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Among the myriad of decisions involved in health care delivery, none are more important to medical outcomes than the interrelated choices by individual patients regarding treatment type and service provider. Because such choices are often complex and difficult, it is not surprising that many patients make sub-optimal decisions that lead to compromises in quality of life. We document a wide quality gap among thirty-five hospitals in New York State that perform mitral valve surgery, using distance based instruments to correct for potential selection bias in care allocation. We find that only 40% of New York patients choose to go to one of the six hospitals with quality superior to the state average. We define these six hospitals as Centers of Excellence (CoEs). If all patients from 2009-2012 had gone to the nearest CoE for their procedure, about 343 additional patients would have had their mitral valves repaired. This would have added 785 years of life expectancy and saved $4,593 in per patient lifetime care costs, in exchange for travelling an average of 10.9 miles further to get to a CoE. We find that the major barriers preventing patients from choosing the best quality care are: lack of information, travel cost and payer restrictions. We evaluate polices for removing these barriers to enable informed patient choice.

Key words: Health care, Hospital quality, Choice model, Information

1. Motivation

How to "fix health care" is one of the most hotly debated topics in all of American society. Academic articles, media programs, legislative debates and water cooler conversations are generating scores of recommendations on how to provide patients with better and more cost effective health care. The vast majority of these proposals, from reimbursement bundling and accountable care organizations to patient care paths and lean transformations, are aimed at changing health care delivery and/or payment. However, a widely overlooked reality is that better and cheaper health care is available right now within the American system. Unfortunately, many patients just can't find it.

To provide a sense of this opportunity, Table 1 summarizes the (risk adjusted) mortality rates for patients with six different medical conditions at a random sample of hospitals that constitutes 10% all US hospitals in 2011.[1] This comparison shows a substantial gap between the mortality rates in the top 20% and the bottom 20% of these hospitals. However, despite the obvious differences in mortality risks among hospitals, the proportion of patients who chose hospitals in the top quintile ranged from 3% to 35%. The majority of patients were treated in higher risk hospitals. Based on these data, we estimate that if all patients (including those not in this sample) with these six medical conditions had been treated at the top quintile of hospitals, roughly 22,000 lives would have been saved in a single year without making any improvements in the hospitals themselves.

Table 1 **Average Mortality Rates Between Top 20% And Bottom 20% Hospitals**

	Number of Patients	Number of Hospitals	Top 20%	Bottom 20%	Relative Gap
Heart Failure	105,470	617	1.7%	2.3%	42%
CABG	22,937	178	0.8%	1.4%	81%
Stroke	67,509	650	2.6%	3.7%	40%
Pneumonia	8,979	578	3.1%	5.0%	62%
Heart Attack	85,806	628	3.2%	4.7%	47%
Sepsis	33,323	612	6.3%	10.1%	60%

Note: Based on a 10% random sample of US Hospitals in 2011.

The simple analysis of Table 1 is only suggestive of the potential for better health care through better patient choice of hospital. Mortality rates are not the only, or even the best, measure of the quality of health care. Furthermore, it is not assured that the top hospitals have capacity to handle the other patients. And even if they did have the capacity, this simple calculation offers no guidance on what it would take to guide patients to hospitals with better records. To get a more accurate sense of what is possible and how it might be achieved, we need to delve into the details of a specific medical condition.

In this paper, we do this by focusing specifically on patients with mitral valve disease and addressing two main questions: (1) How much would patient outcomes improve if patients made better choices of hospitals in which to be treated, and (2) What policies would be most effective in inducing these better choices? Unfortunately, while simple to state, these questions are not straightforward to analyze using currently available data.

[1] The number of patients in the set for each condition ranged from 8,979 to 105,470 and the number of hospitals treating them ranged from 178 to 650.

To begin with, we need to characterize the performance of the hospitals that treat mitral valve patients. There are various consumer-oriented hospital rating systems that attempt to do this. For example, the Centers for Medicare and Medicaid Services maintain the Hospital Compare website that reports on over 4,000 Medicare-certified hospitals across the country with regard to quality of care, safety measures and patient satisfaction. Some states, such as New York, compile risk-adjusted mortality rates for individual hospitals and surgeons that perform cardiac surgery and share these via the web and through direct communications with cardiologists. Various non-profit organizations, including the Leapfrog Group, Consumer Reports and the California Health Care Foundation, and private companies such as US News and Health Grade, also share self-reported hospital quality information and rankings via websites.

While these sources provide useful information, they fall well short of providing the data mitral valve patients need to make accurate comparisons of hospitals because: (1) they generally do not report outcomes specifically for mitral valve patients, but instead aggregate ratings into broad categories such as heart surgery, cancer and general surgery, (2) they focus primarily on mortality rates (and sometimes complication or readmission rates), which are low probability events that do not characterize quality for most patients, (3) ratings often blend outcomes with measures of patient satisfaction, which makes it hard for patients to pick out the information that matters most to them, (4) most ratings do not indicate the magnitude of the difference between levels (e.g., between "two stars" and "three stars", or between "average" and "above average"), and (5) the ratings make use of inconsistent criteria and methods. Presumably because of these, a study by Austin et al. (2015), which compared the ratings of 844 hospitals by four national rating systems, found that no hospital was rated as a high performer by all four national rating systems and only 10% of the hospitals rated as a high performer by one rating system were rated as a high performer by any of the other rating systems.

To address these issues, we start by proposing the *mitral valve repair rate*, which is defined as the fraction of patients whose valves are successfully repaired, as a useful metric with which mitral valve patients can evaluate the quality of a hospital. As we will discuss later, repairing the mitral valve rather than replacing it offers patients longer life expectancy and better quality of life. Also, because a repaired valve leads to fewer complications, it also has lower lifetime costs than does a replaced valve. However, valve repair is a more difficult procedure than is valve replacement. So, while surgeons always prefer repair over replacement, they may be unable to effect a repair for a given patient and be forced to make a replacement instead. The best surgeons/hospitals are able to repair the valves of a higher fraction of patients. As such, the repair rate is a good measure of hospital quality in terms of both institutional skill and patient benefit.

However, because patients differ with respect to the complexity of their condition, we cannot use raw repair rate directly as the quality metric. Because the mix of patients may differ between hospitals (e.g., with some hospitals treating a higher proportion of complex patients), we must risk adjust the repair rate. Furthermore, since there may be unobserved differences in patient characteristics, we must also correct for a possible selection bias beyond those that can be controlled through simple risk adjustment.

Once we have done this, we can make fair comparisons between hospitals. This allows us to answer the first of our two questions by estimating the extent to which outcomes would improve if patients chose their hospital based on accurate quality metrics. Of course, it isn't reasonable to expect all patients to go to the single best surgeon or hospital, since this would create an impossible capacity imbalance. But, as we will show for the case of mitral valve surgery, it is still possible to achieve substantial improvements in outcomes without overloading any hospitals.

To address the second question of what policies are best suited to achieving these potential gains, we analyze the factors that influence current patient decisions. In general, research has shown that, in the absence of accurate, consistent information about quality, customers make use of other available clues (Zeithaml and Bitner, 1996). In the case of mitral valve surgery, we find that patients rely on proxies for quality (e.g., procedure volume, rankings, hospital advertising) and on convenience factors (e.g., proximity, payer network restrictions). The resulting statistical model gives us a basis for evaluating the potential effectiveness of various policy interventions in guiding patients to the best hospitals for them. These policies focus on improving information available to patients, mitigating distance-related costs and relaxing payer restriction.

Finally, in the case of mitral valve surgery, Wang et al. (2015) show that hospitals that are best from a patient outcome perspective are also most cost effective for the payer over the lifetime of the patient. This alignment of patient and payer incentives suggests that getting more patients to high quality hospitals should be feasible and, indeed, payers may be willing and able to serve as important catalysts to make this happen.

The remainder of the paper is organized as follows:

Section 2 reviews the relevant literature. Section 3 summarizes the empirical setting and the data used in our study. Specifically, we made use of discharge data for patients who underwent elective mitral valve surgeries across 35 hospitals in New York state from 2009-2012.

In Section 4 we evaluate hospital quality by constructing a distance-based instrumental variable, which correlates with the probability of choosing a hospital but not with patient characteristics (KC and Terwiesch, 2011). We find that the average repair rate of all NY hospitals is 58.3% with a standard deviation of 17.5% and six hospitals have mitral valve repair rates that are statistically significantly higher than the state average. We define these six hospitals as Centers of Excellence

(CoEs) and note that they are likely to have enough capacity to serve all of the mitral valve patients in New York. If all New York mitral valve patients from 2009-2012 had gone to the CoE nearest to them, the repair rate would have increased by 22%, the dollar value of additional quality adjusted life years per patient would have increased by $12,230 and payer savings per patient would have increased by $4,593.

In Section 5 we analyze patient choices by modeling patient utility as a function of patient benefit, distance-related cost and switching cost, where patient benefit is modelled as a function of patient demographics and available information used by patients as proxies for hospital quality. By constructing and fitting a choice model that is consistent with patients' revealed preferences, we describe how patient choices are influenced by available information, distance and switching cost. By analyzing this model and by comparing the choices of in-state patients with a better informed cohort of out-of-state patients who travelled from out of state to New York for treatment, we conclude that lack of information is the dominant barrier to optimal hospital choice.

In Section 6, we evaluate policy interventions, including improving information transparency, subsidizing travel costs, and relaxing payer restrictions, as means for guiding patients to the best hospitals for them. Using the benefits from the scenario in which all patients go to the CoE nearest to them as a practical upper limit on the impact of better routing of mitral valve patients, we find that subsidizing distance-related costs can achieve up to 29.2% of these benefits, relaxing payer restrictions can achieve up to 5.7%, and providing better quality information can achieve up to 65.1%.

The paper concludes with a summary and observations about future work needed to take advantage of the vast opportunity to improve health care through better patient routing.

2. Literature Review

A number of studies in the operations management literature have examined factors affecting health care quality. Some of these have focused on surgeon experience and its impact on surgical outcome. For example, KC and Staats (2012) investigated the differential effects of focal and related experience, and found that surgeon focal experience has a greater effect than related experience on surgeon performance. KC et al. (2013) examined how surgeons learn from their own and others' experiences, and found that individuals learn more from their own successes but others' failures. Ramdas et al. (2014) studied how learning and forgetting affects surgical outcomes by analyzing a surgeon's experience with specific surgical device versions and the time between their repeat uses. Other studies have analyzed the impact of workload on quality and patient outcome. For instance, Kim et al. (2015) examined the impact of ICU congestion on a patient's care pathway and the subsequent effect on patient outcomes, and found that the impact of ICU admission is highly variable for different patients and different outcomes. Jaeker and Tucker (2015) studied the relationship between workload and patient length of stay (LOS), and found that the effects of inpatient workload on LOS propogate across patient types. Freeman et al. (2015) show that gatekeeper providers (midwifes in their study) ration resource-intensive discretionary services and also increase the rate of specialist referrals when workload increases. In addition to surgeon experience and workload, queue management (Song et al., 2015) and secure messaging between patients and physicians via patient portals (Bavafa et al., 2013) have been found to affect productivity and patient outcome as well. However, none of these studies have compared quality among hospitals or studied the impact of the accessibility of hospital quality information on patient choice and outcomes.

