1)
Hip-Knee complication rate (%)	136	3.1	(0.58)
30-day readmission rate (%)	136	15.8	(0.98)
PSI 4	136	114.5	(19.4)
System member (%)	136	39.7	(49.0)
Non-profit hospital (%)	136	48.3	(50.0)

Obs = observations; SD = Standard deviation

Notes: Patient characteristics for patients choose provider between July 2012 & Dec. 2015

Table 3.3: Estimated marginal utilities - including change in complication rate and interactions

	Est	SE
Change in Hip-Knee rate	-0.410***	(0.0581)
30-day readmission rate (%)	-0.128***	(0.0220)
Distance (in miles)	-0.130***	(0.0238)
Distance^2	0.00147	(0.00110)
Distance^3	-0.0000207	(0.0000150)
Beds	0.00163***	(0.0000948)
Non-profit hospital	1.526***	(0.0636)
System member	-0.516***	(0.0503)
Interaction with change in hip-knee complication rate:		
× Age	-0.0179**	(0.00577)
× Income	-0.00149	(0.00226)
× Elixsum	0.134***	(0.0225)
× Female	0.0629	(0.0738)
Interaction with distance:		
× Age	-0.00115	(0.00227)
× Income	-0.00140	(0.000832)
× Elixsum	-0.00735	(0.00924)
× Female	-0.0161	(0.0299)
Interaction with 30-day readmission rate:		
× Age	-0.00241	(0.00218)
× Income	-0.00307***	(0.000844)
× Elixsum	0.0135	(0.00858)
× Female	0.00863	(0.0279)
Log-likelihood	-11758.5	
N	79977	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Estimated marginal utilities - including complication rate, readmission rate and interactions

	Est	SE
Hip-knee complication rate (%)	-0.432***	(0.0285)
30-day readmission rate (%)	-0.152***	(0.0167)
Distance (in miles)	-0.130***	(0.0166)
Distance^2	0.00110	(0.000768)
Distance^3	-0.0000114	(0.0000104)
Beds	0.00142***	(0.0000686)
Non-profit hospital	1.346***	(0.0436)
System member	-0.408***	(0.0346)
Interaction with hip-knee complication rate:		
× Age	0.00882**	(0.00276)
× Income	0.00153	(0.00116)
× Elixsum	0.0928***	(0.0110)
× Female	-0.0176	(0.0359)
Interaction with distance:		
× Age	-0.00213	(0.00156)
× Income	-0.000966	(0.000574)
× Elixsum	-0.00602	(0.00650)
× Female	-0.000842	(0.0210)
Interaction with 30-day readmission rate:		
× Age	-0.00164	(0.00163)
× Income	-0.00200**	(0.000614)
× Elixsum	-0.00383	(0.00650)
× Female	0.00858	(0.0213)
Log-likelihood	-23289.6	
N	161175	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Estimated marginal utilities - including PSI4 complication rates

	Est	SE
Change in Hip-Knee rate	-0.264***	(0.0586)
30-day readmission rate (%)	-0.146***	(0.0236)
PSI 04 - death rate in 1000	-3.097**	(1.172)
Distance (in miles)	-0.125***	(0.0245)
Distance^2	0.00145	(0.00113)
Distance^3	-0.0000220	(0.0000154)
Beds	0.00147***	(0.000103)
Non-profit hospital	1.492***	(0.0652)
System member	-0.405***	(0.0509)
Interaction with change in hip-knee complication rate:		
× AGE	-0.0157**	(0.00583)
× income	0.00275	(0.00232)
× elixsum	0.130***	(0.0226)
× female	0.0431	(0.0742)
Interaction with distance:		
× AGE	-0.000820	(0.00232)
× income	-0.000988	(0.000855)
× elixsum	-0.00966	(0.00947)
× Female	-0.0193	(0.0307)
Interaction with 30-day readmission rate:		
× AGE	-0.00142	(0.00232)
× income	-0.00129	(0.000946)
× elixsum	0.0197*	(0.00907)
× Female	0.0179	(0.0296)
Interaction with PSI 04 death rate in 1000:		
× AGE	-0.285*	(0.115)
× income	-0.232***	(0.0459)
× elixsum	-1.200**	(0.453)
× Female	0.769	(1.478)
Log-likelihood	-11109.0	
N	69409	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Comparison of marginal utilities for elective and emergency patients - including change in complication rate

	Est	SE
Elective patients:		
Change in Hip-Knee rate	-0.264***	(0.0586)
30-day readmission rate (%)	-0.146***	(0.0236)
PSI 04 - death rate in 1000	-3.097**	(1.172)
Distance (in miles)	-0.125***	(0.0245)
Distance^2	0.00145	(0.00113)
Distance^3	-0.0000220	(0.0000154)
Beds	0.00147***	(0.000103)
Non-profit hospital	1.492***	(0.0652)
System member	-0.405***	(0.0509)
Distance (in miles) × AGE	-0.000820	(0.00232)
Distance (in miles) × income	-0.000988	(0.000855)
Distance (in miles) × elixsum	-0.00966	(0.00947)
Female × Distance (in miles)	-0.0193	(0.0307)
Emergency patients:		
Change in Hip-Knee rate	0.281	(0.836)
30-day readmission rate (%)	0.258	(0.371)
PSI 04 - death rate in 1000	23.07	(19.77)
Distance (in miles)	0.0526	(0.347)
Distance^2	0.000355	(0.0175)
Distance^3	-0.0000220	(0.0000154)
Beds	0.0000756	(0.00145)
Non-profit hospital	-3.324***	(0.819)
System member	0.721	(0.736)
Distance (in miles) × AGE	-0.00328	(0.00456)
Distance (in miles) × income	0.00396	(0.00207)
Distance (in miles) × elixsum	-0.00135	(0.0185)
Female × Distance (in miles)	0.0371	(0.0737)
Log-likelihood	-13330.2	
N	91404	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix A

Appendix A

Table A.1: Marginal Costs by Disproportionate Share Quartile

	Quartile				
Marginal Cost	1	2	3	4	Total
Predicted RR: AMI	-1,858,273.1	-2,179,382.3	-2,487,896.5	-3,169,526.2	-2,406,557.1
	(1,098,097.9)	(1,577,359.8)	(1,757,756.9)	(2,286,957.9)	(1,779,789.2)
Predicted RR: PN	-999,615.7	-1,172,349.1	-1,338,307.2	-1,704,974.4	-1,294,552.6
	(590,696.8)	(848,504.8)	(945,545.3)	(1,230,216.9)	(957,397.0)
Predicted RR: HF	-3,238,561.2	-3,798,183.8	-4,335,856.1	-5,523,786.8	-4,194,099.5
	(1,913,743.1)	(2,748,991.1)	(3,063,383.5)	(3,985,664.4)	(3,101,781.0)
Raw RR: AMI	-1,444,142.7	-1,714,007.4	-1,973,365.5	-2,568,600.9	-1,909,774.2
	(,876,344.7)	(1,290,410.6)	(1,439,997.9)	(1,928,107.2)	(1,474,319.4)
Raw RR: PN	-540,767.2	-641,819.5	-738,937.5	-961,826.7	-715,125.4
	(328,152.1)	(483,201.3)	(539,215.1)	(721,990.3)	(552,067.0)
Raw RR: HF	-807,213.0	-958,055.7	-1,103,025.6	-1,435,736.4	-1067,480.9
	(489,838.6)	(721,283.5)	(804,896.3)	(1,077,728.2)	(824,080.5)
Total # Adverse Events	76,434.7	89,895.0	102,912.5	135,748.6	100,375.2
	(48,178.0)	(70,411.5)	(78,075.1)	(108,693.9)	(81,180.7)
Readmission #: AMI	157,038.5	183,717.5	210,853.8	274,815.4	204,903.2
	(96,713.6)	(137,985.4)	(153,442.4)	(211,861.7)	(159,331.6)
Readmission #: PN	207,493.5	242,744.2	278,599.1	363,110.9	270,736.6
	(127,786.8)	(182,318.8)	(202,741.9)	(279,930.8)	(210,523.4)
Readmission #: HF	-104,110.8	-121,798.0	-139,788.4	-182,192.6	-135,843.3
	(64,117.6)	(91,479.3)	(101,726.7)	(140,456.6)	(105,631.1)
Disproportionate Share (mean)	0.0950	0.2099	0.2957	0.5168	0.2793

