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Reacting to rankings: Evidence from “America’s Best Hospitals”☆

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ABSTRACT

Rankings and report cards have become a popular way of providing information in a variety of domains. I estimate the response to rankings in the hospital market and find that hospitals that improve their rank are able to attract significantly more patients. The average hospital in my sample experiences a 5% change in non-emergency, Medicare patient volume from year to year due to rank changes. These findings have implications regarding the competitiveness of hospital markets and the effect that the dissemination of quality information in hospital markets can have on individual choice.

1. Introduction

Rankings and report cards have become a common way for firms to synthesize and present information about a range of options to consumers. Some popular examples include rankings of restaurants (e.g. Zagat), colleges (e.g. US News and World Report), companies (e.g. Fortune 500), bonds (e.g. Moody’s), cars (J.D. Powers), and books (e.g. New York Times). Additionally, Consumer Reports rank a wide variety of consumer products each year. Academic research has shown that in a variety of situations, rankings can have a significant impact on consumer decision making.[1]

In this paper, I explore the hospital-choice reaction to widely dispersed hospital rankings that are released by US News and World Report. In contrast to many markets where rankings have been shown to have a significant effect, it has been argued that consumers of health care may be relatively unresponsive to changes in hospital quality. Restrictions such as distance from home, heath plan networks, and doctor referrals can make a consumer response to quality difficult. Additionally, information regarding true hospital quality may be difficult for consumers to observe. These restrictions and limitations have raised concerns regarding the competitiveness of hospital markets.[2] Limited evidence exists regarding whether or not consumers respond to changes in hospital quality in part because hospital quality is difficult to measure. Measures that do exist of hospital quality typically change slowly across time, making convincing within-hospital analyses difficult. Rankings on the other hand, provide a year-to-year measure of hospital quality enabling a convincing test for whether consumers respond to changes in perceived quality.[3]

In this paper, I estimate the effect of the US News and World Report hospital rankings on both patient volume and hospital revenues. The data used consist of all hospitalized Medicare patients in California (1998–2004) and a sample of other hospitals around the country (1994–2002). Given the fact that the rankings that US News and World Report produces are broken down by specialty, I produce counts of treated patients at the hospital-specialty level. Using a fixed-effects framework, which allows me to control for unobserved differences that might exist between hospital-specialty groups, I find that an improvement in a given hospital-specialties’

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[1] See, for example, Figlio and Lucas (2004), Jin and Leslie (2003), Sorensen (2007), Ehrenberg and Monks (1999), Jin and Sorensen (2005), Cutler et al. (2004), Dafny and Dranove (2005), and Jin and Whalley (2008).

[2] Gaynor and Vogt (1999) and Gaynor (2006) provide thorough reviews of the literature on hospital competition.

[3] Anecdotal and survey evidence suggests that hospital decisions may very well be affected by quality rankings. For example, a survey in 2000 by the Kaiser Family Foundation finds that 12% of individuals said that “ratings or recommendations from a newspaper or magazine would have a lot of influence on their choice of hospital” (Kaiser Family Foundation, 2000).

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rank leads to a significant increase in both the number of non-emergency patients treated and the total revenue generated from non-emergency patients in that specialty. An improvement in rank by one spot is associated with an increase in both non-emergency patient volume and revenue of approximately 1%. An alternative specification estimates the effect of a hospital-specialty's within-state ranking. I find that a hospital-specialty that improves one spot relative to another hospital-specialty in their state experiences a 6–7% increase in patient volume and revenue.

These effects are economically large. Given the amount of variation in ranks in my data, the size of the rank effect suggests that the average hospital in my sample experiences a 5% change in patient volume from year to year due to rank changes. Assuming that the sample of hospitals used in this analysis is representative of the nation as a whole, changes in these hospital rankings have led to over 15,000 Medicare patients to switch from lower to higher ranked hospitals for inpatient care resulting in over 750 million dollars moving from one hospital to another over the past ten years.

To understand the effect of the rankings relative to other important factors of hospital choice such as distance to hospital, I use individual-level data to estimate a mixed-logit discrete choice model. Unlike the more commonly used conditional logit model, the mixed-logit model allows for more flexible substitution patterns across alternatives and fits into a random coefficients framework. I estimate the distribution of preferences over hospital quality (as represented by the hospital rankings) and geographic proximity. The results demonstrate that both rankings and geographic proximity are important factors in the hospital-choice decisions of consumers. The average value to an individual of a change in rank by ten spots is equivalent to the value placed on the hospital being approximately one mile closer to the individual. I also find that rank changes have the largest impact on patients who live more than 50 miles from the hospital that experienced the rank change.

A fundamental challenge in obtaining empirical estimates for the causal impact that rankings have on patient volume is the possibility that rank changes are correlated with underlying quality observed by individuals but not by researchers. Thus, a positive association between rank changes and consumer behavior will result if changes in rank simply confirm what consumers already learned as opposed to providing new information. This endogeneity may potentially cause the estimates that I find to be biased.

I present three pieces of evidence in the paper that support the causal interpretation of my findings. First, I find that changes in rank have an effect on non-emergency patients yet no effect on emergency patients. Since, emergency patients should be less responsive to quality information than non-emergency patients, one would expect that the rank change effect should be smaller for these groups unless the results I am finding is spurious. Second, I provide a false experiment by showing that a rank change that occurs next year does not have an effect on this year's patient counts. Given that the variables that US News and World Report uses to produce their ranking are 1–3 years old by the time the ranking is released, finding an effect of rank changes after the ranking is released and not before the release lends credibility to the causal interpretation of the results I find. Finally, I propose a novel identification approach which takes advantage of the fact that US News and World Report not only provides a rank for each hospital, but also a continuous measure of hospital quality. By controlling for this continuous quality score when estimating the effect of rank changes on hospital outcomes, I am able to control for the underlying measures that make up the ranking and identify off discontinuous changes in ranks that occur. Even after flexibly controlling for the continuous quality score, I find similar effects of ordinal rank changes on patient volume and revenue.