In the medical field, there has been a growing interest in studying hospital quality since 1989 when the Agency for Health Care Policy and Research was created by Congress in response to a report of wide geographic variations in practice patterns among hospitals in US (Steinwachs and Hughes, 2008). In a seminal paper, Keeler et al. (1992) compared 297 US hospitals for congestive heart failure, acute myocardial infarction, pneumonia, stroke or hip replacement, and found that quality varied from state to state, but that quality was generally better in teaching, large, and urban hospitals than in non-teaching, small, and rural hospitals. Subsequent studies have also found that high-volume hospitals tend to perform better than low-volume hospitals (Birkmeyer et al., 2002, Gammie et al., 2009, Vassileva et al., 2012). However, since patients are not randomly assigned to hospitals, these studies are subject to a potential selection issue if there are unobservable patient characteristics that affect health outcomes and correlate with hospital characteristics (e.g., hospital volume).

Previous research has found that hospital quality (or proxies for hospital quality) is a key consideration in patient choice. Using Medicare claims data from all patients over 65 who suffered from heart attack, Tay (2003) estimated a random-coefficient discrete choice model that predicts patient flow to different hospitals and found that a hospital's demand is correlated with its input measures (e.g., number of nurses per bed, the range of specialized services offered, teaching status and hospital size) and outcome measures (e.g., one-year mortality and complication rates). Howard (2006) used a data set of patient registrations for kidney transplantation in conjunction with a mixed logit model to gauge consumers' responsiveness to quality (i.e., reported graft failure rate) when choosing hospitals, and found that patients care about hospital quality, which in turn leads insurers to consider hospital quality when contracting with providers. Varkevisser et al. (2012) studied the relationship between hospital quality (measured by publicly available quality ratings) and patients' hospital choice for angioplasty, and found that patients prefer hospitals with a good reputation (both overall and for cardiology) and a low readmission rate for treatment of heart failure. Although these studies have considered quality, the quality metrics may not align well with actual outcome probabilities due to either a lack of correlation with the patient's specific needs or selection bias.

Studies have examined the role in patient choice of other hospital characteristics in addition to quality. Dixon et al. (2010) looked at revealed preference data on the characteristics of the chosen hospitals, and found that the most important factors patients consider are cleanliness, quality of care and the standard of facilities. Victoor et al. (2012) carried out a literature survey and found that American patients prefer private, non-profit hospitals to public and commercial ones. They also found that patients generally prefer clean hospitals with complex, high-quality service, but that the data were unclear on whether patients prefer teaching hospitals and large hospitals.

A particularly important factor in patient choice is distance. Because patients are loyal to their local hospital and it is costly (economically and psychologically) to travel to a distant hospital, it is not surprising that many studies have found that patients are averse to travel and prefer nearby hospitals to distant ones. The extent to which patients are averse to travelling depends on their own characteristics; for example, young patients, those with high education and those with a car are less averse to travel (Finlayson et al., 1999, Haynes, et al., 2003 and Dijs-Elsinga, et al., 2010).

3. Empirical Setting and Data

We choose mitral valve surgery as the empirical setting for our analysis of hospital quality and patient choice for several reasons. First, mitral valve disease is the most common form of heart valve disease in US. It affects 5% of the population and results in over 500,000 hospital admissions per year.[2] Second, mitral valve repair is a relatively new and complicated procedure. Because of the high level of skill required, hospitals and surgeons may differ in their outcomes, implying that choice of provider matters. Third, there are many extant medical studies that provide data on the clinical options available to mitral valve patients.

3.1. Mitral Valve Disease

The mitral valve is located between the left chambers of the heart. Its main function is to allow blood to flow from the left atrium to the left ventricle but not in the other direction. Mitral valve disease refers to conditions that compromise the ability of the mitral valve to seal against backflow of blood.

There are two clinical options for the correction of mitral valve disease — mitral valve repair and mitral valve replacement. Mitral valve repair restores the function of the original valve, and is therefore the preferred option. But a repair requires a higher level of surgical skills to perform than does a replacement. When a repair cannot be done, either because the valve is damaged beyond repair or the surgeon lacks the requisite skill, a replacement is done with either a biological valve (from a cow or pig) or a mechanical valve (made of special carbon compounds and titanium). The

[2] http://heartvalvedisease.nm.org/mitral-valve-disease.html

risks of mortality and complications associated with these procedures are summarized in Table 2 (Dumont et al., 2007, Russo et al., 2008, Daneshmand, et al., 2010). These confirm that mitral valve repair is clinically superior to mitral valve replacement.

Table 2 Comparison of Clinical Options for Mitral Valve Surgery

Risks and Complications	Mechanical Replacement	Biological Replacement	Mitral Valve Repair
Operative Mortality	Medium	High	Low
Long-term Mortality	High	High	Low
Risk of Stroke	High	Medium	Low
Risk of Reoperation	Medium	High	Low

3.2. Data Description

We used data from New York state that describe 10 million in- and out-patient discharges from all hospitals in New York from 2009-2012. These data contain patient-level clinical and resource-use information, including admission status, patient demographics and comorbidities, hospital name, principal and secondary diagnoses and procedures. For each discharge, the data indicate whether a patient received a mitral valve repair or replacement. The data also include 5-digit zip codes of patients' home and hospital addresses, which allow us to estimate the Euclidian distance from each patient's home to their hospital. Finally, this data set includes all in- and out-patient visits, which enables us to determine whether a patient has had a prior interaction with the hospital chosen for mitral valve treatment.

We also used data on hospital characteristics from the American Hospital Association. These include detailed hospital-level information such as hospital ownership and teaching status. We supplemented this with data on hospital advertising spending from a leading media and market research company. These data include each hospital's annual spending on syndication, TVs and magazines. Finally, we made use of hospital rankings from US News,[3] which ranks hospitals in 16 specialities based on hospital structure (e.g., hospital volume, technology and other resources), process (determined by a hospital's reputation for developing and sustaining a system that delivers high-quality care) and outcome (e.g., risk adjusted mortality). A hospital is nationally ranked in Cardiology & Heart Surgery if it is within the top 50 in this speciality.

[3] http://health.usnews.com/best-hospitals/rankings

3.3. Data Preparation

We identified discharges related to mitral valve surgery by using the clinical codes 35.12, 35.23 and 35.24 in the International Classification of Disease (9th revision). To focus on isolated mitral valve surgery, we excluded patients who were less than 30 years old, had coronary revascularization, congenital heart disease, excision of ventricular aneurysm, replacement of thoracic aorta, aortic fenestration procedure, closed heart valvuloplasty, heart transplant, or other valvular repair or replacement (Vassileva et al., 2012).

We identified hospitals that perform mitral valve surgery by analyzing their related discharges from 2009-2012. The annual mitral volume of most hospital was quite stable over our study period. However, one hospital was shut down in 2011 and three hospitals had less than 10 mitral valve surgeries from 2009-2012. We excluded patients who were treated in these hospitals due to the low volume. We also excluded patients whose admission type or race was not indicated and patients who are Native Americans (due to the low volume). To study patient choices, we focused on elective patients only, as opposed to emergent or urgent patients whose choice of hospital may be constrained (Batt and Terwiesch, 2015). An elective patient can wait for a year or more from diagnosis to treatment (Carroll et al., 1995), which provides ample time to consider the choice of hospital.

For the majority of our analyses, we focused on New York patients who were treated in New York hospitals. However, at the end of this paper, we describe a comparison of New York patients with patients who travelled from other states to New York City. We do not directly observe New York residents who were treated outside New York.[4] This is unlikely to cause a sampling concern in our context because New York has 4 out of the 50 nationally ranked heart programs. If a patient decides to seek a better hospital than those available locally, the best hospitals in New York are comparable to the best hospitals in the country.

3.4. Summary of Hospital and Patient Characteristic

There are 35 hospitals that performed mitral valve surgeries in New York from 2009-2012, whose characteristics are summarized in Table 3. Of these, 21 (or 60%) are teaching hospitals, 30 (86%) are private hospitals, and 5 (14%) were nationally ranked by US News in 2014. Hospitals spent an average of $5 million on advertising between 2008 and 2012. Of the 35 hospitals, 13 (37%) spent less than $1 million, 11 (31.5%) spent between $1 and $5 million, and 11 (31.5%) spent more than $5 million. Hospitals performed an average of 43 mitral valve surgeries per year across all emergent, urgent and elective patients. But volumes varied greatly, with half of the hospitals performing less than 25 per year, one quarter performing between 25 and 50 per year, and one quarter performing more than 50 surgeries per year.

[4] Although many others states in the US make their inpatient and outpatient discharge data available, most of them do not contain patient-level zip code information. As we anticipate and will show in this paper, distance is a significant

Table 3 Summary of Hospital Characteristic

	Hospitals (%)	Patients Admitted (%)	Unadjusted Repair Rate mean	s.d.
Teaching Status				
teaching	60%	65%	56.9%	49.5%
non-teaching	40%	35%	58.1%	49.4%
Ownership				
private	86%	95%	56.7%	49.6%
government	14%	5%	67.6%	47.0%
US News Ranking				
ranked	14%	38%	66.4%	47.3%
not-ranked	86%	62%	51.7%	50.0%
Advertising (,000)				
below 1000	38%	12%	50.5%	50.1%
1000 to 5000	31%	31%	59.4%	49.1%
above 5000	31%	58%	57.6%	49.4%
Volume/yr				
below 25	54%	21%	49.1%	50.0%
25 to 50	23%	24%	52.0%	50.0%
above 50	23%	55%	62.7%	48.4%
Total	35	2718	57.3%	49.5%

Our sample of New York residents who underwent elective mitral valve surgery at a New York hospital between 2009 and 2012 included 2,718 people. Table 4 summarizes their characteristics. These data show that the average travel distance is longer for patients under 60 than for older patients. This may be because younger patients are better able to travel. But patients over 80 travelled on average further than patients in their 60s and 70s. This could be because their medical condition is too delicate for a local hospital to handle. Presumably, for similar reasons, the percentage of patients who switched to a new hospital was higher for those under 60 or over 80 than those in their 60s and 70s. The average travel distance was 18.4 miles for female patients and 19.6 miles for male patients with white patients travelling further than non-white patients. For both female and male patients, 66% switched to a new hospital with more white patients than non-white patients switching to a new hospital. Patients with private insurance or self pay were also more likely to travel further and switch to a new hospital than were patients with HMO or Medicare/Medicaid coverage.

4. Hospital Quality

While it is incontrovertible that hospitals differ with regard to quality, the size and significance of the quality gap is unknown. Estimation of true hospital quality can be challenging for several reasons. First, each hospital admits a different mix of patients. What may look like a hospital

factor affecting choices. However, we cannot actually estimate distances to out-of-state hospitals without patient-level zip code information.