Table A.2: Mean Marginal Cost by disproportionate share quartile (with ttest)

Marginal Cost	Mean (Quartiles 1-3)	Mean (Quartile 4)	Mean (Total)	Diff.	Std. Error	Obs.
Predicted RR: AMI	-2,012,530.9	-2,899,891.2	-2,206,040.4	887,360.3***	50,427.7	6695
Predicted RR: PN	-1,082,595.1	-1,559,930.4	-1,186,689.1	477,335.3***	27,126.4	6695
Predicted RR: HF	-3,507,398.5	-5,053,872.3	-3,844,643.0	1,546,473.8***	87,884.3	6695
Raw RR: AMI	-1,729,573.6	-2,568,600.9	-1,909,774.2	839,027.4***	46,186.1	5713
Raw RR: PN	-647,648.3	-961,826.7	-715,125.4	314,178.4***	17,294.6	5713
Raw RR: HF	-966,756.5	-1,435,736.4	-1,067,480.9	468,979.9***	25,816.0	5713
Total # Adverse Events	90,699.9	135,748.6	100,375.2	-45,048.7***	2,546.8	5713
Readmission #: AMI	185,780.9	274,815.4	204,903.2	-89,034.4***	4,996.6	5713
Readmission #: PN	245,470.6	363,110.9	270,736.6	-117,640.4***	6,601.9	5713
Readmission #: HF	-123,166.0	-182,192.6	-135,843.3	59,026.6***	3,312.5	5713

Figure A.1: Trend in Raw 30-day Readmission Rates

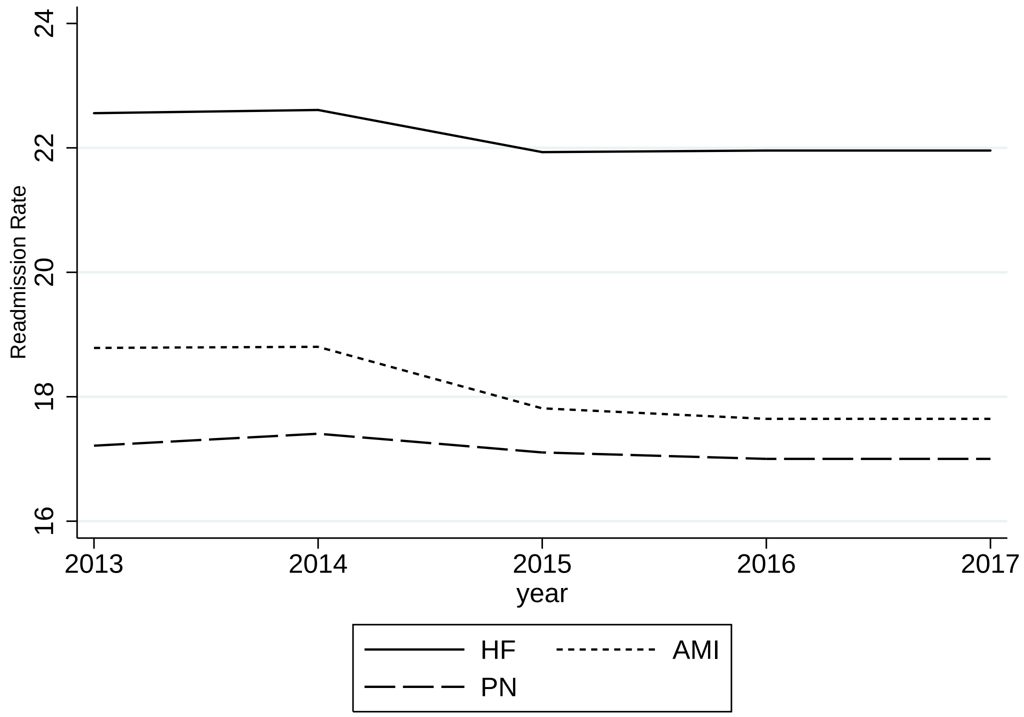


Figure A.2: Trend in Expected 30-day Readmission Rates

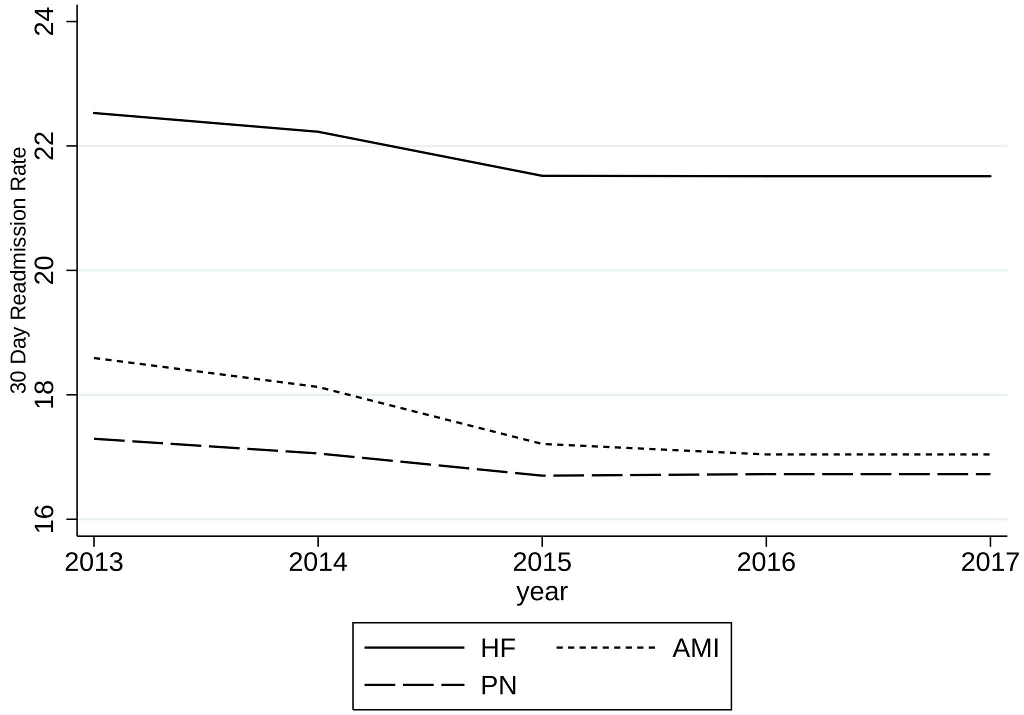
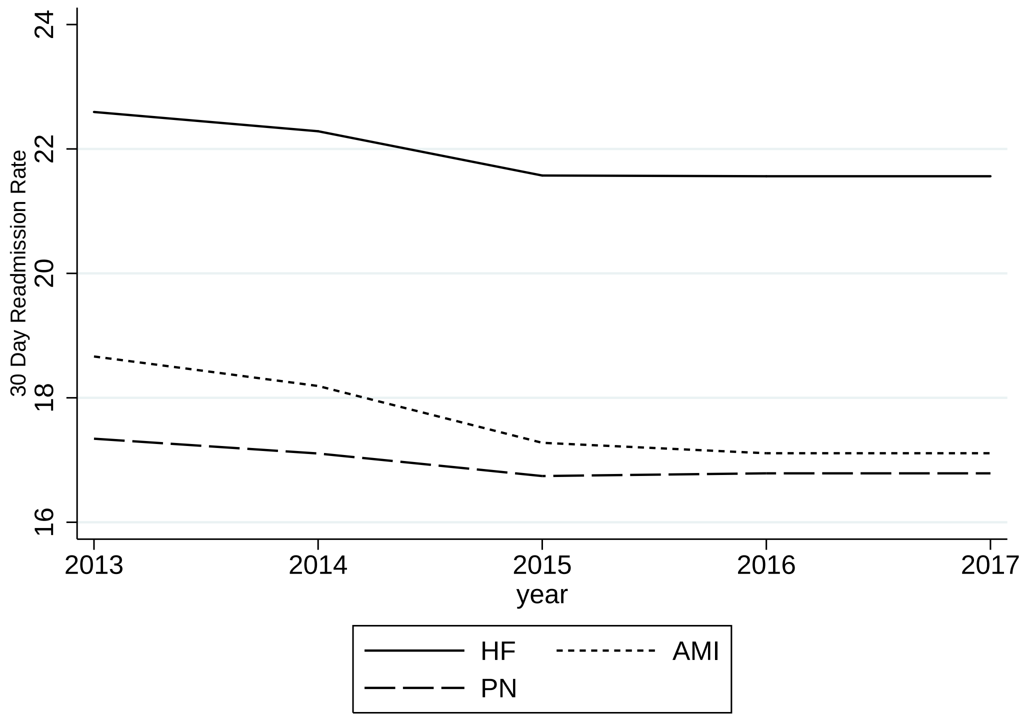