The outline of this paper proceeds as follows. In Section 2, I review the literature on rankings and report cards. Section 3 provides background information about the specific USNWR hospital rankings studied in this analysis. In Section 4, I describe the data. Section 5 provides the empirical strategy that I employ. The results are presented in Section 6. Section 7 provides a discussion and concludes.

2. Review of literature

This paper is related to a larger literature that looks at the effect of rankings and report cards in the health-care industry. In particular, several studies address the impact of health-plan ratings on consumer choice (Wedig and Tai-Seale, 2002; Beaulieu, 2002; Scanlon et al., 2002; Chernew et al., 2004; Jin and Sorensen, 2005; Dafny and Dranove, 2005). The majority of these studies find evidence of a significant consumer response to health-plan ratings.

Less work has been done on the effect of rankings and report cards on hospital choice. The key exception to this is research regarding the impact of the New York State Cardiac Surgery Reporting System. Released every 12–18 months by the New York State Department of Health since 1991, this rating system provides information regarding the risk-adjusted mortality rates that each hospital experienced in their recent treatment of patients needing coronary artery bypass surgery. At the state level, Dranove et al. (2003) find that because of selection behavior by providers, the state of New York did significantly worse relative to control states because of the release of these rankings. More similar to my analysis, Cutler et al. (2004) test to see if hospitals that saw an improvement in their risk-adjusted mortality rates that were published in the New York report were subsequently able to attract more patients. They demonstrate a decrease in patient volume for the small percentage of hospitals that were flagged as performing significantly below the state average. However, they find no evidence that hospitals flagged as performing significantly above average attracted a greater number of patients. In contrast, Jha and Epstein (2006) argue that the data do not suggest any change in the market share of cardiac patients due to the NY Cardiac Surgery ratings.

A further issue regarding whether or not rankings affect hospital-choice decisions is whether or not hospitals are operating at full capacity. If they are capacity constrained, then increases in demand (due to a better ranking) will not be identified by looking at patient volume. Keeler and Ying (1996) argue that due primarily to technological advances through the 1980s, hospitals had substantial excess bed capacity in the 1990s. One final issue worth discussing is whether patients are really the people who respond to changes in the rankings. It is possible that rather than patients, doctors are paying attention to the rankings and tend to refer patients to the hospitals that improve their rank. Whether patients or doctors are responding to rank changes is a question that plagues both my study as well as the studies on the New York State Cardiac Surgery Reporting System. While these two mechanisms that cause rank changes to affect patient volume are observationally equivalent in my analysis, the implications are similar. Whether patients or doctors are using the information, the findings suggest that publicly released information that people believe reflects hospital quality can have a large impact on hospital-choice decisions.

3. Rankings methodology

3.1. America's Best Hospitals

In 1990, US News and World Report (USNWR) began publishing hospital rankings, based on a survey of physicians, in their weekly magazine. Beginning in 1993, USNWR contracted with the National Opinion Research Center at the University of Chicago to publish an "objective" ranking system that used underlying hospital data to calculate which hospitals they considered to be "America's Best Hospitals". Each year since 1993, USNWR has published in their magazine the top 40–50 hospitals in each of up to 17 specialties. The majority of these specialties are ranked based on several measures of hospital quality, while a few continue to be ranked solely by a survey of hospital reputation.[4] This study focuses on the specialties that are ranked using characteristics beyond simply a survey of hospital reputation.[5]

USNWR claims that the rankings are determined in the following manner. First, they identify hospitals that meet one of three criteria: membership in the Council of Teaching Hospitals, affiliation with a medical school, or availability of a certain number of technological capabilities that USNWR considers to be important. Each year about one-third of the approximately 6000 hospitals in the US meet one of these three criteria. These hospitals are then assigned a final score, one-third of which is based on a survey of physicians, one-third by the hospital-specialty's mortality rate, and the final one-third by a combination of other observable hospital characteristics (nurses-to-beds ratio, board-certified M.D.'s to beds, the number of patients treated, and the specialty-specific technologies and services that a hospital has available).[6] The statistics that USNWR uses are 1–3 years old by the time the rankings are actually released. After obtaining a final score for each eligible hospital, USNWR assigns the hospital with the highest raw score in each specialty a quality score of 100%. The other hospitals are given a quality score (in percent form) which is based on how their final scores compared to the top hospital's final score (by specialty). The hospitals are then assigned a number rank based on the ordering of the continuous quality scores. Fig. 1 contains an example of what is published in the USNWR magazine for each specialty. As can be seen, the name, rank, and continuous quality score of each hospital is provided in the magazine along with a subset of the other variables that are used in the rankings process.