Table 4 Summary of Patient Characteristic

	Patients	Distance Travelled		Switched Hosp	
	(%)	mean	s.d.	mean	s.d.
Age (mean 65)					
below 50	12%	19.2	29.0	73%	44%
50 to 60	22%	22.1	29.2	70%	46%
60 to 70	27%	17.5	25.9	65%	48%
70 to 80	27%	17.3	22.4	60%	49%
above 80	13%	18.8	21.9	68%	47%
Gender					
female	45%	18.4	26.8	66%	47%
male	55%	19.6	25.9	66%	47%
Race					
white	73%	21.4	27.8	65%	48%
black	8%	7.6	19.3	56%	50%
hispanic	5%	7.7	16.6	55%	50%
asian	2%	9.0	9.8	53%	50%
others	13%	18.3	22.1	84%	37%
Payer					
blue cross	17%	24.3	29.7	74%	44%
commercial	5%	29.0	30.7	80%	40%
medicaid	2%	19.9	41.3	59%	50%
medicaid hmo	5%	7.4	9.7	57%	50%
medicare	35%	18.9	24.1	62%	49%
medicare hmo	16%	13.4	18.9	57%	50%
other hmo	17%	19.6	29.8	73%	44%
self-pay	1%	20.0	22.5	86%	35%
other payers	2%	22.8	34.5	71%	46%
Total	2718	19.0	26.3	66%	47%

effect could be due to the hospital treating healthier or sicker patients. Second, even if we control for patient demographics and common comorbidities, there are usually conditions (e.g., test result details) that medical professionals and/or patients themselves can observe but we cannot, which may affect both hospital selection and clinical outcome. Third, there may be insufficient data to discern statistically significant gaps in quality between hospitals. This is particularly a problem for quality metrics that measure rare events. In this section, we evaluate hospital outcomes for mitral valve surgery and quantify the quality gap using repair rate as the quality measure, while controlling for patient risk factors and adjusting for the potential selection bias. In subsequent sections, we use this risk-adjusted and unbiased measure of quality to quantify the sub-optimality of patient choices and to assess policies for guiding patients to better medical care.

4.1. Mitral Valve Repair Rate

Repair rate is a good quality metric from a patient standpoint, because repairing the mitral valve avoids the negative consequences associated with replacement valves. Mechanical valves tend to cause blood clotting, which can lead to strokes, and so patients need to take anticoagulation drugs (blood thinners), which can cause bleeding problems, for life. Biological valves do not pose a blood clotting risk, but they are less durable, which increases the risk of re-operation. In addition to avoiding these problems, mitral valve repair has lower operative risk (Gammie et al., 2009). It also leads to lower risk of complication and cheaper costs (LaPar et al., 2010), better long-term survival (Daneshmand et al., 2009, Vassileva et al., 2013). For these reasons, the medical literature advocates mitral valve repair for nearly all mitral pathologies and all patient age groups. However, not all mitral valve patients are able to receive repair as it involves a more complex surgical procedure than replacement, which requires superior skills from the medical team to repair a valve.[5]

Using repair rate as a measure of mitral valve treatment also has advantages from an analysis standpoint over more commonly used metrics like mortality rate, complication rate, and readmission rate. First, unlike mortality, repair is not a rare event, and hence lends higher statistical power. The average observed operative mortality rate for mitral valve procedures in the U.S. was 0.24% - 2.48% from 2008 to 2012 (Wang et al. 2015), while the average observed repair rate was 57% - 61% in the same time period. Second, the clinical definition of a repair is completely objective, which is not the case for complications. For example, it can be difficult to distinguish hospital-acquired complications from present-on-admission complications (Bastani, Goh and Bayati, 2015). Third, repair rate is a more comprehensive measure of total quality because repair rate has been shown to be associated with both better short-term outcomes (operative mortality, procedure related re-operation, short-term complication) and long term outcomes (long-term complication and survival), while other common measures (mortality rate, complication rate, and 30-day readmission rate) are all short-term measures of quality.

4.2. Factors Affecting Repair Rate

Although patients almost always prefer mitral valve repair over replacement, not all valves can be repaired. The repairability of a mitral valve is affected by patient demographics and comorbidities. Bolling et al. (2010) and Vassileva et al. (2013) separately found that younger and elective patients are more likely to receive a repair, whereas females are less likely to receive a repair. Presence of certain comorbidities also affects the likelihood of mitral valve repair. Savage et al. (2003), Daneshmand et al. (2009), and Vassileva et al. (2013) found that presence of atrial fibrillation, chronic obstructive pulmonary disease, diabetes, heart failure, renal disease and hypertension reduces the likelihood of mitral valve repair.

Of more direct interest to us in this study is the impact of hospital choice on the likelihood of a repair. Presumably a hospital with more skilled surgeons, more experienced support teams, and an organizational structure that promotes learning and quality improvement will have a higher repair rate than will hospitals without these assets. Unfortunately, these are not generally observable, so

[5] http://my.clevelandclinic.org/services/heart/disorders/valvetreatment/mitral-valve-repair

patients and researchers alike must rely on proxies to gauge the hospital effect on quality. One of the most common proxies is volume. Birkmeyer et al. (2002) studied the relationship between hospital volume and mortality of 14 different types of cardiovascular and cancer procedures (including mitral valve surgery) by studying 2.5 million Medicare patients who underwent one of the 14 high-risk surgical procedures from 1994 to 1999, and found that mortality rate decreases as volume increases. Gammie et al. (2009), Vassileva et al. (2012) and Vassileva et al. (2013) all found that mitral valve repair rate increases as a function of a hospital's mitral volume. There are two mechanisms by which volume promotes quality: (1) practice helps surgeons and support teams maintain or improve their skills, and (2) scale justifies investment in advanced technology and equipment. Because of the documented relationship between hospital volume and quality, we include mitral volume in our hospital quality model.

We use hospital volume instead of surgeon volume for several reasons. First, the distribution of mitral volume by surgeon is skewed with majority of surgeons performing less than 10 mitral valve surgeries per year, which significantly impacts the statistical power of quality measures at surgeon level. Second, prior literature suggests that for high-risk procedures such as cancer and cardiac surgery, hospitals have a strong impact on surgical quality and so surgeon performance is not fully portable across hospitals (Pisano et al., 2001, Schrag et al., 2003, Huckman and Pisano, 2006). Third, high performance surgeons are typically found in high performance hospitals due to selection and peer learning (KC et al., 2013). Lastly, from the policy maker's standpoint, guiding patients to institutions is more feasible and sustainable than to individual surgeons.

To allow for unobserved factors beyond those characterized by volume, we include hospital fixed effects via dummy variables in our model. However, we do this only for hospitals with at least 50 mitral valve surgeries per year because observed effects for smaller hospitals are unlikely to be statistically significant or scalable to higher volumes.

4.3. Hospital Quality Model

We let Y_{ij}^* be a latent variable, representing repair propensity of patient i at hospital j, which we model as follows:

$$\begin{aligned} Y_{ij}^* = {} & \gamma_0 + \gamma_1 Age_i + \gamma_2 Gender_i + \gamma_3 Race_i + \gamma_4 Comorb_i \\ & + \gamma_5 HospVol_j + \gamma_6 HospDum_j + \epsilon_{ij} \end{aligned}$$

We cannot observe Y_{ij}^*, but instead observe whether patient i received mitral valve repair at hospital j. Letting Y_{ij} be a binary variable indicating the outcome, where $Y_{ij} = 1$ indicates repair and $Y_{ij} = 0$ indicates replacement, we define

$$Y_{ij} = \mathbf{1}\{Y_{ij}^* > 0\} \tag{1}$$

We assume that the error term ϵ_{ij} follows a standard normal distribution, which allows us to estimate the probability of repair using a Probit model.

4.4. Instrumental Variable Approach

If patients were randomly assigned to hospitals, or if we could control for all patient characteristics that affect medical outcome, we could use observed repair rate as a direct indictor of quality. Unfortunately, this simple approach is not valid because patients may select hospitals on the basis of unobserved factors (e.g., a patient is referred to a particular hospital by his/her cardiologist because information from the echocardiogram suggests they are a complex case). Consequently, even after risk adjustment using observed patient characteristics, observed repair rate may be distorted by selection bias.

Because the medical literature and hospital rating systems (such as that of the Leapfrog Group) suggest that hospital volume is a good indicator of hospital quality, it is likely that patients make choices based on hospital volume instead of other hospital characteristics. Therefore, the selection bias is mainly related to hospital volume, and therefore, after controlling for hospital volume, potential endogeneity of hospital dummy variables should be of minimal concern in this study.

The instrumental variable (IV) method can be used to estimate a causal relationship when selection bias may be present. There are two requirements for a good IV: (1) it must correlate with the endogenous explanatory variable (i.e., hospitals' mitral volume in our study), and (2) it cannot correlate with the error term (i.e., unobservable patient characteristics).

Previous studies have used distance from a patient's home to the hospital as an instrumental variable to study medical outcomes. For example, McClellan et al. (1994) used distance as an IV to evaluate whether more intensive treatment of acute myocardial infarction helps the elderly reduce mortality. Brooks et al. (2006) used distance as an IV to study the effect of dialysis status on survival. McConnell et al. (2005) and Pracht et al. (2007) used distance as an IV to study treatment outcomes at different trauma centers. Distance is a good instrument for our purposes because it is correlated with the likelihood of choosing a hospital. That is, the closer a hospital is to a patient's home, the more likely it will be chosen. At the same time, it is unlikely to be correlated with remaining unobserved characteristics after controlling for demographics (gender, race, and age) and common comorbidities.

Any function of distance will also meet the two requirements mentioned above and so can serve a valid IV. KC and Terwiesch (2011) used patient's propensity to choose a focused hospital as an IV to study whether focused hospitals have lower mortality and shorter length of stay. In their study, a patient has a choice set of hospitals, each of which has a degree of focus. They first calculated the probability of a patient going to each hospital based on distance only, and then used this probability as a weight to calculate the patient's propensity for a focused hospital.

We use a similar approach in this study. First, we estimate the probability of patient i going to hospital j (denoted as p_{ij}) as a function of distance using a multinomial logit model. We then use this probability as a weight to calculate patient i's propensity to choose a high-volume hospital (denoted as $PropVol_i$) as follows

$$PropVol_i = \sum_{j \in H_i} HospVol_{ij} \times p_{ij}$$

where $HospVol_{ij}$ is hospital j's mitral volume and H_i is patient i's choice set. Note that due to the nonlinearity of the Probit model, the standard two-stage least squares (2SLS) method cannot be used as explained in Amemiya (1990). Therefore, to estimate parameters of a probit model with an instrumental variable, we use the maximum-likelihood estimation approach discussed by Wooldridge (2002).

4.5. Results on Hospital Quality

To determine whether patients with certain characteristics select high-volume hospitals, we regress hospital mitral volume on patient demographics and comorbidities. The results are shown in Table 5 (left). These show that high-volume hospitals admitted more Hispanic patients and fewer Asian patients. High-volume hospitals also admitted more patients with atrial fibrillation, deficiency anemias, chronic heart failure, fluid and electrolyte disorders, and neurological disorders, and admitted fewer patients with chronic heart failure, chronic lung disease, coagulopathy, and hypertension. Because it is possible that correlations between hospital volume and patient demographics/comorbidities are driven by where patients live, we also ran the regression with travel distance as an explanatory variable. Table 5 shows that this does not alter the main results, suggesting that the correlations are not distance driven. However, the statistically significant coefficients of several of these variables indicate a potential selection issue. Although we control for these variables in our quality model, there could be other unobservable patient characteristics that correlate with hospital volume. If these patient characteristics also affect the probability of mitral valve repair, a simple probit model may yield a biased effect of hospital volume on outcomes due to the confounding effect of patient selection. To control for this, we make use of a distance-based instrumental variable.