Figure A.3: Trend in Predicted 30-day Readmission Rates



Appendices

A.1 Disproportionate Share & CMI

- DSH Patient Percent = (Medicare SSI Days / Total Medicare Days) + (Medicaid, Non-Medicare Days / Total Patient Days)
- A hospital's CMI represents the average diagnosis-related group (DRG) relative weight for that hospital.
- It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges.
- CMIs are calculated using both transfer-adjusted cases and unadjusted cases.

A.2 Base Medicare payments

- The operating reimbursement formula follows:

$$
\begin{aligned}
&Operating\,Payment \\
&\quad = [(Standardized\,Labor\,Share \times Operating\,Wage\,Index) \\
&\qquad + (Standardized\,Non-Labor\,Share)] \\
&\quad \times (1 + Operating\,IME + Operating\,DSH\,Adjustment\,Factor) \\
&\quad \times (DRG\,Weight)
\end{aligned}
$$

- The capital reimbursement formula follows:

$$
\begin{aligned}
&Capital\,Payment \\
&\quad = [(Standard\,Federal\,Rate) \times (GAF) \\
&\quad \times (1 + DSH\,Adjustment\,Factor + IME\,Adjustment\,Factor) \\
&\quad \times (DRG\,Weight)
\end{aligned}
$$

- All data is observable and thus can be calculated for each DRG for each year

A.3 CMS's estimation of readmission rates:

CMS computes r_i and r_i^e for every hospital using patient level discharge and readmission data as follows: Let Y_{ilk} be a binary variable indicating whether discharge l of disease k in hospital i is associated with a readmission (either to the same hospital or to another hospital). For each discharge CMS collects the corresponding patient case covariates, denoted by Z_{ilk} for discharge l in disease k and hospital i. The logistic hierarchical generalized linear model is used to estimate the average and individual hospital intercepts to predict the readmission probability for each discharge:

$$\log\left(P\left(Y_{ilk}=1\right)\right) = \alpha_{ik} + \beta_k' Z_{ilk}$$
$$\alpha_{ik} = \mu_k + \omega_{ik}, \quad \omega_i \in N\left(0, \tau^2\right)$$

where, for each disease k, α_{ik} is the hospital-level intercept for hospital i, μ_k is the average intercept, and β_k is the coefficient of case mix covariates.

With hospital-level and average intercepts as well as the coefficient of case mix covariates, CMS calculates the risk-adjusted predicted and the expected readmission rate for each hospital i by taking the average of the predicted readmission probabilities for all discharges of that hospital:

$$r_{ik}^e = \frac{1}{N_{ki}} \sum_{l=1}^{N_{ki}} \frac{1}{1+e^{-\mu_k - \beta_k Z_{ilk}}}$$
$$r_{ik}^p = \frac{1}{N_{ki}} \sum_{l=1}^{N_{ki}} \frac{1}{1+e^{-\alpha_{ik} - \beta_k Z_{ilk}}}$$

where N_{ki} is the number of Medicare discharge cases with disease k in hospital i.

A.3.1 Formulas to Calculate Readmission Adjustment Factor:

- Aggregate payments for excess readmissions $= \sum_i \left[SumBasePayments_i \times (ERR_i - 1)\right]$
  where $i \in \{AMI, HF, PN\}$ for 2013-2014 and $i \in \{AMI, HF, PN, COPD, THA/TKA\}$ for 2015 onwards
- Aggregate payments for all discharges = sum of base operating DRG payments for all discharges
- Ratio $= 1 - \left(\frac{\text{Aggregate payments for excess readmissions}}{\text{Aggregate payments for all discharges}}\right)$
- Readmissions Adjustment Factor = the higher of the Ratio or 0.97(3% reduction)
  - For FY 2013, the higher of the Ratio or 0.99% (1% reduction), and for FY 2014, the higher of the Ratio or 0.98% (2% reduction).

- https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html

Appendix B

Appendix B

B.1 HRRP Details

B.1.1 Risk adjustment

Calculating the conversion from raw readmission rates to the excess readmission ratio requires some simplifying assumptions. It is impossible to precisely re-calculate this change because it would require replicating the exact methodology used by CMS when they calculate the HRRP penalties. CMS calculates these measures using national discharge-level data from every hospital that treats Medicare patients for the monitored diseases.

They estimate a hierarchical generalized linear model (HGLM) to calculate predicted readmission rates and expected readmission rates for each hospital and measurement period. This models the log-odds of readmission within 30 days of discharge as a function of patient clinical and demographic characteristics, including a random hospital-specific intercept. The "expected readmission rate" is calculated using a hospital's own patient mix along with the average hospital-specific intercept. The "predicted readmission rate" is different in that it is calculated using an estimated hospital-specific intercept.

Specifically, they account for within-hospital clustering by estimating a HGLM linking patient risk factors to outcomes and a hospital-specific random effect:

$$\text{logit}(\text{Prob}(Y_{ih}=1)) = \alpha_h + \beta \mathbf{Z}_{ih} + \varepsilon_i$$
$$\alpha_h = \mu + \omega_h; \omega_h \sim N(0, \tau^2)$$

where $Y_{ih} = 1$ if the patient was readmitted within 30 days (zero otherwise), $\mathbf{Z}_{ih}$ is a set of patient-specific characteristics, α_h represents the hospital-specific intercept, μ is the adjusted average national hospital intercept, τ^2 is the between-hospital variance component and $\varepsilon \sim N(0, \sigma^2)$ captures over or under-dispersion.

Then the predicted and expected readmission rates are estimated as:

$$\textbf{Predicted:} \qquad \hat{y}_{ih}(Z) = \text{logit}^{-1}(\hat{\alpha}_h + \hat{\beta}\mathbf{Z}ih)$$
$$\textbf{Expected:} \qquad \hat{e}_{ih}(Z) = \text{logit}^{-1}(\hat{\mu} + \hat{\beta}\mathbf{Z}ih)$$
$$\hat{s}_h(Z) = \frac{\sum_{i=1}^{n_h} \hat{y}_{ih}(Z)}{\sum_{i=1}^{n_h} \hat{e}_{ih}(Z)} \times \bar{y}$$

where n_h is the number of index admissions to hospital h and $\bar{y}$ is the unadjusted national mean readmission rate.