While USNWR claims that the rankings use the three factors indicated above equally in determining a hospital's rank, it can shown that the rankings are actually being driven almost entirely by reputation score. To see this, Table 1 presents the results from regressing the continuous quality scores for hospital-specialties in 2000 on the reputation scores (% of surveyed physicians who indicated the hospital-specialty as one of the top five hospitals in that specialty) and risk-adjusted mortality rates of each hospital-specialty (actual deaths/expected deaths).[7] Column (1) indicates that hospitals do indeed receive higher quality scores as their reputation scores increase and as their risk-adjusted mortality rates decrease. Columns (2) and (3) present the results of the regression of continuous quality scores on each of these factors individually. As can be seen, the reputation scores can explain over 95% of the variation in the final quality scores while the risk-adjusted mortality rates explain less than 1%. In fact, without controlling for the reputation scores, the sign on risk-adjusted mortality rates is even in the wrong direction. Since the variables are not normalized, reputation scores (which are much more variable than risk-adjusted mortality rates) represent more of the final score than the claim of one third. Thus, the continuous quality score that is provided for each hospital can be essentially thought of as an affine transformation of the reputation score.

Table 1
Estimating the components of the continuous quality score—hospitals.

	Dependent variable: continuous quality score (%)		
	(1)	(2)	(3)
Reputation (%)	1.17(0.01)***	1.16(0.01)***	
Risk-adjusted mortality rate	−6.10(0.81)***		2.64(3.93)
R-squared	0.959	0.952	0.001
Observations	350	350	350

Notes: Observations are at the hospital-specialty level. The dependent variable is the continuous quality score (%) reported in the US News and World Report's Best Hospitals issue in 2000. Data for reputation and risk-adjusted mortality rates were also taken from the magazine issue.
*Significant at 10%. **Significant at 5%.
*** Significant at 1%.

Are these hospital rankings popular? There are several indications that suggest that people pay attention to these rankings. Anecdotally, many health-care professionals are aware of the rankings and know when they are published each year. There have been several articles published in premier medical journals debating whether or not the methodology that is used in these rankings identifies true quality (Chen et al., 1999; Goldschmidt, 1997; Hill et al., 1997). A tour of major hospital websites illustrates that hospitals actively use the rankings as an advertising tool.[8] Just two years after the release of the "objective" USNWR rankings, Rosenthal et al. (1996) found survey evidence that over 85% of hospital CEOs were aware of and had used USNWR rankings for advertising purposes. In addition, USNWR magazine has a circulation of over 2 million and the full rankings are available online each year for free suggesting that if interested, most people can gain access to the rankings.

4. Data

Two main sources of hospital data are used in this analysis. First, I obtained individual-level data from California's Office of Statewide Health Planning & Development on all inpatient discharges for the state of California from 1998 to 2004. The data include demographic information about the patient (race, gender, age, and zip code) and information about each hospital visit (admission quarter, hospital attended, type of visit (elective or emergency), diagnosis-related group (DRG), length of stay, outcome (released, transferred, or died), primary insurer, and total dollars charged). The second source of data used is the National Inpatient Sample (NIS) produced by the Healthcare Cost and Utilization Project from 1994 to 2002. These data contain all inpatient

[4] In 1993, USNWR calculated "objective" rankings in the following specialties: Aids, Cancer, Cardiology, Endocrinology, Gastroenterology, Geriatrics, Gynecology, Neurology, Orthopedics, Otolaryngology, Rheumatology, and Urology. The following specialties were ranked by survey: Ophthalmology, Pediatrics, Psychiatry, and Rehabilitation. In 1997, Pulmonary Disease was included as an additional objectively measured specialty. In 1998, the Aids specialty was removed. In 2000, Kidney Disease was added as an objectively ranked specialty.

[5] The specialties ranked solely by survey typically only rank 10–20 hospitals. These specialties are not given a continuous quality score in the same way as the other specialties making one of the identification strategies used in this paper difficult. Furthermore, the specialties ranked solely by survey (ophthalmology, pediatrics, psychiatry, and rehabilitation) treat very few inpatients for which I have data available.

[6] The exact methodology used by USNWR has changed slightly since 1993. A detailed report of the current methodology used can be found on USNWR's website at www.usnews.com/usnews/health/best-hospitals/methodology.htm.

[7] The third factor used in the ranking – process measures – is not included in Table 1. This is due to the fact that process measures vary by specialty and thus cannot be included in this analysis which aggregates across specialties in order to obtain sufficient statistical power. However, given that 95% of the variation in the continuous quality measure can be explained by reputation, the process measures are obviously given very little weight in the ranking system.

[8] For example, see www.clevelandclinic.org and www.uchospitals.edu.

GYNECOLOGY. Gynecology, derived from the Greek for woman, has a wide-ranging focus. Gynecologists deal with infertility and menopause-related problems, sexually transmitted diseases and cancers of the reproductive tract. Usually intertwined with obstetrics, top gynecology departments can draw from a variety of subspecialists.