For distance to be an effective instrument, we need it to correlate with the choice of a high volume (and hence, statistically, a high quality) hospital, but not to correlate with unobserved patient characteristics. To check, we define high-volume hospitals as those with more than 70 mitral valve surgeries per year. In our sample, 7 of the 35 hospitals meet this definition, and collectively admitted about half of the patients. Table 6 compares patients who live within 5 miles, between 5 and 30 miles and more than 30 miles from a high-volume hospital in terms of their choice of a

Table 5 Relationship Between Hospital Volume and Patient Characteristic

	Without Distance		With Distance	
	Coefficient	Standard Error	Coefficient	Standard Error
Patient Demographics				
age	−0.001	0.001	0.000	0.001
female	−0.032	0.034	−0.030	0.034
black	0.045	0.066	0.101	0.066
hispanic	0.181**	0.076	0.236***	0.076
asian	−0.292**	0.121	−0.239**	0.120
others	0.474***	0.051	0.486***	0.051
Existence of Comorbidities				
cm_af	0.070**	0.035	0.065*	0.034
cm_alcohol	0.107	0.125	0.123	0.124
cm_anemdef	0.164***	0.050	0.161***	0.050
cm_arth	0.109	0.114	0.110	0.113
cm_bldloss	−0.359	0.241	−0.429*	0.240
cm_chf	0.488**	0.249	0.510**	0.247
cm_chrnlung	−0.118***	0.045	−0.109**	0.045
cm_coag	−0.139***	0.038	−0.132***	0.038
cm_depress	−0.086	0.067	−0.090	0.066
cm_dm_all	−0.028	0.047	−0.025	0.046
cm_drug	−0.070	0.161	−0.050	0.160
cm_htn_c	−0.108***	0.035	−0.103***	0.035
cm_hypothy	0.001	0.059	0.002	0.059
cm_liver	0.134	0.140	0.130	0.139
cm_lymph	−0.164	0.196	−0.170	0.195
cm_lytes	0.318***	0.036	0.319***	0.036
cm_mets	0.694*	0.388	0.715*	0.386
cm_neuro	0.223**	0.093	0.206**	0.092
cm_obese	−0.122*	0.065	−0.128**	0.065
cm_para	−0.175	0.141	−0.149	0.140
cm_perivasc	0.133*	0.071	0.128*	0.070
cm_psych	−0.221	0.168	−0.224	0.167
cm_pulmcirc	0.213	0.400	0.245	0.398
cm_renlfail	0.033	0.058	0.032	0.058
cm_tumor	−0.150	0.224	−0.127	0.223
cm_valve	−0.305	0.276	−0.281	0.274
cm_wghtloss	−0.080	0.083	−0.098	0.083
Distance			0.004***	0.001
Constant	4.087***	0.094	3.959***	0.096

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

high-volume hospital, age, number of chronic conditions and number of comorbidities. We see that 74% of patients chose a high-volume hospital when the distance was within 5 miles and only 27% of patients chose a high-volume hospital when the distance was more than 30 miles. We also see that the average age, number of chronic conditions and number of comorbidities are almost the same for these three groups of patients. These results suggest that distance, or any function of distance, is a good instrument for our study.

Table 7 (left) summarizes the results from the hospital quality model using the distance-based instrumental variable (IV). Mitral volume refers to the average number of mitral valve surgeries a

Table 6 Relationship Between Distance, Patients' Choice of High-Volume Hospital and Patient Characteristics

Distance (in miles)	Number of Patients	Choice of High-Volume Hospitals	Patients' Mean Age	Number of Chronic Conditions	Number of Comorbidities
below 5	499	74%	65.6 (12.8)	6.4 (2.7)	2.2 (1.5)
5 to 30	1274	60%	64.7 (12.9)	6.5 (2.5)	2.2 (1.4)
above 30	945	27%	64.9 (12.2)	6.7 (2.6)	2.3 (1.5)
Total	2718	51%	64.9 (12.7)	6.5 (2.6)	2.2 (1.5)

Note: High-volume hospitals are those with more than 70 surgeries per year.
Standard deviations are displayed in parentheses.

hospital performed from 2009-2012. Variables *hospdum1* to *hospdum10* are dummies for hospitals that performed more than 50 mitral valve surgeries per year. We group hospitals with fewer than 50 mitral valve surgeries per year and use one dummy to indicate these hospitals as a control group for reasons noted previously. From Table 7, we see that mitral valve repair rate increases in hospital mitral volume with a 90% confidence interval. However, three of the high-volume hospitals, those with indexes 3, 6 and 9, have significantly negative coefficients, indicating negative fixed effects for these hospitals.

From Table 7, we also see that repair rate is lower for patients with certain characteristics. Not surprisingly, repair rate decreases as patient age increases. Compared with male patients, female patients are less likely to receive mitral valve repair. Compared with white patients, patients of black and Hispanic races are less likely to receive mitral valve repair. Finally, the mitral valve repair rate is lower for patients with comorbidities of atrial fibrillation, chronic lung disease, coagulopathy, diabetes, obesity or renal disease. These results are consistent with those of previous studies (see for example, Bolling et al., 2010 and Vassileva et al., 2013).

We compare our model (with an IV) with the corresponding model with no IV (Table 7, right). This results in different coefficients for hospital volume and the hospital dummies. However, we cannot compare the coefficients of *ln(volume)* directly to study the impact of hospital volume, because the probit model we used to study hospital quality model is nonlinear. So, we calculate the marginal effect of hospital volume in the two models. This shows that the average marginal effect of hospital volume in the model with an IV (0.447) is larger than that in the model without an IV (0.156). These results indicate that a higher percentage of sicker patients selected high-volume hospitals, which means that failure to control for selection bias would have underestimated the quality gap between high-volume and low-volume hospitals.

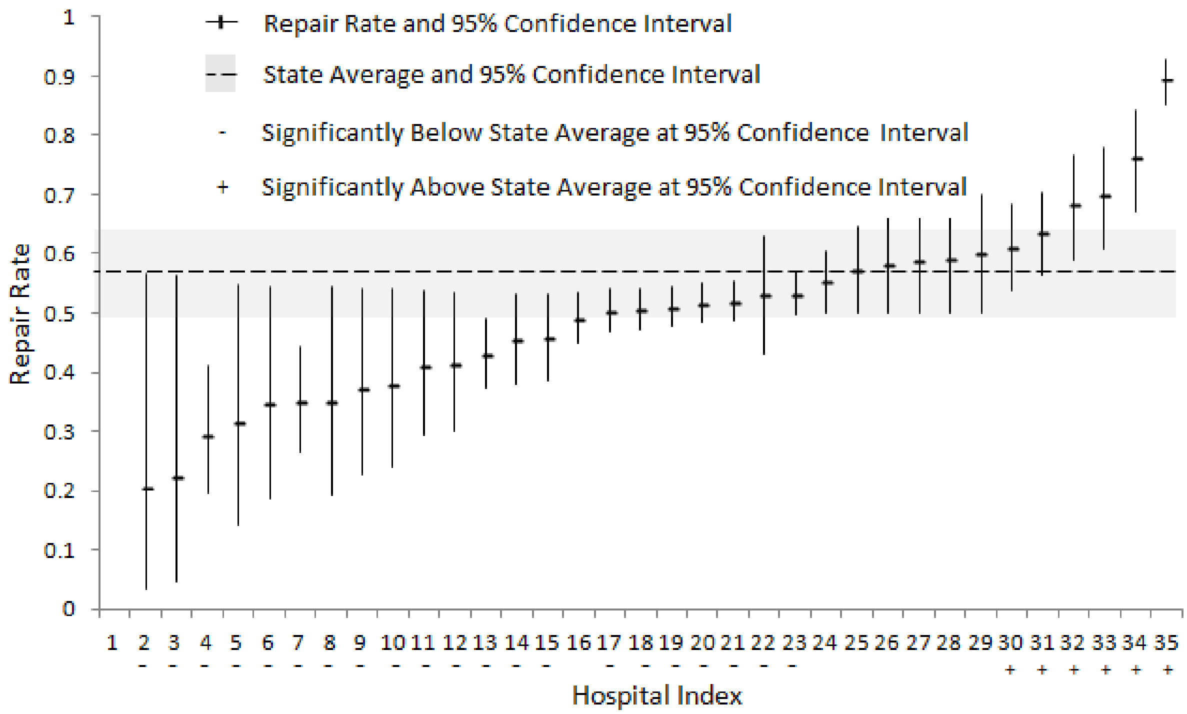
Figure 1 shows the average mix and selection bias adjusted repair rates with 95% confidence interval of each hospital. This shows that the average adjusted repair rate across all hospitals is around 58%. The hospitals with indices 2-15 and 17-23 had repair rates significantly lower than this average. Eight hospitals had repair rates that are not significantly different from the average.

Table 7 Mitral Valve Repair Rate

	With IV		Without IV	
	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Volume				
ln(volume)	0.447*	0.263	0.474***	0.088
Hospital Dummies				
hospdum1	0.304	0.546	0.248	0.211
hospdum2	−0.541	0.477	−0.589***	0.189
hospdum3	−1.182**	0.579	−1.241***	0.211
hospdum4	−0.306	0.372	−0.343**	0.158
hospdum5	0.119	0.349	0.086	0.182
hospdum6	−0.959***	0.333	−0.991***	0.166
hospdum7	−0.456	0.323	−0.486***	0.169
hospdum8	0.073	0.284	0.047	0.159
hospdum9	−0.899***	0.244	−0.918***	0.177
hospdum10	0.132	0.229	0.113	0.149
Patient Demographics				
age	−0.020***	0.002	−0.020***	0.002
female	−0.287***	0.054	−0.287***	0.054
black	−0.265**	0.105	−0.264**	0.105
hispanic	−0.439***	0.125	−0.437***	0.125
asian	−0.305	0.207	−0.300	0.201
others	0.083	0.092	0.084	0.092
Existence of Comorbidities				
cm_af	−0.135**	0.055	−0.135**	0.054
cm_alcohol	0.231	0.206	0.232	0.206
cm_anemdef	0.070	0.083	0.070	0.083
cm_arth	−0.232	0.176	−0.232	0.176
cm_bldloss	0.006	0.401	0.006	0.401
cm_chf	0.001	0.401	0.000	0.401
cm_chrnlung	−0.235***	0.070	−0.235***	0.070
cm_coag	−0.158***	0.061	−0.159***	0.060
cm_depress	0.039	0.106	0.038	0.106
cm_dm_all	−0.145**	0.072	−0.144**	0.072
cm_drug	0.010	0.258	0.010	0.258
cm_htn_c	0.068	0.056	0.068	0.056
cm_hypothy	0.061	0.091	0.061	0.091
cm_liver	−0.140	0.215	−0.142	0.214
cm_lymph	−0.161	0.304	−0.163	0.304
cm_lytes	0.052	0.062	0.050	0.060
cm_mets	−0.497	0.654	−0.499	0.654
cm_neuro	0.104	0.146	0.104	0.146
cm_obese	−0.220**	0.102	−0.221**	0.101
cm_para	−0.080	0.219	−0.078	0.218
cm_perivasc	−0.003	0.108	−0.004	0.108
cm_psych	−0.356	0.252	−0.355	0.252
cm_pulmcirc	−0.328	0.671	−0.325	0.670
cm_renlfail	−0.291***	0.090	−0.291***	0.090
cm_tumor	−0.173	0.339	−0.174	0.339
cm_valve	−0.566	0.432	−0.564	0.432
cm_wghtloss	−0.176	0.134	−0.177	0.134
Constant	0.284	0.840	0.198	0.314

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1 Mitral Valve Repair Rate by Hospital



For hospitals with indexes 1 and 16, this insignificance is partly due to their small sample size.[6] The hospitals with indices 30-35 have repair rates that are significantly higher than the average. All six of these hospitals performed more than 100 mitral valve surgeries per year. We deem these six hospitals Centers of Excellence (CoEs). Figure 2 shows risk- and selection-adjusted repair rates are remarkably different from unadjusted repair rates.