B.1.2 Variables

- DSH Patient Percent = (Medicare SSI Days / Total Medicare Days) + (Medicaid, Non-Medicare Days / Total Patient Days)
- A hospital's CMI represents the average diagnosis-related group (DRG) relative weight for that hospital.
- It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges.
- CMIs are calculated using both transfer-adjusted cases and unadjusted cases.

B.1.3 Base Medicare payments

- The operating reimbursement formula follows:

$$\begin{aligned} & Operating\,Payment \\ & \quad = [(Standardized\,Labor\,Share \times Operating\,Wage\,Index) \\ & \qquad + (Standardized\,Non-Labor\,Share)] \\ & \times (1 + Operating\,IME + Operating\,DSH\,Adjustment\,Factor) \\ & \qquad \times (DRG\,Weight) \end{aligned}$$

- The capital reimbursement formula follows:

$$\begin{aligned} & Capital\,Payment \\ & \quad = [(Standard\,Federal\,Rate) \times (GAF) \\ & \times (1 + DSH\,Adjustment\,Factor + IME\,Adjustment\,Factor) \\ & \qquad \times (DRG\,Weight) \end{aligned}$$

- All data is observable and thus can be calculated for each DRG for each year

B.1.4 CMS's estimation of readmission rates:

CMS computes r_i and r_i^e for every hospital using patient level discharge and readmission data as follows: Let Y_{ilk} be a binary variable indicating whether discharge l of disease k in hospital i is associated with a readmission (either to the same hospital or to another hospital). For each discharge CMS collects the corresponding patient case covariates, denoted by Z_{ilk} for discharge l in disease k and hospital i. The logistic hierarchical generalized linear model is used to estimate the average and individual hospital intercepts to predict the readmission probability for each discharge:

$$\log\left(P\left(Y_{ilk}=1\right)\right) = \alpha_{ik} + \beta_k' Z_{ilk}$$
$$\alpha_{ik} = \mu_k + \omega_{ik}, \quad \omega_i \in N\left(0, \tau^2\right)$$

where, for each disease k, α_{ik} is the hospital-level intercept for hospital i, μ_k is the average intercept, and β_k is the coefficient of case mix covariates.

With hospital-level and average intercepts as well as the coefficient of case mix covariates, CMS calculates the risk-adjusted predicted and the expected readmission rate for each hospital i by taking the average of the predicted readmission probabilities for all discharges of that hospital:

$$r_{ik}^{e} = \frac{1}{N_{ki}} \sum_{l=1}^{N_{ki}} \frac{1}{1+e^{-\mu_k - \beta_k Z_{ilk}}}$$

$$r_{ik}^{p} = \frac{1}{N_{ki}} \sum_{l=1}^{N_{ki}} \frac{1}{1+e^{-\alpha_{ik} - \beta_k Z_{ilk}}}$$

where N_{ki} is the number of Medicare discharge cases with disease k in hospital i.

B.1.4.1 Formulas to Calculate Readmission Adjustment Factor:

- Aggregate payments for excess readmissions $= \sum_i [SumBasePayments_i \times (ERR_i - 1)]$
  where $i \in \{AMI, HF, PN\}$ for 2013-2014 and $i \in \{AMI, HF, PN, COPD, THA/TKA\}$ for 2015 onwards
- Aggregate payments for all discharges = sum of base operating DRG payments for all discharges
- Ratio $= 1 - \left(\frac{\text{Aggregate payments for excess readmissions}}{\text{Aggregate payments for all discharges}}\right)$
- Readmissions Adjustment Factor = the higher of the Ratio or 0.97(3% reduction)
  - For FY 2013, the higher of the Ratio or 0.99% (1% reduction), and for FY 2014, the higher of the Ratio or 0.98% (2% reduction).
- https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html