EXCLUSIVE 1993 RANKINGS

REGION KEY: Northeast South West Midwest

Rank	Hospital	Overall score	Reputational score	Mortality rate	Residents to beds	Technology score	R.N.'s to beds	Board-certified M.D.'s to beds	Inpatient operations to beds
1	**Mayo Clinic,** Rochester, Minn.	100.0	20.6%	0.65	NA	16	0.86	1.40	21.9
2	**Johns Hopkins Hospital,** Baltimore	96.8	19.7%	0.76	0.44	16	1.28	0.97	14.7
3	**University of Texas (M. D. Anderson Cancer Center),** Houston	93.4	18.9%	0.77	0.21	11	1.92	0.55	12.2
4	**Brigham and Women's Hospital,** Boston	86.0	16.1%	0.74	0.62	17	0.77	1.20	20.1
5	**Memorial Sloan-Kettering Cancer Center,** New York	69.7	11.4%	0.71	0.32	10	1.29	0.52	17.9
6	**Duke University Medical Center,** Durham, N.C.	67.8	11.0%	0.85	0.38	19	1.37	0.59	13.6
7	**UCLA Medical Center,** Los Angeles	64.1	7.5%	0.78	1.29	17	1.61	1.64	16.8
8	**Massachusetts General Hospital,** Boston	63.6	9.0%	0.78	0.47	19	1.20	1.06	19.3
9	**Cleveland Clinic**	59.3	7.7%	0.75	0.50	14	1.44	0.36	20.4
10	**Los Angeles County–USC Medical Center**	58.1	9.3%	0.94	0.03	13	1.18	0.14	31.1
11	**University of Chicago Hospitals**	57.6	7.3%	0.90	0.77	17	1.53	0.74	17.5
12	**Columbia-Presbyterian Medical Center,** New York	51.5	6.0%	0.75	0.30	16	1.01	0.63	7.6
13	**Hospital of the University of Pennsylvania,** Philadelphia	49.0	4.2%	0.83	1.06	15	1.18	0.94	15.0
14	**University of Washington Medical Center,** Seattle	47.6	3.5%	0.74	0.31	15	1.88	1.86	15.0
15	**Yale–New Haven Hospital,** New Haven, Conn.	47.2	5.4%	0.96	0.43	13	1.22	1.23	12.9
16	**Parkland Memorial Hospital,** Dallas	46.4	6.0%	1.24	0.72	13	0.93	1.16	10.9
17	**Roswell Park Cancer Institute,** Buffalo	45.7	2.4%	0.63	0.30	10	1.69	0.39	30.8
18	**University of California, San Francisco Medical Center**	45.7	2.8%	0.76	0.32	17	1.85	1.59	19.0
19	**Northwestern Memorial Hospital,** Chicago	45.2	4.7%	0.93	0.40	14	1.16	1.00	14.6
20	**Stanford University Hospital,** Stanford, Calif.	45.2	4.4%	0.94	0.72	14	0.85	1.56	15.8
21	**New York Hospital–Cornell Medical Center,** New York	44.4	3.5%	0.72	0.36	15	0.88	0.95	11.0
22	**University of Virginia Medical Center,** Charlottesville	43.3	2.4%	0.85	0.78	17	1.70	0.44	16.4
23	**Beth Israel Hospital,** Boston	42.7	3.4%	0.75	0.01	13	1.36	0.83	14.1
24	**Thomas Jefferson University Hospital,** Philadelphia	42.0	1.0%	0.68	0.71	17	1.41	1.11	16.5
25	**University of North Carolina Hospitals,** Chapel Hill	41.9	2.7%	0.93	0.55	15	1.78	0.91	15.0
26	**New England Medical Center,** Boston	41.8	1.7%	0.75	0.58	13	1.66	1.70	15.9
27	**Mount Sinai Medical Center,** New York	41.6	2.0%	0.78	0.52	16	1.58	1.18	12.8
28	**Barnes Hospital,** St. Louis	41.5	3.6%	0.74	0.41	5	0.79	0.85	11.2
29	**Georgetown University Hospital,** Washington, D.C.	40.9	1.8%	0.76	0.34	15	1.60	1.29	16.3
30	**Cedars-Sinai Medical Center,** Los Angeles	40.3	2.9%	0.83	0.24	15	0.99	1.13	17.7
31	**Baylor University Medical Center,** Dallas	39.9	3.4%	0.94	0.14	14	1.23	0.49	18.7
32	**University of Miami Hospital and Clinics**	39.6	1.5%	0.64	0.00	4	0.93	5.92	9.3
33	**Indiana University Medical Center,** Indianapolis	39.4	0.0%	0.64	0.37	17	1.82	0.90	17.6
34	**University of Wisconsin Hospital and Clinics,** Madison	39.3	0.5%	0.68	0.65	16	1.25	0.67	18.2
35	**University of California, Irvine Medical Center,** Orange	38.6	2.8%	1.04	NA	15	1.97	1.73	11.6
36	**New York University Medical Center,** New York	38.4	1.0%	0.64	0.20	12	1.15	1.15	13.6
37	**University of California, Davis Medical Center,** Sacramento	38.2	0.5%	0.94	0.63	18	2.59	0.60	16.1
38	**Rush-Presbyterian–St. Luke's Medical Center,** Chicago	38.1	1.0%	0.75	0.61	16	1.18	0.84	13.4
39	**University of Utah Hospital,** Salt Lake City	37.9	2.3%	1.00	0.37	15	1.60	0.91	13.3
40	**University of Iowa Hospitals and Clinics,** Iowa City	37.8	1.0%	0.89	0.78	18	1.31	0.49	24.6
41	**University of California, San Diego Medical Center**	37.5	0.9%	0.89	0.27	17	2.66	0.91	18.7
42	**Presbyterian University Hospital,** Pittsburgh	37.4	0.5%	0.83	0.66	11	2.12	1.20	17.7

"Reputational score" is the percentage of doctors surveyed who named the hospital. "Mortality rate" is the ratio of actual to expected deaths (lower is better). "Residents to beds" is the ratio of interns and residents to beds. "Technology score" is an index from 0 to 19. "R.N.'s to beds" is the ratio of registered nurses to beds. "Board-certified M.D.'s to beds" is the ratio of doctors certified in a specialty to beds. "Inpatient operations to beds" is the ratio of annual inpatient operations to beds. NA = Not available.