5. Patient Choice

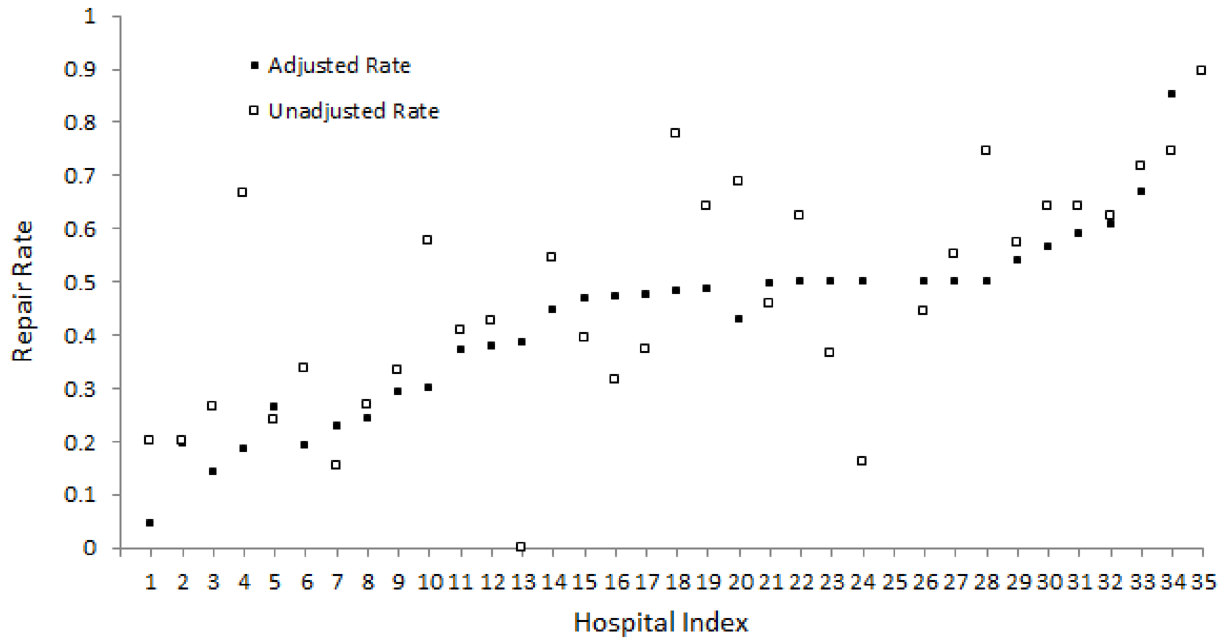
We use a multinomial logit model to analyze factors that influence patients' choice of hospitals. We model patients' utility as a function of perceived benefit, distance-related cost and switching cost, where patient benefit is modelled as a function of available quality information, distance-related cost is modelled as a function of travel distance, and switching cost is modelled as a function of whether a patient has previously visited the hospital.

5.1. Patient Benefit

Because patients and their physicians do not have complete information about hospital quality in mitral valve surgeries, they must rely on proxies. Hospital websites and public quality report cards are sources from which patients can calculate unadjusted repair rates. While they can be used as proxies, these unadjusted repair rates differ from the true repair rates we discussed in the

[6] Hospital with index 1 did not have elective cases, so we could not predict its mitral valve repair rate.

Figure 2 Adjusted vs. Unadjusted Repair Rate by Hospital



previous section because they do not correct for patient mix. Since some patients may rely more than others on unadjusted repair rate, we are also interested in the interaction of unadjusted repair rate with patient demographics such as age, gender and race and common comorbidities such as atrial fibrillation, chronic obstructive pulmonary disease, diabetes, heart failure, renal disease and hypertension.

Hospital volume is another proxy for quality. Some sites, such as LeapFrog, explicitly predict outcome quality based on hospital volume.[7] Another quality proxy, word-of-mouth referral, is also correlated with volume because large hospitals have more patients to talk about them. Other available indicators of quality include hospital type (teaching vs. non-teaching, governmental vs. non-governmental), hospital advertising and ratings (e.g., US News).

To capture the various indicators of quality used by patients in choosing a hospital for mitral valve surgery, we model the benefit patient i would get from hospital j as:

$$\begin{aligned} PatBenefit_{ij} = {} & \alpha_0 + \alpha_1 UnadjRate_j + \alpha_2 Age_i UnadjRate_j + \alpha_3 Gender_i UnadjRate_j \\ & + \alpha_4 Race_i UnadjRate_j + \alpha_5 Comorb_i UnadjRate_j + \alpha_6 HospVol_j \\ & + \alpha_7 HospTeach_j + \alpha_8 HospGov_j + \alpha_9 HospAdv_j + \alpha_{10} HospRank_j + \epsilon_{ij} \end{aligned}$$

where the variables are defined as:

[7] http://www.leapfroggroup.org/media/file/Leapfrog-Evidence-based_Hospital_Referral_Fact_Sheet.pdf

Age : patient's actual age minus the mean age of all the patients (around 65);

Gender : equals 1 for a male patient, and 0 for a female patient;

Race : includes white (baseline), black, Asian, Hispanic and other;

Comorb : includes no common comorbidities (baseline), atrial fibrillation, chronic obstructive pulmonary disease, diabetes, heart failure, renal disease and hypertension;

HospVol : a hospital's average mitral volume per year from 2009-2012;

HospTeach : equals 1 if it is a major teaching hospital and 0 otherwise;

HospAdv : the total amount a hospital spent on advertising from 2008-2012;

HospRank : equals 1 if a hospital is nationally ranked according to 2014 US News.

5.2. Distance-related Cost

Travel to a distant hospital is costly in both time and money. Direct costs may include auto mileage, plane fare, taxi fare, lodging for family members, etc. Indirect inconvenience costs include driving/flying time, searching for accommodations and planning for the trip. We expect total distance-related costs to increase with travel distance, but at a diminishing marginal rate. To capture this, we make use of linear and quadratic distance terms in our cost model.

The cost of travelling is higher for some patients than for others. For example, older and sicker patients may incur higher costs than younger and healthier patients, because of their medical condition and immobility. Female patients may have more difficulty travelling if they have young children. To allow for differences in the perceived cost of travel, we include in our cost models interactions between distance and patient characteristics such as age, gender and race and common comorbidities including atrial fibrillation, chronic obstructive pulmonary disease, diabetes, heart failure, renal disease and hypertension.

For modelling purposes, we estimate travel distance from a patient's home to a hospital by using the Euclidean distance between the centroid of a patient's zip code and that of the hospital, which has been shown to be highly correlated with actual travel distance and travel time (Boscoe, Henry and Zdeb, 2012).

We incorporate the above distance-related costs into the following model:

$$\begin{aligned} DistCost_{ij} = {} & \beta_0 + \beta_1 Dist_{ij} + \beta_2 Dist_{ij}^2 + \beta_3 Age_i Dist_{ij} + \beta_4 Gender_i Dist_{ij} \\ & + \beta_5 Race_i Dist_{ij} + \beta_6 Comorb_i Dist_{ij} + e_{ij} \end{aligned}$$

where $Dist$ is the Euclidean distance between the centroid of the patient's zip code and that of hospital and Age, $Gender$, $Race$ and $Comorb$ are defined the same as before.

5.3. Switching Cost

In addition to travel related costs, patients may perceive other costs of seeking treatment from a hospital they have not visited previously. One source of these "switching costs" is the familiar network of providers the patient has relied on. This includes their primary care physician and/or cardiologist who may help the patient decide where to have mitral valve surgery. Because they lack clear and comparable outcome information across hospitals, these physicians may have a propensity to refer the patient to hospitals they know well, namely those within his/her exiting health care network. Going against the advice of a primary care physician or cardiologist constitutes a psychological switching cost. Patients may also be encouraged to select hospitals they have visited before by payers who impose higher co-pays or out of network hospitals. These constitute monetary switching costs.

To identify a patient's prior visits, we merged outpatient discharge data with the inpatient discharge data using the link provided by the Agency for Healthcare Research and Quality. We focus on one year prior to a patient's mitral valve surgery and analyze if he/she visited any of the 35 hospitals during this period of time. We include both inpatient visits (i.e., stay in a hospital while under treatment) and outpatient visits (i.e., received medical treatment without being admitted to a hospital). We use a dummy $Switch_{ij}$ to indicate if patient i did not visit hospital j in the year prior to mitral valve surgery, which indicates that hospital j is outside patient j's normal network.

Because the willingness of a patient to switch to a new hospital may depend on his/her characteristics, we include in our model interactions between patient demographics (i.e., age, gender, race), common comorbidities (atrial fibrillation, chronic obstructive pulmonary disease, diabetes, heart failure, renal disease and hypertension), and payers (Medicare, Medicaid, Blue Cross, commercial, Medicare HMO, Medicaid HMO, other HMO, self-pay and others). We capture the costs of switching to a new hospital in the following cost model:

$$\begin{aligned} SwitchCost_{ij} = {} & \theta_0 + \theta_1 Switch_{ij} + \theta_2 Age_i Switch_{ij} + \theta_3 Gender_i Switch_{ij} \\ & + \theta_4 Race_i Switch_{ij} + \theta_5 Comorb_i Switch_{ij} + \theta_6 Payer_i Switch_{ij} + e_{ij} \end{aligned}$$

where $Switch_{ij}$ equals 1 if patient i did not visit hospital j in a year before his mitral valve surgery and 1 otherwise. Age, $Gender$, $Race$, $Comorb$ and $Payer$ are defined as before.

5.4. Patient Choice Model

We model the perceived utility to patient i of choosing hospital j as:

$$Utility_{ij} = PatBenefit_{ij} - DistCost_{ij} - SwitchCost_{ij} + \varepsilon_{ij}, \forall i, j = 1, 2, ..., 35$$

where ε_{ij} is the utility shock with type I extreme value (Gumbel) distribution.

Under these assumptions, we can use the multinomial logit model to estimate the probability that patient i chooses hospital j to be:

$$Pr\{Y_i = j\} = \frac{exp(PatBenefit_{ij} - DistCost_{ij} - SwitchCost_{ij})}{\sum_{j=1}^{35} exp(QltyBenefit_{ij} - DistCost_{ij} - SwitchCost_{ij})}$$

5.5. Results on Patient Choice

To determine whether and how patient choice correlates with hospital adjusted repair rate, we include in the choice model hospital adjusted repair rate and its interactions with patient demographics and common comorbidities. We do not include other information (e.g., hospital volume), distance or switching, because these factors would play a less significant role if patients knew the true quality of a hospital. Model 0 of Table 8 shows that the coefficient of quality is positive, indicating that patients are more likely to choose high-quality hospitals than low-quality hospitals. Younger patients and male patients are more likely to choose high-quality hospitals than are older and female patients. Compared with white patients, Hispanic and Asian patients are less likely to choose high-quality hospitals. Compared with those with no common comorbidities, patients with heart failure are more likely to choose high-quality hospitals and patients with diabetes are less likely to choose high-quality hospitals. However, the model explains only 4.5% of the observed variation in choices, indicating (as we anticipated) that patients do not behave as if they had access to true quality information.

To analyze the impact of information, distance and switching on patients' choice, we tested three models with different independent variables (1) patient benefit only, (2) patient benefit and distance, and (3) patient benefit, distance and switching. Table 8 summarizes results from these three models. As expected, patient benefit, distance and switching are all drivers of patient hospital choice. However, patient benefit alone drives only 11.2% of the variation in observed choices, while including distance and switching increases the model explanatory power substantially to 51.0% and 60.3%. The implication is that without access to good information with which to evaluate benefit, patients make hospital choices on the basis of other (less relevant) things.