B.2 Appendix Tables and Graphs

Figure B.1: Trend in Raw 30-day Readmission Rates

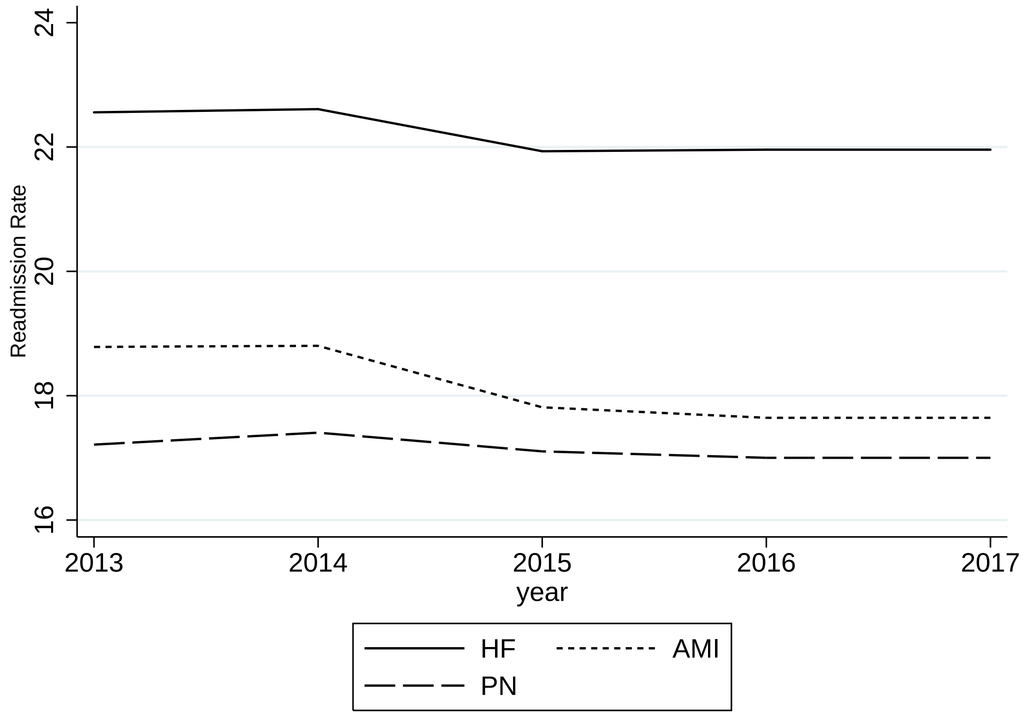


Figure B.2: Trend in Expected 30-day Readmission Rates

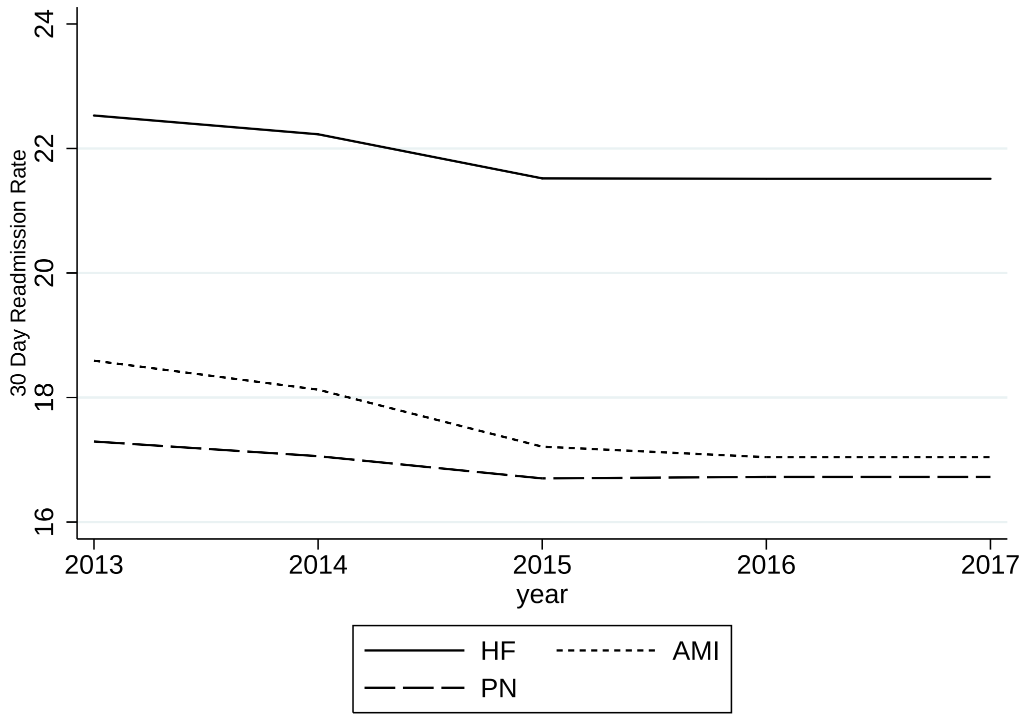


Figure B.3: Trend in Predicted 30-day Readmission Rates

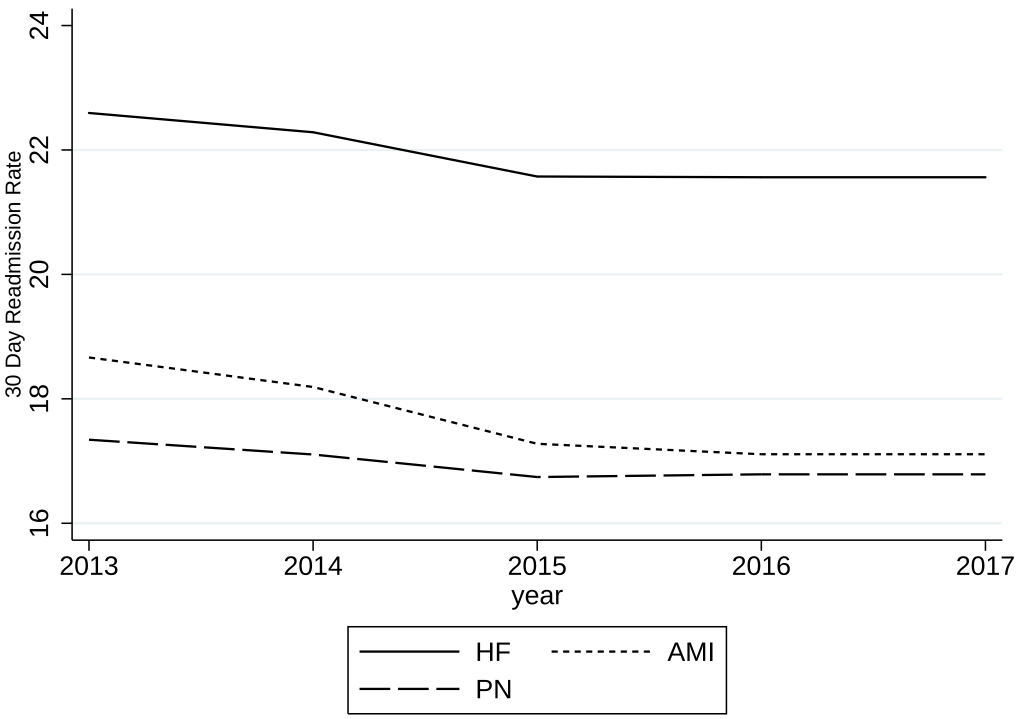


Table B.1: Marginal Costs by Disproportionate Share Quartile

	Quartile				
Marginal Cost	1	2	3	4	Total
Predicted RR: AMI	-1,858,273.1	-2,179,382.3	-2,487,896.5	-3,169,526.2	-2,406,557.1
	(1,098,097.9)	(1,577,359.8)	(1,757,756.9)	(2,286,957.9)	(1,779,789.2)
Predicted RR: PN	-999,615.7	-1,172,349.1	-1,338,307.2	-1,704,974.4	-1,294,552.6
	(590,696.8)	(848,504.8)	(945,545.3)	(1,230,216.9)	(957,397.0)
Predicted RR: HF	-3,238,561.2	-3,798,183.8	-4,335,856.1	-5,523,786.8	-4,194,099.5
	(1,913,743.1)	(2,748,991.1)	(3,063,383.5)	(3,985,664.4)	(3,101,781.0)
Raw RR: AMI	-1,444,142.7	-1,714,007.4	-1,973,365.5	-2,568,600.9	-1,909,774.2
	(,876,344.7)	(1,290,410.6)	(1,439,997.9)	(1,928,107.2)	(1,474,319.4)
Raw RR: PN	-540,767.2	-641,819.5	-738,937.5	-961,826.7	-715,125.4
	(328,152.1)	(483,201.3)	(539,215.1)	(721,990.3)	(552,067.0)
Raw RR: HF	-807,213.0	-958,055.7	-1,103,025.6	-1,435,736.4	-1067,480.9
	(489,838.6)	(721,283.5)	(804,896.3)	(1,077,728.2)	(824,080.5)
Total # Adverse Events	76,434.7	89,895.0	102,912.5	135,748.6	100,375.2
	(48,178.0)	(70,411.5)	(78,075.1)	(108,693.9)	(81,180.7)
Readmission #: AMI	157,038.5	183,717.5	210,853.8	274,815.4	204,903.2
	(96,713.6)	(137,985.4)	(153,442.4)	(211,861.7)	(159,331.6)
Readmission #: PN	207,493.5	242,744.2	278,599.1	363,110.9	270,736.6
	(127,786.8)	(182,318.8)	(202,741.9)	(279,930.8)	(210,523.4)
Readmission #: HF	-104,110.8	-121,798.0	-139,788.4	-182,192.6	-135,843.3
	(64,117.6)	(91,479.3)	(101,726.7)	(140,456.6)	(105,631.1)
Disproportionate Share (mean)	0.0950	0.2099	0.2957	0.5168	0.2793

Table B.2: Mean Marginal Cost by disproportionate share quartile (with ttest)

Marginal Cost	Mean (Quartiles 1-3)	Mean (Quartile 4)	Mean (Total)	Diff.	Std. Error	Obs.
Predicted RR: AMI	-2,012,530.9	-2,899,891.2	-2,206,040.4	$887,360.3^{***}$	50,427.7	6695
Predicted RR: PN	-1,082,595.1	-1,559,930.4	-1,186,689.1	$477,335.3^{***}$	27,126.4	6695
Predicted RR: HF	-3,507,398.5	-5,053,872.3	-3,844,643.0	$1,546,473.8^{***}$	87,884.3	6695
Raw RR: AMI	-1,729,573.6	-2,568,600.9	-1,909,774.2	$839,027.4^{***}$	46,186.1	5713
Raw RR: PN	-647,648.3	-961,826.7	-715,125.4	$314,178.4^{***}$	17,294.6	5713
Raw RR: HF	-966,756.5	-1,435,736.4	-1,067,480.9	$468,979.9^{***}$	25,816.0	5713
Total # Adverse Events	90,699.9	135,748.6	100,375.2	$-45,048.7^{***}$	2,546.8	5713
Readmission #: AMI	185,780.9	274,815.4	204,903.2	$-89,034.4^{***}$	4,996.6	5713
Readmission #: PN	245,470.6	363,110.9	270,736.6	$-117,640.4^{***}$	6,601.9	5713
Readmission #: HF	-123,166.0	-182,192.6	-135,843.3	$59,026.6^{***}$	3,312.5	5713

Figure B.4: Change in RAF and Penalty due to one less heart failure readmission, by initial predicted readmission rate