U.S.NEWS & WORLD REPORT, JULY 12, 1993 87

Fig. 1. Example of Hospital Ranking Magazine Display.

discharges for a 20% random sample of hospitals each year from certain states. States varied their participation in the program such that hospitals from some states are overrepresented in the sample. The NIS data contain similar information about each patient and hospital visit as the California data.

In this analysis, the main findings are presented for Medicare patients. There are several reasons to restrict the focus of this paper to Medicare patients only. First, Medicare patients represent over 30% of all inpatient procedures. Also, in contrast to privately insured individuals (who may want to react to changes in a hospital's rank but cannot because of network-provider limitations) Medicare patients have flexible coverage. Most importantly, however, the prices that a hospital charges for Medicare procedures are fixed. The goal of this paper is to empirically test the elasticity of demand with respect to perceived hospital quality. In order to estimate this elasticity, it is a requirement that prices are exogenous. If prices are allowed to endogenously adjust to changes in perceived quality (as they may with non-Medicare patients), estimated elasticities would be biased. For this reason the main findings presented in this paper are restricted to this set of patients. While potentially biased, the results of perceived quality changes on patients from other payer categories will be presented in Appendix A. Within Medicare patients, we will also estimate models separately for patients who were admitted as non-emergency patients and those who were admitted as emergency patients.[9]

I aggregate the hospital data to create a panel dataset at the hospital-specialty-year level. Thus, I create counts for the number of Medicare inpatients treated in a given specialty at a given hospital for each year that the data are available. All hospital-specialty groups that received a USNWR rank in the prior year were included in the sample. Diagnosis-related group codes (DRGs) were used to classify each individual into a specialty.[10] Hospital-specialty rankings for AIDS and Kidney Disease were not used because USNWR did not consistently rank these specialties during the sample period. Furthermore, hospital-specialty rankings for Endocrinology, Otolaryngology (Ear, Nose and Throat), and Rheumatology were dropped because hospitals very rarely treated non-emergency inpatients in these specialties.[11] All other hospital-specialty-year groups from the remaining eight specialties that treated at least ten non-emergency and emergency patients were included in the analysis.[12]

The timing of the release of the USNWR rankings each year is important when attempting to capture the effect of rankings on consumer behavior. Each year, USNWR releases the rankings in a fall magazine issue. Since the available hospital data only contains quarter of admission and given that many patients often have to make appointments a month or more in advance of admission, it is difficult to know which issue individuals who were admitted in the 3rd or 4th quarter of each year would use in their decision. Therefore, in the main specifications that I present, I created counts for patient volume and revenue for individuals who were admitted between January and June of each year—nearly all of whom would have used the previous fall's rankings (log rank).[13]

Table 2
Hospital data by state, year, and specialty.

State	Obs.	Data year	Obs.	Specialty	Obs.
Arizona	2	1994	29	Cancer	58
California	212	1995	16	Digestive	79
Colorado	8	1996	22	Gynocology	19
Connecticut	7	1997	36	Heart	67
Florida	1	1998	60	Neuro	70
Illinois	53	1999	64	Ortho	66
Iowa	30	2000	59	Respiratory	32
Maryland	47	2001	49	Urology	55
Massachussetts	26	2002	51		
New York	10	2003	30		
Pennsylvania	16	2004	30		
Virginia	1				
Washington	8				
Wisconsin	25				
Total	446		446		446

Notes: Data are from the NIS sample created by the HCUP and from the state of California's OSHPD office. Observations are at the hospital-specialty-year level. Observations are included for hospital-specialties that have a non-missing lagged rank.

Table 3
Summary statistics—hospital data.

	Mean	Standard deviation	Minimum	Maximum
Total Medicare patients within a specialty	342	308	26	1942
Non-emergency	120	104	10	1334
Emergency	222	257	10	1709
Total Medicare patients by specialty				
Cancer	122	53	26	342
Digestive	422	232	88	1019
Gynocology	92	26	42	133
Heart	741	470	147	1942
Neurology	321	134	69	671
Orthopedics	277	203	26	1401
Respiratory	380	219	135	946
Urology	142	65	44	280
Observations	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. The data represent patient counts for the first and second quarters of the observation years. Observations are included for hospital-specialties that have a non-missing lagged rank.

Table 2 provides a breakdown of the aggregate-level observations for Medicare patients admitted between January and June of each year by state, year, and specialty. As indicated in the Table, nearly half of the data points in the sample come from the state of California. This is due both to the fact that many of the top hospitals are in California and because the hospital data that I use contains a full sample of California hospitals. All years and specialties have a significant number of observations. Table 3 presents the average number of patients that each hospital treats by specialty and patient type. The mean number of Medicare patients treated in a given specialty for the average hospital in my sample is 342. Approximately one-third of those patients are non-emergency patients while the remainder is emergency patients. Significant variation exists across specialties regarding the number of patients that are treated. For example, the specialty that treats the most

[9] Non-emergency patients are identified in the California data as patients "not scheduled within 24 hours or more prior to admission" and in the NIS as patients simply classified somehow as "non-emergency patients".

[10] The matching between DRGs and specialties was chosen to be the same as that used by USNWR when measuring patient volume by specialty. See the USNWR methodology report for this matching procedure, www.usnews.com/usnews/health/best-hospitals/methodology.htm.

[11] The dataset consists of inpatients only. Thus, while there are many non-emergency outpatients in these specialties, the inpatients are nearly 100% emergent cases.