However, patients differ in the extent to which they act as though hospital quality affects their decision making. Older patients consider quality less than do younger patients and black, Hispanic or Asian patients are influenced less by quality than are white patients. Patient choices do correlate with proxies of quality, including mitral volume, teaching and private hospital status, and US News ranking. However, their choices are also influenced by hospital advertising.

With only imperfect proxies for quality, distance between a patient's home and a hospital becomes an important factor in his/her decision. Patients of all types are more likely to choose a nearby hospital than a distant hospital, as indicated by the negative coefficient of *distance*. The impact of distance is larger for older patients than that for younger patients, probably because older patients find it more inconvenient to travel. The impact of distance is also higher for Hispanic patients than for white patients. But the coefficient of $distance^2$ is positive, indicating that the marginal effect of distance decreases as distance increases. This is as expected because the cost of travelling an extra mile generally decreases with the length of a trip.

In addition to distance, whether a patient has previously visited a hospital significantly affects his/her choice, as indicated by the coefficient of the *switch* variable. In general, patients are less likely to switch to a new hospital, presumably for reasons of comfort, physician referral and payer restriction. However, our results show that white patients are more likely to choose a new hospital than are black, Hispanic and Asian patients, possibly because they face fewer financial limitations or because they have better access to information about hospital quality. Patients with Medicaid, Medicaid HMO, Medicare HMO are less likely to switch to new hospitals compared to patients with other (especially commercial) insurance types. This suggests that Medicaid, Medicaid HMO and Medicare HMO are more restrictive about allowing patients to switch to hospitals outside their network.

5.6. Comparison of Patient Choices: More Informed vs. Less Informed Groups

A primary, and disheartening, conclusion from the previous analysis is that quality information is not the main driver of the hospital choice. Instead, convenience factors, such as geographical proximity and prior familiarity, dominate in the choice of hospital. We conjecture that making better outcome information available would change this. Lacking a formal experiment to test this, we sought a group of people who are likely to be better informed about quality and whose decisions are less driven by distance or switching costs. We chose the set of people who travelled from other states to New York City to receive mitral valve surgery. The fact that they travelled to another state suggests an investment in their care that required research to carry out. It also implies that the relative cost to visit any hospital in New York City is largely the same. Furthermore, out-of-state patients are unlikely to have a record of prior visits with any of the New York hospitals. To contrast their behavior with in-state patients, we first test whether this group of patients do indeed select higher quality hospitals. We then examine demographical differences between this better informed group and the in-state New York population of mitral valve patients.

Most patients who travel from outside New York state tend to travel to New York City rather than other cities/towns in New York, presumably due to the high density of renowned hospitals

Table 8 Patient Choice Model Results

	Model 0		Model 1		Model 2		Model 3	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Patient Benefit								
quality†	4.098***	0.298	1.034***	0.240	0.728***	0.274	0.783**	0.310
quality_age	−0.074***	0.012	−0.039***	0.009	−0.043***	0.010	−0.039***	0.011
quality_female	−0.571**	0.259	−0.223	0.205	−0.278	0.228	−0.308	0.254
quality_black	−0.643	0.490	−0.891**	0.402	−1.188***	0.421	−1.641***	0.493
quality_hispanic	−1.189**	0.573	−1.466***	0.477	−1.772***	0.486	−1.211**	0.582
quality_others	1.226***	0.400	1.210***	0.306	0.439	0.316	0.268	0.336
quality_asian	−5.525***	1.055	−3.598***	0.836	−2.941***	0.811	−2.195**	0.947
quality_af	0.324	0.266	0.227	0.210	0.136	0.233	0.299	0.263
quality_chf	2.769**	1.353	3.102**	1.333	2.549**	1.281	3.139*	1.891
quality_chrnlung	−0.205	0.326	−0.185	0.272	−0.063	0.312	0.034	0.350
quality_dm_all	−0.788**	0.341	−0.541*	0.284	−0.564*	0.314	−0.609*	0.358
quality_htn_c	0.022	0.272	0.195	0.214	0.277	0.239	0.358	0.267
quality_renlfail	−0.463	0.419	−0.127	0.354	−0.208	0.385	0.021	0.458
mitral volume			0.861***	0.040	0.835***	0.047	0.882***	0.052
teaching hosp			−0.094**	0.047	0.356***	0.059	0.362***	0.066
government hosp			−0.369***	0.093	−0.455***	0.107	−0.329***	0.119
advertising			0.039**	0.018	0.076***	0.023	0.073***	0.027
US News (ranked = 1)			−0.337***	0.066	0.198**	0.089	0.249**	0.099
Distance-related Cost								
distance					−10.249***	0.403	−8.087***	0.410
distance2					2.129***	0.124	1.535***	0.130
distance_age					−0.059***	0.010	−0.045***	0.011
distance_female					0.109	0.266	0.046	0.272
distance_black					−7.624***	1.626	−3.004*	1.676
distance_hispanic					−12.598***	2.161	−8.111***	2.070
distance_asian					−7.510***	2.872	−4.364	3.090
distance_others					1.152***	0.319	0.892***	0.342
distance_af					0.624**	0.273	0.545*	0.281
distance_chf					0.322	2.288	0.790	1.843
distance_chrnlung					−0.799	0.504	−0.792	0.497
distance_dm_all					−0.320	0.553	0.022	0.512
distance_htn_c					−0.822***	0.317	−0.892***	0.322
distance_renlfail					0.547	0.597	0.783	0.550
Switching Cost								
Switch								
switch							−3.226***	0.230
switch_age							−0.010	0.010
switch_female							0.275	0.169
switch_black							−0.755**	0.316
switch_hispanic							−1.346***	0.444
switch_others							0.690**	0.273
switch_asian							−1.688***	0.622
switch_af							−0.036	0.170
switch_chf							−0.953	1.055
switch_chrnlung							0.052	0.217
switch_dm_all							−0.087	0.229
switch_htn_c							0.540***	0.177
switch_renlfail							−0.564**	0.281
Payer Restriction								
switch_commercial							−0.333	0.475
switch_other							−0.165	0.807
switch_otherhmo							−0.255	0.277
switch_medicare non-hmo							Baseline	
switch_bluecross							−0.058	0.282
switch_medicarehmo							−0.461*	0.254
switch_medicaidhmo							−0.707	0.452
switch_medicaid							−1.783*	0.915
switch_self							−13.055	672.886
Pseudo R2	0.045		0.112		0.511		0.603	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
†True quality is used in Model 0 and observed quality is used in Models 1-3.
‡For the interaction terms, white is the baseline for race and medicare(non-hmo) is the baseline for payer.

in New York City and its convenient transportation options. Among the thirteen New York City (Manhattan, Flushing, Brooklyn, Bronx and Staten Island) hospitals, three hospitals have a mitral volume of more than 100 per year, while all other hospitals perform less than 50 mitral valve procedures a year. These three hospitals have indices 13, 30 and 35 in Figure 1. Even though all three hospitals have high volumes, there are significant quality gaps among them. Hospitals 30 and 35 have mitral valve repair rates significantly higher than the state average, while hospital 13, with the second highest volume in the state, has a repair rate significantly lower than the state average (see Figure 1). If patients travelling from out of state do have better quality information, they should be significantly more likely to choose hospitals 30 and 35. In particular, we would expect a high percentage of travellers to hospital 35 because it has the best record in the state, with a repair rate of nearly 90% compared to the 58% state average.

To make our comparison, we stratify patients by states (NY state, nearby states of NJ and CT, and distant states) and by distance (less than 100 miles, between 100 and 300 miles, and more than 300 miles). Since the three high-volume hospitals are within 2 miles of each other, distance should not favor any of them, either for in-state or out-of-state patients. We analyze only patients who have not visited any of these three hospitals in the year prior to their mitral valve surgery to avoid a confounding effect of switching costs. Since we have eliminated (or reduced) the impact of distance and switching costs, any difference in choice probability should be driven by information about quality.

From Table 9, among those who chose one of the three hospitals, we see that only 38% of NY state residents chose hospital 35, the hospital with the best repair rate. This figure increases to 51% for patients from NJ and CT, and to 78% for patients from other states. We observe similar patterns for patients stratified by distance. For those who live within 100 miles from New York City, around 41% of patients chose hospital 35. This figure increases to nearly 79% when distance is more than 100 miles. These results strongly suggest that patients who travelled far away from other states have better quality information, and use it to choose a hospital with a higher repair rate. Anecdotal evidence from these patients indicates that such information requires considerable time and effort (searching the web and making phone calls to hospitals) to acquire. But the behavior of these patients suggests that making quality information more accessible to the general public could lead to more patients selecting CoEs and an increase in repair rate. However, these patients do not behave as if they have full access to true qualify information, since some of them still select hospital 13, which has below average outcomes. This suggests that there is opportunity to improve choices and outcomes, even among the best informed patients.

Table 9 Patients Treated at New York City's Top 3 Medical Centers (by Volume)

	By State			By Distance		
Hospital Index	NY State	Nearby States	Distant States	Less than 100 miles	100 - 300 miles	More than 300 miles
13	199 (31%)	68 (25%)	12 (10%)	263 (29%)	7 (13%)	9 (11%)
30	203 (31%)	64 (24%)	15 (12%)	268 (30%)	4 (8%)	10 (12%)
35	248 (38%)	136 (51%)	97 (78%)	373 (41%)	42 (79%)	66 (78%)
Sub-total	650	268	124	904	53	85
Total	1800	295	148	2078	74	95

Note: Based on 2009-2012 inpatient data. Nearby states refer to NJ and CT. There are ten other medical centers in New York City (Manhattan, Flushing, Brooklyn, Bronx and Staten Island). All of these have annual volume <50, while the top three all with annual volume >100.

We next compare the demographics of this better informed group of out-of-state patients with those of an average New York resident (Table 10). We find that the out-of-state cohort is younger (mean age of 60.6 vs. 64.9), has more white patients (91.2% vs. 72.7%), fewer black patients (0.6% and 7.5%) and fewer Hispanic patients (1.8% vs. 5.2%). It also has more patients with chronic heart failure (1.8% vs. 0.6%), fewer patients with diabetes (8.2% vs. 16.6%) and fewer patients with hypertension (42.1% vs. 57.7%). It may be the case that younger white patients have the time, resources and connections (e.g., acquaintances in the medical filed) to search for quality information. Patients with diabetes and hypertension may be under-represented in the out-of-state group because their health makes long distance travel too difficult. Finally, the out-of-state group has more patients with Blue Cross (24.0% vs. 17.2%), commercial (7.6% vs. 4.9%) and Medicare (42.7% vs. 34.9%), and fewer patients with Medicare HMO (2.3% vs. 15.8%) and Medicaid HMO (0% vs. 5.4%). A plausible reason for this is that Blue Cross, commercial insurance and Medicare have larger networks of providers and are less restrictive about allowing patients to visit out-of-state hospitals.