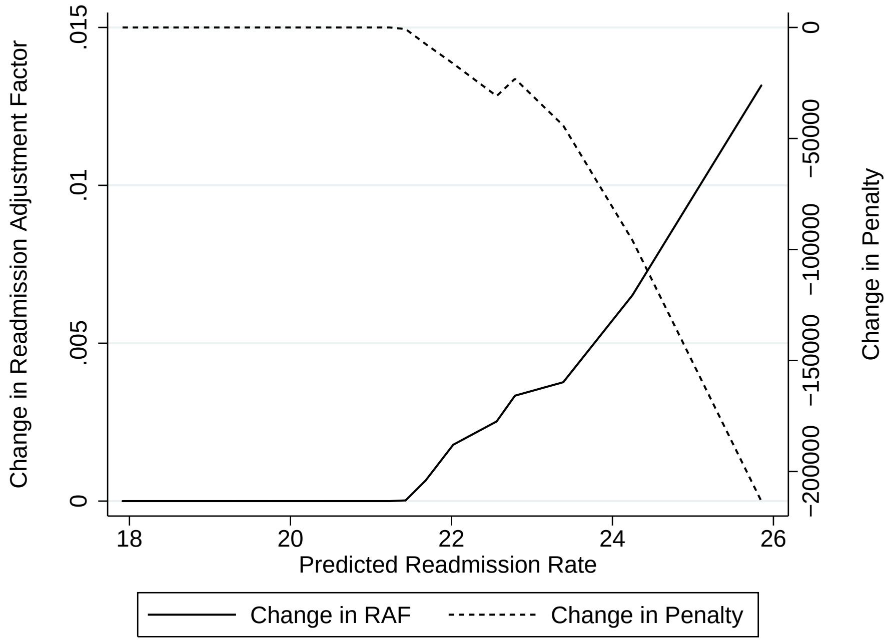


Figure B.5: Change in RAF and Penalty due to one more heart failure readmission, by initial predicted readmission rate

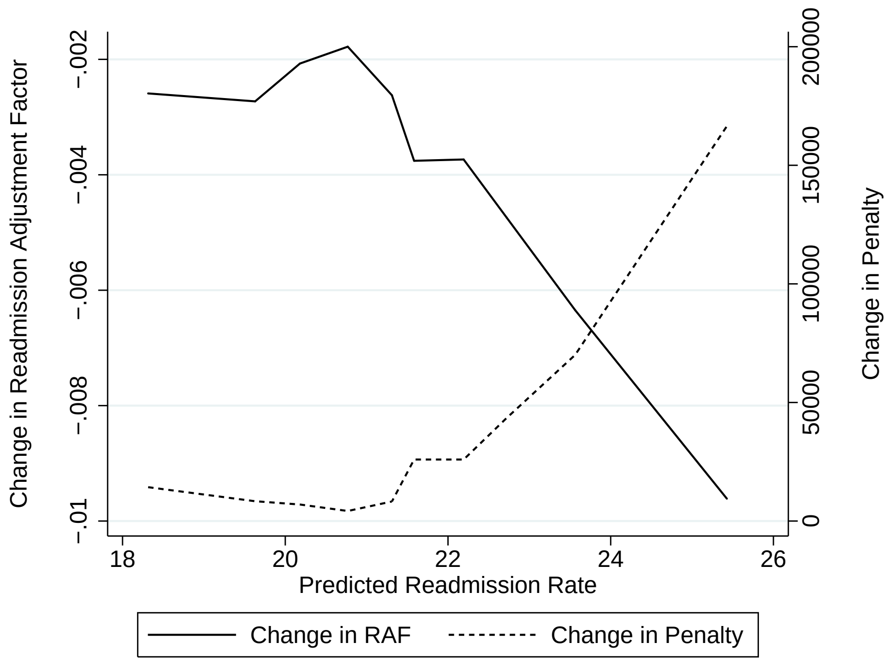


Figure B.6: Change in RAF and Penalty due to one less AMI readmission, by initial predicted readmission rate

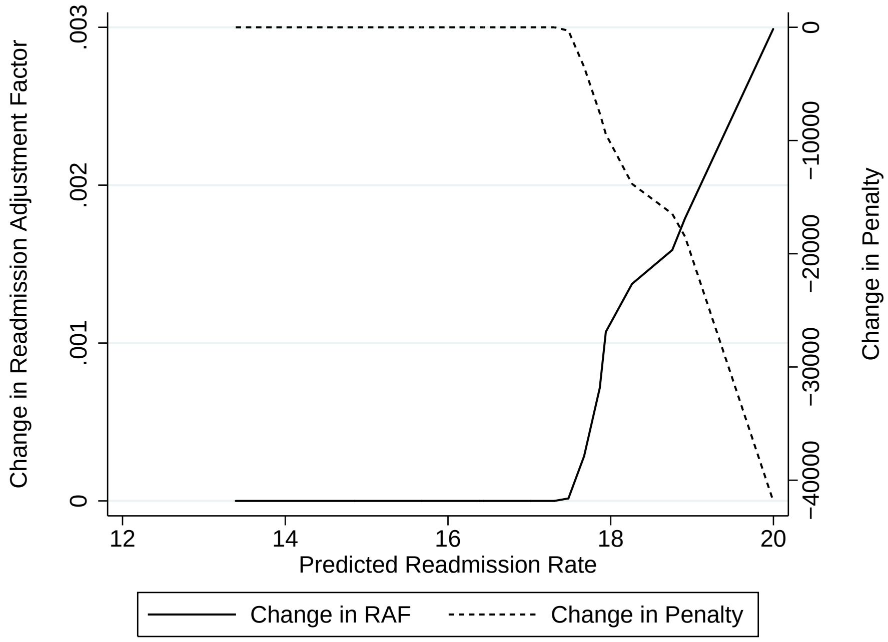


Figure B.7: Change in RAF and Penalty due to one more AMI readmission, by initial predicted readmission rate

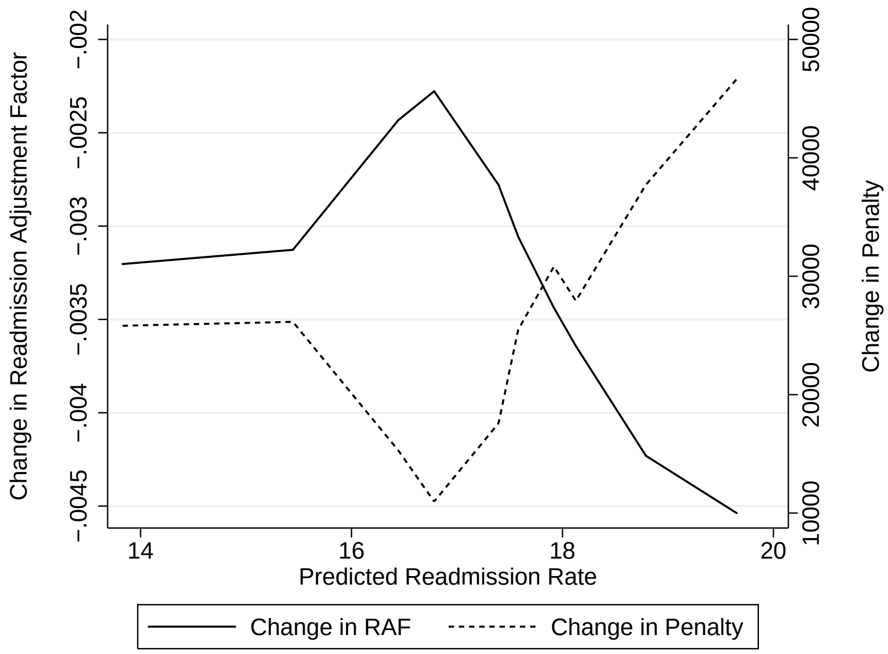


Figure B.8: Change in RAF and Penalty due to one less pneumonia readmission, by initial predicted readmission rate