[12] These specialties include cancer, digestive, gynecology, heart, neurology, orthopedics, respiratory, and urology. Hospital-specialties with non-emergency and emergency-patient counts of less than 10 cases were dropped in order to reduce the noise involved with hospitals that did not regularly treat inpatients of the given type.

[13] Appendix Table A1 presents the regression results if patients from the 3rd quarter of the year (who may or may not be using the previous fall's rankings) are also included.

patients is the Heart specialty where the average hospital treats 741 patients each half of year. On the other end of the spectrum, the average hospital in my sample only treats 92 gynecology patients each half of year.

An obvious question regarding the hospitals in this sample is whether they truly compete with each other for patients given their geographic diversity. Clearly, most non-emergency patients choose hospitals that are nearby when choosing medical care. However, in some cases patients may cast a wide net when deciding which hospital to visit and thus these ranking could significantly affect their decisions. Furthermore, even if someone is choosing between two local hospitals (one of which is ranked), an improvement in the ranking of the ranked hospital may increase the likelihood that the patient will choose that hospital over a different local hospital that is unranked. This may be a large factor in driving our results. In the empirical specification, however, I also test for the effect of a hospital-specialty that improves its rank such that it surpasses another hospital-specialty's rank that is in the same state. Thus, I can test for the effect of changes in a hospital-specialty's state rank from year to year where one might expect to find larger effects given the increased amount of competition for patients within a state.

5. Empirical strategy

5.1. Aggregate-level analysis

The key advantage to using rankings to test whether consumers respond to changes in perceived hospital quality is that the rankings that I study are disseminated and have variation from year to year. Thus, I am able to control for unobserved heterogeneity at the hospital-specialty level and identify off changes in rank that occur within a hospital-specialty across time.

The baseline econometric specification used is

$$Y_{jt} = \alpha_j + \delta_t + \beta Rank_{jt-1} + \varepsilon_{jt}$$

where Y_{jt} represents either the log number of Medicare discharges or the log total revenue generated from Medicare patients at hospital-specialty j during the first or second quarter of year t. $Rank_{jt-1}$ is the USNWR rank of hospital-specialty j in year $t-1$. Depending on the specification, I include the overall USNWR rank as well as where each hospital ranks within their respective state. Hospital-specialty and year fixed effects are also included in the specification.

A fundamental challenge of identifying the effect of rankings on consumer behavior is the possibility that rank changes are correlated with changes in hospital quality that are observed by consumers but unobserved by the econometrician. For example, it is possible that a hospital builds a new cancer wing. This might simultaneously improve the hospital's rank for cancer and allow the hospital to attract more patients. If this happened, I would find an effect of rankings on patient volume. However, the correlation between rank changes and changes in patient volume would not be due to consumers responding to rank changes, but rather consumers responding to something that caused a change in the hospital's rank.

I propose three robustness checks that allow me to be confident that the results I find are causal and not spurious. First, I test whether or not rank changes affect changes in the number of *emergency* patients treated by each hospital. Since emergency patients are less likely to be able to respond to rankings, I would expect a smaller or no effect of rank changes on the number of emergency patients treated by hospitals. However, if the effect that I find of rank changes on patient volume were spurious (due to, for example, a change in local demographics, a change in the size of the hospital, etc.), I would expect the rank changes to affect emergency patients as well as non-emergency patients.

While this robustness check may rule out certain endogeneity stories, it is still possible that patients do not react to the hospital rankings, but instead react to changes in hospital quality that the rank changes reflect. The second robustness check that I employ attempts to overcome this further potential bias. As explained earlier in the paper, the statistics that USNWR uses to produce its annual rankings are 1–3 years old by the time the rankings are actually published. Thus, if patients are not using the actual rankings and only responding to the quality changes at hospitals that the rankings represent, then one would expect a current increase in patient volume for hospitals whose rank improves in the following period. Evidence that the response to rank changes occur *after* the rankings are published as opposed to *before* suggests that consumers must be using the actual rankings when making their hospital-choice decisions. For this robustness check, I estimate the baseline econometric specification including both the lag overall rank, which rank came out in the Fall prior to the hospital-choice decisions, as well as the current overall rank which came out after the hospital-choice decisions were made.

Finally, I consider one additional robustness check which relies on a unique institutional detail of the rankings. For each hospital, not only are consumers provided with a rank, but also with a continuous quality measure. If the rankings simply reflect information that is unobserved to the econometrician but observed by consumers, then consumers should be responding to changes in the continuous quality measure as opposed to discontinuously reacting to changes in rank. Thus, after flexibly controlling for the continuous quality score, changes in the ordinal rankings of hospitals should not affect consumer decisions. However, if consumers are causally affected by rank changes, then the ordinal rankings may still influence consumer choices even after controlling for the continuous quality score. This strategy simultaneously tests that: (i) consumer decisions are causally affected by the rankings and (ii) consumers ignore the more informative measure of hospital and college quality and focus their attention on changes in the ordinal rankings. To clarify this, consider the following example. In 1997, UCSF was ranked as the 6th best hospital for treating digestive disorders while UCLA was ranked 7th. In 1998, UCSF's continuous quality score decreased causing its rank to fall to the 8th spot while UCLA continued to hold the 7th spot. Between 2002 and 2003, the difference between UCLA and UCSF's continuous quality scores changed by the same amount as it did between 1997 and 1998 yet their ranks remained the same. If rank changes simply reflect differences in hospital quality that consumers observe, then the consumer response to these two events should on average be equal. However, if consumers react exclusively to changes in ordinal rankings (and ignore the more detailed measure at their disposure), then a larger consumer response to the first event should occur.