Table 10 Comparison of Patients from NY State and Far-away States

	NY State		Far-away States		
	mean	s.d.	mean	s.d.	p-value
Demographics					
age	64.9	0.2	60.6	1.1	0.000
female	44.9%	1.0%	38.6%	3.7%	0.055
white	72.7%	0.9%	91.2%	2.2%	0.000
black	7.5%	0.5%	0.6%	0.6%	0.000
hispanic	5.2%	0.4%	1.8%	1.0%	0.022
asian	2.0%	0.3%	1.2%	0.8%	0.234
others	12.6%	0.6%	5.3%	1.7%	0.002
Comorbidities					
cm_af	50.5%	1.0%	51.5%	3.8%	0.407
cm_chf	0.6%	0.1%	1.8%	1.0%	0.034
cm_chrnlung	16.9%	0.7%	12.9%	2.6%	0.087
cm_dm_all	16.6%	0.7%	8.2%	2.1%	0.002
cm_htn_c	57.7%	0.9%	42.1%	3.8%	0.000
Payers					
bluecross	17.2%	0.7%	24.0%	3.3%	0.012
commercial	4.9%	0.4%	7.6%	2.0%	0.056
medicare	34.9%	0.9%	42.7%	3.8%	0.020
medicaid	1.7%	0.2%	1.2%	0.8%	0.302
medicarehmo	15.8%	0.7%	2.3%	1.2%	0.000
medicaidhmo	5.4%	0.4%	0.0%	0.0%	0.001
otherhmo	17.3%	0.7%	21.6%	3.2%	0.076
self-pay	0.8%	0.2%	0.6%	0.6%	0.748
Total	2718		148		

6. Managerial Implications

The 2014 American Heart Association/American College of Cardiology Valvular Heart Disease Guidelines state that mitral valve diseases should be repaired at a Center of Excellence (CoE), but they do not give a precise definition of a CoE. With the analysis we have done here, we can define CoEs as hospitals that perform statistically significantly better than the state average. In New York this leads to six hospitals (with indexes 30 to 35 in Figure 1) being classified as CoEs. Referring patients to CoEs is clearly beneficial to patients, because they have by definition higher mitral valve repair rates. Wang et al. (2015) studied the cost effectiveness of referring patients to CoEs for mitral valve surgery, and found that such referral would result in an average gain of 3.77 to 9.88 of months life expectancy, depending on patients' age and comorbidities. Furthermore, despite higher reimbursement costs for CoEs, they also found that referring patients to CoEs is beneficial to payers because the short term cost increase is offset by long term savings. Therefore, referring patients with mitral valve diseases to CoEs leads to both better outcomes and lower costs.

6.1. Degree of Treatment Centralization

Guiding all patients to one of the six CoEs would result in a substantial increase in patient benefit and a reduction in payer cost relative to the current situation. In theory, sending everyone to the hospital with the highest mitral valve repair rate would result in even greater benefits. However, this would require such a huge increase in capacity of hospital 35 that, even if it were feasible, it would likely lead to a degradation in quality. Moreover, it would require all patients to travel to New York City, which would greatly increase distance-related cost and inconvenience for many patients. This raises the question of what policy strikes the best balance between the repair rate benefits and the travel and capacity costs among those that send patients to the nearest of the top N hospitals, where $1 \leq N \leq 6$.

We perform cost and benefit analyses for each of these scenarios in Table 11. For the extreme case where $N = 1$, mitral valve repair rate increases by 52% relative to the current performance (from 58% to 88%), patient benefit and payer savings per patient increase by \$30,576 and \$11,766 respectively.[8] But the annual volume at hospital 35 would have to increase by 780% and patients would have to travel an average of 75 extra miles.

As N, the number of hospitals that perform mitral valve surgery, increases, the overall repair rate decreases, but so does the extra patient volume each hospital must handle and the extra distance patients must travel. This comparison suggests that including all six of the hospitals with above average repair rates is both feasible and effective. This strategy would increase average repair rate by 58% to 70% overall, which would result in an average gain in life expectancy valued at \$12,230

[8] We converted life expectancy into monetary value using the formula $1000k \times age^{-0.66}$ (Mason, et al., 2009).

by patients, and positive savings of $4,593 per patient by payers. Average travel distance per patient would increase by only 10.9 miles, because these six hospitals are spread across the state. Finally, the increase in volume at the six hospitals would range from 32 to 142 patients per year, which seems very manageable from a facilities standpoint.

But we also need to consider the impacts of shifting patients to the six CoEs from a surgeon standpoint. If the hospital differences we have observed are really a surgeon effect, and the top surgeon at each hospital is both better and busier than his/her fellow surgeons, then adding patients to a hospital may result in their being treated by a less skilled surgeon and hence achieving worse outcomes than we have predicted. To test if this is the case, we compared the patient volume and risk-adjusted repair rate for the top two surgeons at each CoE (see Table 12). From these we draw the following conclusions: (1) The busiest surgeon performed 228 mitral valve procedures over the four-year interval, while all other surgeons had volumes of 83 or less, suggesting considerable surgeon capacity in the CoEs. (2) Eleven out of the twelve surgeons had risk-adjusted repair rates near or above the average of their respective hospitals. (Only hospital 33, which had all but one of its procedures done by two surgeons, had a number two surgeon with a repair rate significantly below the hospital average.) This suggests that rerouting patients from other hospitals to the top two surgeons in the six CoEs would result in a larger increase in repair rate than we predicted. Furthermore, if higher volumes result in an experience effect that improve repair rates, as predicted by research on the correlation between volume and quality (Birkmeyer et al., 2002), then the impact on overall repair rate of routing patients to the nearest CoE will be even larger.

Table 11 Scenarios for Centralizing Mitral Valve Surgery

Number of Hospitals Performing MV Surgery	Average Volume Per Hospital Per Year	Average Travel Distance Per Patient	Overall Mitral Valve Repair Rate	Average Increase in Patient's Benefits	Average Increase in Payer Savings Per Patient
1	680	94.0	88%	$30,576	$11,766
2	340	91.3	84%	$25,480	$9,774
3	227	41.4	78%	$19,365	$7,383
4	170	41.1	74%	$16,307	$6,187
5	136	30.2	72%	$14,269	$5,390
6	113	29.9	70%	$12,230	$4,593
Current	-	19.0	58%	-	-

6.2. Impact of Information, Distance and Payer

To evaluate the relative effectiveness of information, distance subsidies and payer changes as policy interventions, we use the current situation — patients travelled 19.0 miles on average, 40% of them chose a CoE, and overall repair rate was 58% as our baseline.

Table 12 Comparison of Top 2 Surgeons (by Volume) at The Six Hospitals

	Hospital Index					
	30	31	32	33	34	35
Top Surgeon						
4-yr Volume	71	64	54	83	31	228
Repair Rate (mean)	65.51%	77.41%	57.52%	73.74%	94.94%	95.00%
Repair Rate (s.d.)	6.56%	6.83%	8.06%	7.15%	11.55%	4.78%
Second Surgeon						
4-yr Volume	70	55	33	43	30	21
Repair Rate (mean)	69.00%	62.16%	80.27%	48.72%	96.75%	87.33%
Repair Rate (s.d.)	6.54%	7.09%	8.30%	10.55%	12.33%	10.32%
Total						
4-yr Volume	230	219	111	127	101	309
Repair Rate (mean)	61.28%	63.56%	68.28%	69.94%	76.49%	89.50%
Repair Rate (s.d.)	3.70%	3.68%	4.57%	4.41%	4.37%	1.88%

The practical upper limit on improvement is given by the scenario in which all patients go to the nearest among the six CoEs, which results in an increase in overall repair rate of 22% (from 58% to 70%) and an increase in average travel distance of only 10.9 miles (from 19.0 miles to 29.9 miles). Ideally, providing patients with understandable information about the health benefits of a mitral valve repair, and transparent outcome information like that shown in Figure 3, would induce many patients to choose CoEs. But it would not guide everyone to a CoE because travel aversion and payer restrictions would still exist. So we first estimate the impact of removing each of these barriers and then compute the impact of information as the remaining improvement.

To evaluate the effectiveness of subsidizing travel to a distant hospital, we use a post-estimation analysis of our model in which equalize the distance of patients' nearest CoE to the distance of their nearest hospital while keeping other variables the same. This predicts that a distance subsidy to CoEs will guide 38.9% more patients (from 40% to 56%) to CoEs, which will increase the overall repair rate by 6.2% (from 58% to 61%). An example of such a travel subsidy is the Healthcare Travel Costs Scheme in the UK, which was set up to provide financial assistance to patients who do not have a medical need for ambulance transport, but who require assistance with their travel costs.[9] Another is the example of Walmart and Lowes, who joined Pacific Business Group On Health to subsidize employees' costs of traveling and lodging when treated at Centers of Excellence for high risk procedures such as heart surgery or knee/hip replacement.[10]

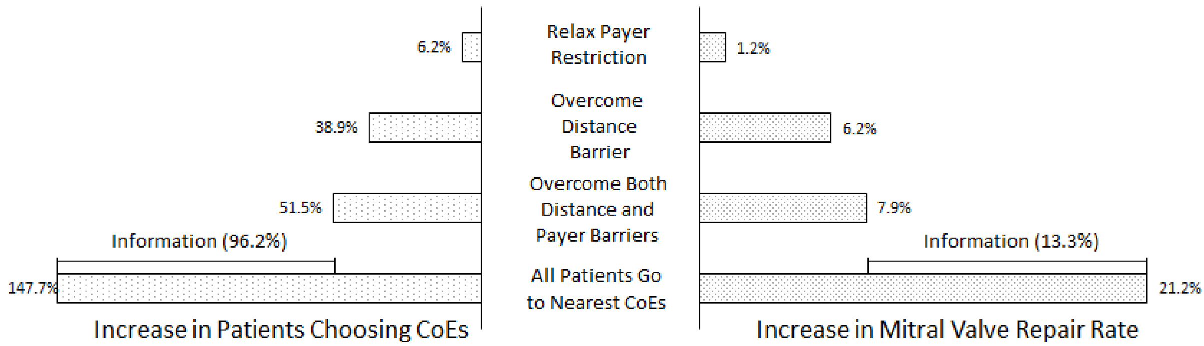
In the same manner, we can estimate the impact of relaxing payer restrictions by changing the payer variable to commercial (the least restrictive case) for the patient's nearest CoE.[11] We note

[9] http://www.nhs.uk/NHSEngland/Healthcosts/Pages/Travelcosts.aspx

[10] Walmart, Lowe's and Pacific Business Group On Health Announce A First Of Its Kind National Employers Centers Of Excellence Network. Walmart News & Views. October, 2013.

[11] We assume commercial insurance is unrestrictive enough to permit choosing the nearest CoE.

Figure 3 Comparison of Different Policies



that relaxing payer restrictions for CoEs is also incentive compatible for payers themselves, because the higher short-term costs at CoEs can be offset by long-term savings due to avoidance of future complications (Wang et al. 2015). This predicts that 6.2% more patients (from 40% to 43%) will go to CoEs, which will increase repair rate by 1.2% (from 58% to 59%). To estimate the combined impact of subsidizing travel costs and relaxing payer restrictions, we change both the distance and payer variables as above. This leads to an increase of 51.5% in the percentage of patients (from 40% to 61%) who choose CoEs, and results in an increase in overall repair rate of 7.9% (from 58% to 62%).

Though somewhat effective, these policy interventions achieve only a fraction of the benefits that would result from guiding all patients to the nearest CoEs (i.e., a 7.9% increase in repair rate vs. 21.2% increase in repair rate). Based on our analysis, we believe the remaining 13.3% gap is primarily the result of a lack of information in the hands of physicians/cardiologists (who make referrals) and patients (who make the ultimate choice of hospital). We conservatively estimate that providing better medical description and statistical outcome information will increase the number of patients who choose CoEs by 96.2% and the overall repair rate by 13.3%. If this more transparent information causes patients to put less weight on travel and payer restrictions (e.g., copays), the impact of information could be even larger.