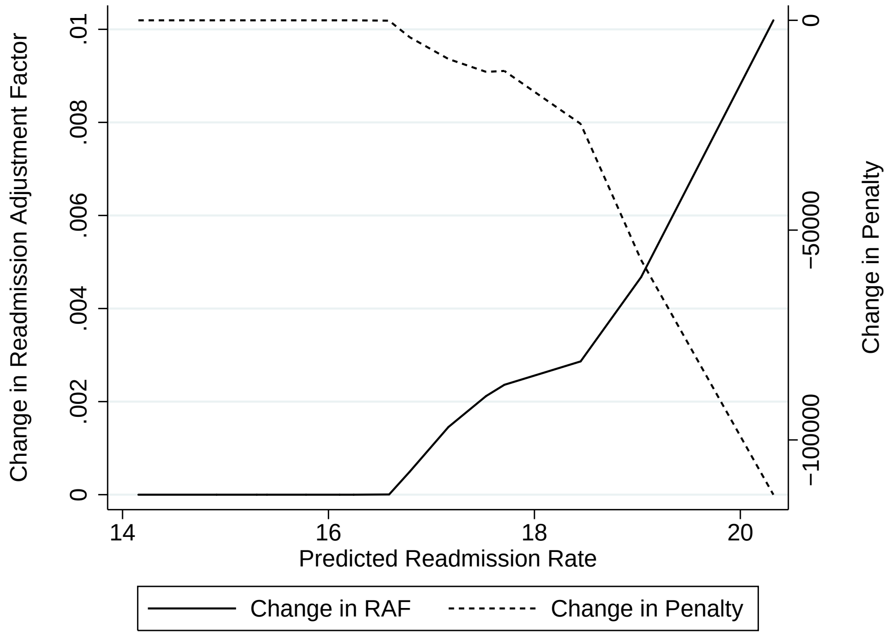
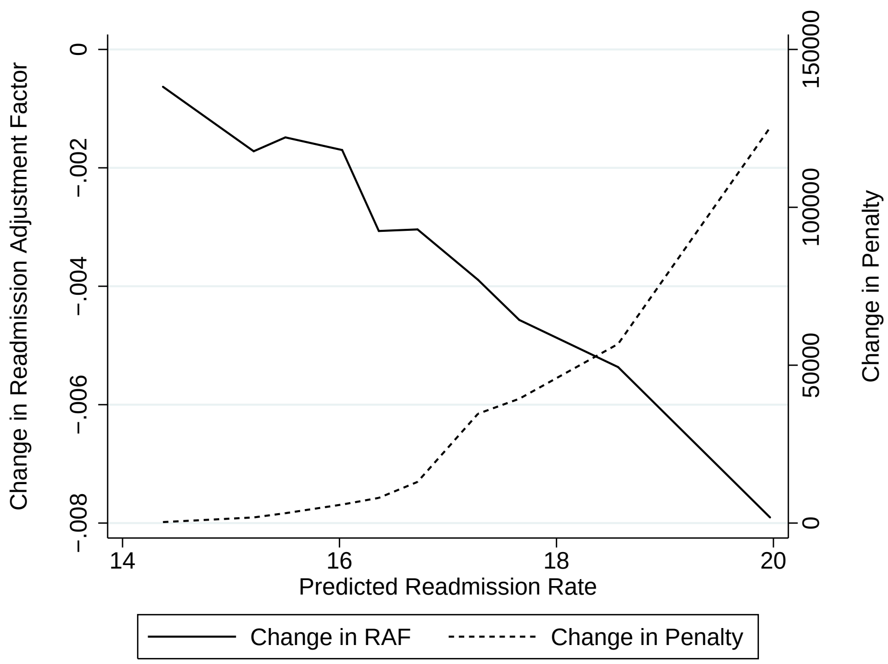


Figure B.9: Change in RAF and Penalty due to one more pneumonia readmission, by initial predicted readmission rate



Appendix C

Appendix C

C.1 Appendix tables and graphs

C.1.1 Alternative specifications

Table C.1: Estimated marginal utilities - baseline specification

	Est	SE
Hospital system member	-0.353***	(0.0199)
Non-profit hospital	1.628***	(0.0251)
Beds	0.000951***	(0.0000291)
Distance (in miles)	-0.0332*	(0.0151)
Distance^2	0.00157***	(0.000441)
Distance^3	-0.0000172**	(0.00000598)
Distance*Age	-0.00140***	(0.000152)
Distance*Female	-0.00173	(0.00196)
Distance*High Charlson Score	-0.00947	(0.0114)
Distance*Income ($000, demeaned)	-0.0000511	(0.0000538)
Log-likelihood	-27421.8	
N	194856	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Estimated marginal utilities - including complication rate and interactions

	Est	SE
Hip-knee complication rate (%)	-0.471***	(0.0283)
Hip-knee complication rate (%) × AGE	0.00756**	(0.00274)
Hip-knee complication rate (%) × income	-0.0000265	(0.00115)
Hip-knee complication rate (%) × elixsum	0.0925***	(0.0109)
female=1 × Hip-knee complication rate (%)	-0.0172	(0.0357)
Distance (in miles)	-0.127***	(0.0166)
Distance (in miles) × AGE	-0.00213	(0.00156)
Distance (in miles) × income	-0.000900	(0.000573)
Distance (in miles) × elixsum	-0.00537	(0.00649)
female=1 × Distance (in miles)	-0.00165	(0.0210)
Distance^2	0.000928	(0.000768)
Distance^2 × AGE	0.0000113	(0.0000736)
Distance^2 × income	0.0000355	(0.0000273)
Distance^2 × elixsum	-0.0000125	(0.000302)
female=1 × Distance^2	0.00000872	(0.000972)
Distance^3	-0.00000868	(0.0000104)
Distance^3 × AGE	0.000000155	(0.00000101)
Distance^3 × income	-0.000000413	(0.000000380)
Distance^3 × elixsum	0.00000128	(0.00000411)
female=1 × Distance^3	-0.000000917	(0.0000132)
Log-likelihood	-23388.3	
N	161175	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.3: Estimated marginal utilities - including complication rate, PSI 4 and interactions

	Est	SE
Hip-knee complication rate (%)	-0.490***	(0.0281)
Hip-knee complication rate (%) × AGE	0.00472	(0.00273)
Hip-knee complication rate (%) × income	-0.00128	(0.00115)
Hip-knee complication rate (%) × elixsum	0.0898***	(0.0108)
female=1 × Hip-knee complication rate (%)	-0.0122	(0.0354)
Distance (in miles)	-0.125***	(0.0171)
Distance (in miles) × AGE	-0.00206	(0.00161)
Distance (in miles) × income	-0.000818	(0.000594)
Distance (in miles) × elixsum	-0.00392	(0.00668)
female=1 × Distance (in miles)	-0.00421	(0.0216)
Distance^2	0.00106	(0.000791)
Distance^2 × AGE	0.0000141	(0.0000759)
Distance^2 × income	0.0000342	(0.0000282)
Distance^2 × elixsum	-0.0000899	(0.000311)
female=1 × Distance^2	0.000131	(0.00100)
PSI 04 - death rate in 1000	-2.644**	(0.852)
PSI 04 - death rate in 1000 × AGE	-0.314***	(0.0829)
PSI 04 - death rate in 1000 × income	-0.258***	(0.0316)
PSI 04 - death rate in 1000 × elixsum	0.271	(0.333)
female=1 × PSI 04 - death rate in 1000	0.657	(1.089)
Distance^3	-0.0000116	(0.0000107)
Distance^3 × AGE	5.95e-08	(0.00000105)
Distance^3 × income	-0.000000401	(0.000000392)
Distance^3 × elixsum	0.00000225	(0.00000423)
female=1 × Distance^3	-0.00000231	(0.0000136)
Log-likelihood	-21900.0	
N	137767	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Estimated marginal utilities - including PSI4 complication rates