5.2. Individual-level analysis

Using the individual-level inpatient data, I estimate a discrete choice model for hospital choice. The individual-level analysis enables me to control for the proximity of hospitals to patients. This can both increase the precision of the analysis and also allow for the comparison between the effect of distance and the rankings on hospital decisions. I estimate a mixed-logit discrete choice model (McFadden and Train, 2000; Train, 2003) which is a flexible extension of the more traditional conditional logit model (McFadden, 1974). The mixed-logit model has become the state of the art method used in hospital-choice analyses (see Tay, 2003). Unlike the conditional logit model, the mixed-logit model estimates random

Table 4
The effect of USNWR hospital rankings on patient volume and revenue.

	Dependent variable: log volume and revenue of non-emergency Medicare discharges					
	Log number of patients			Log revenue generated from patients		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall rank (lagged)	0.0088(0.0023)***		0.0074(0.0028)**	0.0106(0.0028)***		0.0101(0.0033)***
State rank (lagged)		0.068(0.019)***	0.031 (0.025)		0.060(0.025)**	0.010 (0.031)
Hospital-specialty F.E.	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
R-squared	0.939	0.937	0.939	0.965	0.964	0.971
Observations	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of non-emergency Medicare patients (Columns (1)–(3)) or the log revenue generated from non-emergency Medicare patients (Columns (4)–(6)) that were admitted between January and June of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. State rank (lagged) represents the rank of the hospital-specialty relative to other hospital-specialties in the same state (e.g. a state rank of 2 means that there was one other hospital-specialty with a higher rank). Hospital-specialty and year fixed effects are included. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
*Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

coefficients on the product characteristics in the indirect utility function. Allowing random taste variations eliminate the need for assuming the independence of irrelevant alternative assumption, which is likely to be violated in a model of hospital choice. In order to obtain this increased flexibility in substitution patterns, the mixed-logit model has a more complicated functional form whose likelihood function does not have a closed-form solution. However, recent advances in simulation techniques have made estimating mixed-logit coefficients possible even for large datasets. Thus, mixed-logit models have recently been used, particularly in the industrial organization and marketing literatures, to model a variety of choices (Berry et al., 1995; Train and Winston, 2006; Nevo, 2001; Hastings et al., 2006).

The specific mixed-logit model I use, which can easily be generated from a standard random utility framework (see Train, 2003), has choice probabilities that are expressed as

$$P_{ijt} = \int \left(\frac{e^{\beta x_{ijt}}}{\sum_j e^{\beta x_{ijt}}} \right) f(\beta)\, d\beta \qquad (1)$$

where P_{ijt} represents the probability that person i chooses hospital-specialty j in year t. x_{ijt} includes variables relating to each hospital (e.g. rank) as well as individual-hospital characteristics (e.g distance from the individual's home to the hospital). The probability that person i chooses each of the possible alternatives is a weighted average of the logit formula (with a linear indirect utility function) evaluated at different values of β according to the density function $f(\beta)$ (the mixing distribution). In this analysis, I use the normal distribution as the mixing distribution for distance, hospital rank, and the controls for the continuous quality scores. Through numeric integration, the log likelihood function of Eq. (1) is maximized to yield estimates of both the mean and variance of β.

Only the California data are used to estimate the mixed-logit model since patients' zip code is not available in the NIS data. Using patient and hospital zip codes, I calculate the distance between each patient and every hospital in California.[14] The resulting dataset is much too large to work with due to computational and space constraints. In order to limit the number of observations, I reduce the dataset to patients admitted for a heart procedure.[15] This reduces the sample to 127,141 non-emergency Medicare patients that were admitted to one of 374 hospitals in California between January and June from 1998 to 2004. However, this sample continues to be too large to work with (more than 47.5 million patient–hospital pairs). Thus, I further reduce the sample by eliminating patients of hospitals that received less than 10 patients per year. 12,498 patients (9.8%) and 210 hospitals were eliminated resulting in the elimination of approximately 18.8 million patient–hospital observations. I proceed by generating a 25% random sample of these patient–hospital observations leaving me with 28,647 patients and 4,698,108 patient–hospital observations—a large, yet feasible number with which to estimate a mixed-logit model. I report results for the mixed-logit model as well as the conditional logit model for comparison. Alternative-specific constants (dummy variables for each hospital) are included in all specifications so that, as with the aggregate-level analysis, I continue to be identifying the effect of the rankings by analyzing changes in the rankings across time within hospitals. I also continue to control for a cubic polynomial of the quality scores in all regressions.

6. Results

6.1. Aggregate-level results

Using the baseline econometric specification provided in the previous section, Table 4 presents the first set of results regarding the impact of changes in USNWR rankings on patient volume and revenue. For this table and all others, robust standard errors are presented in parenthesis, clustered at the hospital-year level. The rank variable for this and all other specifications was inverted so that an increase in rank represents an improvement in rank. The estimate in Column (1) suggests that an increase (improvement) in a hospital-specialty's overall USNWR rank by one spot increases the number of non-emergency patients treated at that hospital-specialty by 0.88%. This result is significant at the 1% confidence level. As opposed to looking at the effect of an overall rank movement, Column (2) estimates the effect of a hospital-specialty which changes their relative ranking within their state. The coefficient suggests that a hospital-specialty that improves their within-state rank by one spot (e.g. 3rd place to 2nd place) experiences a 6.8% increase in patient volume. Thus the effect of improving one's within-state rank by one spot (which typically requires moving several overall rank positions) is roughly 8 times as large as improving one's overall rank by one spot. Column (3) includes both the overall rank and the state rank in the regression. Including both of these

[14] This is done by using the latitude and longitude of the patient and hospital's zip-code centroids.
[15] The majority of studies looking at health-care rankings focus on heart patients (e.g. studies of the New York State Coronary Artery Bypass Surgery Report-Card System, Tay (2003), etc.).