7. Conclusion

Although research and hospital ratings suggest that hospital quality varies greatly, many Americans underestimate, or are unaware of, the quality gap among hospitals. As a result, they choose hospitals that do not offer them the best chances of successful outcomes. Using mitral valve surgery as the clinical setting, we have developed a method for determining true quality of hospitals. We have assessed the factors patients use in place of the quality information they lack. And we have evaluated policies for guiding patients to the most effective (and cost efficient) hospitals for their needs.

A potential limitation of our study is that we use risk adjusted and selection bias adjusted repair rate to compare hospital performance. It is possible that the difference in outcome quality between hospitals depends on patient characteristics, particularly on the complexity of mitral valve disease. We conjecture that the gap between hospitals is likely to be small for simple cases (because many patients will get their mitral valves repaired regardless of which hospital they visit) and large for complex cases (because repair in such cases require the specialized skills available only at CoEs). However, it may be that the gap in quality is small for extremely complex cases because not even CoEs are able to repair the valves of such patients. If this is the case, then even more cost effective patient routing is possible by targeting information by patient categories. Future research is needed to characterize the quality gap by case complexity.

Finally, our approach to analyzing patient choices for mitral valve surgery needs to be extended to broader categories of healthcare treatments. Providing patients with accurate and understandable information about hospital outcomes will enable them to receive higher quality care in the immediate term. For some procedures, like mitral valve repair, these benefits can also be achieved at a reduced cost to payers, due to a reduction in post-surgical complications. In the long term, aligning patient patient choices with the quality of care will provide economic incentive for providers to improve their systems and to focus on the procedures they are most capable of delivering.

References

Austin, J. M., Jha, A. K., Romano, P. S., Singer, S. J., Vogus, T. J., Wachter, R. M., Pronovost, P. J. (2015). National hospital ratings systems share few common scores and may generate confusion instead of clarity. Health Affairs, 34(3):423-430.

Bastani, H., Goh, J., Bayati, M. (2015). Evidence of Strategic Behavior in Medicare Claims Reporting. Working Paper.

Batt, R. J., Terwiesch, C. (2015). Waiting patiently: An empirical study of queue abandonment in an emergency department. Management Science, 61(1), 39-59.

Bavafa, H., Hitt, L. M., Terwiesch, C. (2013). Patient portals in primary care: Impacts on patient health and physician productivity. Working Paper.

Birkmeyer, J. D., Siewers, A. E., Finlayson, E. V., Stukel, T. A., Lucas, F. L., Batista, I., ..., Wennberg, D. E. (2002). Hospital volume and surgical mortality in the United States. New England Journal of Medicine, 346(15), 1128-1137.

Bolling, S. F., Li, S., O'Brien, S. M., Brennan, J. M., Prager, R. L., Gammie, J. S. (2010). Predictors of mitral valve repair: clinical and surgeon factors. The Annals of Thoracic Surgery, 90(6), 1904-1912.

Boscoe, F. P., Henry, K. A., and Zdeb, M. S. (2012). A nationwide comparison of driving distance versus straight-line distance to hospitals. The Professional Georgrapher, 64(2):188-196.

Brooks, J. M., Irwin, C. P., Hunsicker, L. G., Flanigan, M. J., Chrischilles, E. A., Pendergast, J. F. (2006). Effect of Dialysis Center Profit Status on Patient Survival: A Comparison of Risk - Adjustment and Instrumental Variable Approaches. Health Services Research, 41(6), 2267-2289.

Carroll, R. J., Horn, S. D., Soderfeldt, B., James, B. C., Malmberg, L. (1995). International comparison of waiting times for selected cardiovascular procedures. Journal of the American College of Cardiology, 25(3):557-563.

Daneshmand, M. a, Milano, C. a, Rankin, J. S., Honeycutt, E. F., Shaw, L. K., Davis, R. D., ... , Smith, P. K. (2010). Influence of patient age on procedural selection in mitral valve surgery. The Annals of Thoracic Surgery, 90(5):147-985.

Daneshmand, M. a, Milano, C. a, Rankin, J.S., et al. (2009). Mitral valve repair for degenerative disease: a 20-year experience. The Annals of Thoracic Surgery, 88(6):1828-37.

Dixon, A., Robertson, R., Appleby, J., Burge, P., Devlin, N. J. (2010). Patient choice: how patients choose and how providers respond.

Dijs-Elsinga, J., Otten, W., Versluijs, M., Smeets, H., Kievit, J., Vree, R., et al. (2010). Choosing a hospital for surgery: the importance of information on quality of care. Medical Decision Making, 30:544.

Dumont, E., Gillinov, A.M., Blackstone, E.H., et al. (2007). Reoperation after mitral valve repair for degenerative disease. The Annals of Thoracic Surgery, 84(2):444-50.

Finlayson, S., Birkmeyer, J., Tosteson, A., Nease, R. (1999). Patient preferences for location of care, implications for regionalization. Medical Care, 37:204-209.

Freeman, M., Savva, N., Scholtes, S. (2015). Gatekeepers at Work: An Empirical Analysis of a Maternity Unit. History.

Gammie, J. S., Sheng, S., Griffith, B. P., Peterson, E. D., Rankin, J. S., O'Brien, S. M., Brown, J. M. (2009). Trends in mitral valve surgery in the United States: results from the Society of Thoracic Surgeons Adult Cardiac Surgery Database. The Annals of Thoracic Surgery, 87(5):1431-7.

Haynes, R., Lovett, A., Sunnenberg, G. (2003). Potential accessibility, travel time and consumer choice: geographical variations in general medical practice registrations in Eastern England. Environment and Planning A, 35:1733-1750

Howard, D. H. (2006). Quality and consumer choice in healthcare: evidence from kidney transplantation. Topics in Economic Analysis and Policy, 5(1).

Huckman, R. S., Pisano, G. P. (2006). The firm specificity of individual performance: Evidence from cardiac surgery. Management Science, 52(4), 473-488.

Isaac, T., Zaslavsky, A. M., Cleary, P. D., Landon, B. E. (2010). The relationship between patients' perception of care and measures of hospital quality and safety. Health Services Research, 45(4):1024-1040.

Jaeker, Jillian B. and Tucker, Anita L. (2015). Past the Point of Speeding Up: The Negative Effects of Workload Saturation on Efficiency and Quality. Management Science, forthcoming.

KC, D., Staats, B. R. (2012). Accumulating a portfolio of experience: The effect of focal and related experience on surgeon performance. Manufacturing & Service Operations Management, 14(4), 618-633.

KC, D., Staats, B. R., Gino, F. (2013). Learning from my success and from others' failure: Evidence from minimally invasive cardiac surgery. Management Science, 59(11), 2435-2449.

KC, D., Terwiesch, C. (2011). The effects of focus on performance: Evidence from California hospitals. Management Science, 57(11), 1897-1912.

Keeler, E. B., Rubenstein, L. V., Kahn, K. L., Draper, D., Harrison, E. R., McGinty, M. J., ... , Brook, R. H. (1992). Hospital characteristics and quality of care. JAMA, 268(13):1709-1714.

Kim, S. H., Chan, C. W., Olivares, M., Escobar, G. (2014). ICU Admission Control: An Empirical Study of Capacity Allocation and Its Implication for Patient Outcomes. Management Science, 61(1), 19-38.

LaPar, D. J., Hennessy, S., Fonner, E., Kern, J. a, Kron, I. L., Ailawadi, G. (2010). Does urgent or emergent status influence choice in mitral valve operations? An analysis of outcomes from the Virginia Cardiac Surgery Quality Initiative. The Annals of Thoracic Surgery, 90(1):153-60.

Mason, H., Lee, M., Donaldson, C. (2009). Modelling the monetary value of a QALY: a new approach based on UK data. Health Economics, 18(8), 933-950.

McClellan, M., McNeil, B. J., Newhouse, J. P. (1994). Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality: analysis using instrumental variables. JAMA, 272(11), 859-866.

McConnell, K. J., Newgard, C. D., Mullins, R. J., Arthur, M., Hedges, J. R. (2005). Mortality Benefit of Transfer to Level I versus Level II Trauma Centers for Head Injured Patients. Health Services Research, 40(2), 435-458.

Pisano, G. P., Bohmer, R. M., Edmondson, A. C. (2001). Organizational differences in rates of learning: Evidence from the adoption of minimally invasive cardiac surgery. Management Science, 47(6), 752-768.

Pracht, E. E., Tepas, J. J., Celso, B. G., Langland-Orban, B., Flint, L. (2007). Survival Advantage Associated with Treatment of Injury at Designated Trauma Centers A Bivariate Probit Model with Instrumental Variables. Medical Care Research and Review, 64(1), 83-97.

Ramdas, K., Saleh, K., Stern, S., Liu, H. (2014). Variety and Experience: Learning and Forgetting in the Use of Surgical Devices. Working Paper.

Russo, A., Grigioni, F., Avierinos. J-F, et al. (2008). Thromboembolic complications after surgical correction of mitral regurgitation incidence, predictors, and clinical implications. Journal of the American College of Cardiology, 51(12):1203-11.

Savage, E.B., Ferguson, T.B., DiSesa, V.J. (2003). Use of mitral valve repair: analysis of contemporary United States experience reported to the Society of Thoracic Surgeons National Cardiac Database. The Annals of Thoracic Surgery, 75(3):820-5.

Schrag, D., Panageas, K. S., Riedel, E., Hsieh, L., Bach, P. B., Guillem, J. G., Begg, C. B. (2003). Surgeon volume compared to hospital volume as a predictor of outcome following primary colon cancer resection. Journal of Surgical Oncology, 83(2), 68-78.

Song, H., Tucker, A. L., Murrell, K. L. (2015). The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. Management Science.

Steinwachs, D.M., Hughes, R.G. (2008). Health services research: scope and significance. Patient Safety and Quality: An Evidence-Based Handbook for Nurses, 08-0043.

Tay, A. (2003). Assessing competition in hospital care markets: the importance of accounting for quality differentiation. RAND Journal of Economics, 786-814.

Varkevisser, C. M., van der Geest, S. A., Schut, F. T. (2012). Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands. Journal of Health Economics, 31(2):371-378.

Vassileva, C. M., Shabosky, J., Boley, T., Markwell, S., Hazelrigg, S. (2012). Cost analysis of isolated mitral valve surgery in the United States. The Annals of Thoracic Surgery, 94:1429-1436.

Vassileva, C. M., Mishkel, G., McNeely, C., Boley, T., Markwell, S., Scaife, S., Hazelrigg, S. (2013). Long-term survival of patients undergoing mitral valve repair and replacement: a longitudinal analysis of Medicare fee-for-service beneficiaries. Circulation, 127(18):1870-6.

Vassileva, C.M., Boley, T., Standard, J., Markwell, S., Hazelrigg, S. (2013). Relationship between patient income level and mitral valve repair utilization. Heart Surg Forum, 16(2):E89-95.

Victoor, A., Delnoij, D. M., Friele, R. D., Rademakers, J. J. (2012). Determinants of patient choice of healthcare providers: a scoping review. BMC Health Services Research, 12(1), 272.

Wang, G., Li, J., Hopp, W., Fazzalari, F., Bolling, S. (2015). Cost-effectiveness of referring patients to centers of excellence for mitral valve surgery. Working Paper. Ross School of Business, University of Michigan, Ann Arbor, MI.

Zeithaml, V.A., Bitner, M.J. (1996), Services Marketing, McGraw-Hill, New York, NY.