	Est	SE
Hip-knee complication rate (%)	-0.445***	(0.0286)
30-day readmission rate (%)	-0.142***	(0.0178)
PSI 04 - death rate in 1000	-1.146	(0.875)
Distance (in miles)	-0.128***	(0.0172)
Distance^2	0.00119	(0.000791)
Distance^3	-0.0000136	(0.0000107)
Beds	0.00101***	(0.0000733)
Non-profit hospital	1.307***	(0.0444)
System member	-0.282***	(0.0350)
Interaction with hip-knee complication rate:		
× AGE	0.00569*	(0.00277)
× income	-0.00000729	(0.00118)
× elixsum	0.0882***	(0.0110)
× Female Hip-knee complication rate (%)	-0.0157	(0.0359)
Interaction with distance:		
× AGE	-0.00207	(0.00161)
× income	-0.000836	(0.000594)
× elixsum	-0.00436	(0.00670)
× Female	-0.00445	(0.0216)
Interaction with 30-day readmission rate:		
× AGE	-0.000259	(0.00172)
× income	-0.000551	(0.000696)
× elixsum	0.000657	(0.00682)
× Female 30-day readmission rate (%)	0.0125	(0.0224)
Interaction with PSI 04 death rate in 1000:		
× AGE	-0.305***	(0.0845)
× income	-0.226***	(0.0328)
× elixsum	0.160	(0.337)
× Female	0.431	(1.111)
Log-likelihood	-21825.7	
N	137767	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure C.1: Percentage of emergency patients who went to the Nth nearest hospital

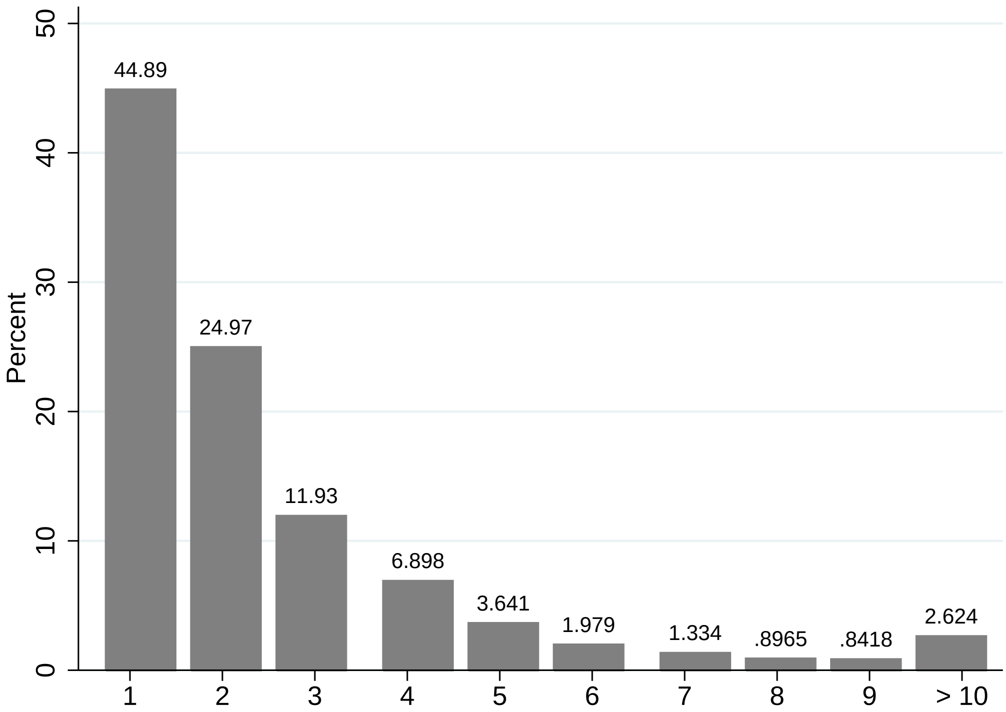


Table C.5: Descriptive statistics - emergency sample

	Obs	Mean	SD
Patient characteristics			
Distance traveled (in miles)	3,289	28.32	(10.6)
Age	3,289	83.1	(7.9)
Female (%)	3,289	70.5	(45.7)
Number of chronic conditions	3,289	6.3	(3.2)
Elixsum	3,289	3.5	(2.1)
Charlson Score	3,289	1.2	(1.6)
Length of stay	3,289	5.9	(3.5)
Median income (zipcode)	3,289	40.25	(18.4)
Provider characteristics			
Observed volume	136	2051.6	(1252.6)
Beds	136	296.6	(262.6)
Medicare percentage	136	42.4	(13.1)
Hip-Knee complication rate (%)	136	3.1	(0.58)
30-day readmission rate (%)	136	15.8	(0.98)
PSI 4	136	114.5	(19.4)
System member (%)	136	39.7	(49.0)
Non-profit hospital (%)	136	48.3	(50.0)

Obs = observations; SD = Standard deviation

Notes: Patient characteristics for patients choose provider between July 2012 & Dec. 2015

Table C.6: Comparison of marginal utilities for elective and emergency patients - including complication rate

	Est	SE
Elective patients:		
Hip-knee complication rate (%)	-0.445***	(0.0286)
30-day readmission rate (%)	-0.142***	(0.0178)
PSI 04 - death rate in 1000	-1.146	(0.875)
Distance (in miles)	-0.128***	(0.0172)
Distance^2	0.00119	(0.000791)
Distance^3	-0.0000136	(0.0000107)
Beds	0.00101***	(0.0000733)
Non-profit hospital	1.307***	(0.0444)
System member	-0.282***	(0.0350)
Distance (in miles) $\times$ AGE	-0.00207	(0.00161)
Distance (in miles) $\times$ income	-0.000836	(0.000594)
Distance (in miles) $\times$ elixsum	-0.00436	(0.00670)
Female $\times$ Distance (in miles)	-0.00445	(0.0216)
Emergency patients:		
Hip-knee complication rate (%)	0.669	(0.383)
30-day readmission rate (%)	0.242	(0.253)
PSI 04 - death rate in 1000	27.60*	(13.85)
Distance (in miles)	-0.256	(0.241)
Distance^2	0.0101	(0.0121)
Distance^3	-0.0000961	(0.000173)
Beds	0.000139	(0.000964)
System member	0.558	(0.508)
Non-profit hospital	-3.569***	(0.574)
Distance (in miles) $\times$ AGE	0.00190	(0.00317)
Distance (in miles) $\times$ income	0.00246	(0.00152)
Distance (in miles) $\times$ elixsum	-0.000118	(0.0127)
Female $\times$ Distance (in miles)	0.0481	(0.0528)
Log-likelihood	-26480.3	
N	183383	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.7: Estimated marginal utilities - including change in complication rate and interactions

	Est	SE
Change in Hip-Knee rate	-0.425***	(0.0583)
Change in Hip-Knee rate × AGE	-0.0189**	(0.00578)
Change in Hip-Knee rate × income	-0.00206	(0.00228)
Change in Hip-Knee rate × elixsum	0.135***	(0.0225)
female=1 × Change in Hip-Knee rate	0.0564	(0.0740)
Distance (in miles)	-0.131***	(0.0238)
Distance (in miles) × AGE	-0.00136	(0.00226)
Distance (in miles) × income	-0.00121	(0.000827)
Distance (in miles) × elixsum	-0.00620	(0.00923)
female=1 × Distance (in miles)	-0.0170	(0.0299)
Distance^2	0.00141	(0.00110)
Distance^2 × AGE	-0.0000367	(0.000106)
Distance^2 × income	0.0000626	(0.0000391)
Distance^2 × elixsum	-0.0000603	(0.000429)
female=1 × Distance^2	0.000682	(0.00139)
Distance^3	-0.0000191	(0.0000150)
Distance^3 × AGE	0.000000872	(0.00000146)
Distance^3 × income	-0.000000907	(0.000000544)
Distance^3 × elixsum	0.00000195	(0.00000584)
female=1 × Distance^3	-0.00000818	(0.0000188)
Log-likelihood	-11802.7	
N	79977	

Notes: Conditional logit model of choice of hospital for elective hip/knee replacement patients treated between July 2012 - December 2015. Quality metrics are published before the fiscal year. Coefficients are marginal utilities.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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