Table 5
The effect of USNWR hospital rankings on patient volume—by specialty.

	Dependent variable: log number of non-emergency Medicare patient discharges by specialty						
	Cancer (1)	Digestive (2)	Heart (3)	Neurology (4)	Orthopedics (5)	Respiratory (6)	Urology (7)
Overall rank (lagged)	0.0083(0.0064)	0.0067(0.0047)	0.0166(0.0070)**	0.0010(0.0032)	0.0031(0.0058)	0.0044(0.0101)	0.0124(0.0106)
Hospital-specialty F.E.	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X
R-squared	0.871	0.949	0.945	0.977	0.971	0.980	0.891
Observations	58	79	67	70	66	32	55

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of non-emergency Medicare patients that were admitted between Jan. and Jun. of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. State rank (lagged) represents the rank of the hospital-specialty relative to other hospital-specialties in the same state (e.g. a state rank of 2 means that there was one other hospital-specialty with a higher rank). Hospital-specialty and year fixed effects are included. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
* Significant at 10%.
*** Significant at 1%.
** Significant at 5%.

regressors requires more variation and thus the standard errors for both coefficients increase. However, the overall rank coefficient continues to be positive and significant (although it is slightly smaller) and the coefficient on state rank becomes insignificant. The point estimate on state rank, while insignificant, suggests that even after controlling for changes in overall rank, there is an additional benefit for hospitals to improve their rank relative to other nearby hospitals.

Columns (4)–(6) present analogous results to the first three columns. The dependent variable in these regressions, however, is the total log revenue generated from non-emergency Medicare patients. Both the size of the coefficients and the significance levels are very similar to the results on patient volume, as one might expect.

Table 5 presents the effect of overall rank changes on non-emergency Medicare patient volume by each of the seven specialties used in our analysis (the gynecology specialty drops out due to insufficient observations). This table indicates that no single specialty is driving all of the results presented in Table 4. In fact, while statistical power is lacking in nearly all of these regressions, the point estimate for rank changes is positive for every specialty. The specialty with the strongest coefficient is the Heart specialty (which is also the specialty that treats the most patients). This suggests that people who are scheduling a non-emergency inpatient procedure related to a heart problem may be particularly likely to rely on these rankings when making a hospital-choice decision.

Tables 6–8 present the results of the three robustness specifications discussed in the empirical strategy section. Table 6 begins by looking at the effect of rank changes on *emergency* patient volume and revenue. Using the same specification as the one used in Table 4, I find that rank changes do not have a significant effect on the number of emergency patients treated by a given hospital. In fact, although not statistically distinguishable from zero, the majority of coefficients are negative. This provides the first piece of evidence that the effects found in Table 4 are causal.

Table 7 analyzes whether the effect of rank changes occur before or after the rankings are released. Controlling for both lagged and non-lagged rank changes, I find that lagged rank changes are those that significantly affect changes in patient volume and revenue and not lead rank changes. Specifically, the coefficients on the rank variables that are not lagged are less than half the size of the lagged rank variable coefficients for patient volume and are close to zero or negative for patient revenue. Thus, even though rank changes reflect changes in hospital statistics that occurred 1–3 years ago, they do not appear to have an effect on patient volume until after they are released.

Table 8 presents the final robustness check. Aside from simply including the overall rank variables, these regressions also control for the underlying continuous quality score provided by USNWR.

Table 6
Robustness check: rank effect on emergency patients.

	Dependent variable: log volume and revenue of emergency Medicare discharges					
	Log number of patients			Log revenue generated from patients		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall rank (lagged)	−0.0034(0.0038)		−0.0021(0.0046)	0.0015(0.0034)		0.0022(0.0045)
State rank (lagged)		−0.039(0.036)	−0.028 (0.044)		−0.004(0.034)	−0.016 (0.045)
Hospital-specialty F.E.	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
R-squared	0.971	0.971	0.971	0.973	0.973	0.973
Observations	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of emergency Medicare patients (Columns (1)–(3)) or the log revenue generated from emergency Medicare patients (Columns (4)–(6)) that were admitted between January and June of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. State rank (lagged) represents the rank of the hospital-specialty relative to other hospital-specialties in the same state (e.g. a state rank of 2 means that there was one other hospital-specialty with a higher rank). Hospital-specialty and year fixed effects are included. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 7
Robustness check: lead rank effect on patient volume and revenue.

	Dependent variable: log volume and revenue of non-emergency Medicare discharges					
	Log number of patients			Log revenue generated from patients		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall rank (lagged)	0.0084(0.0026)***		0.0078(0.0038)**	0.0106(0.0038)***		0.0097(0.0048)**
State rank (lagged)		0.064(0.027)**	0.013 (0.039)		0.087(0.039)**	0.023 (0.048)
Overall rank (not lagged)	0.0035 (0.0031)		0.0028 (0.0032)	0.0002 (0.0036)		0.0012 (0.0041)
State rank (not lagged)		0.023 (0.028)	0.015 (0.027)		−0.030(0.032)	−0.028 (0.035)
Hospital-specialty F.E.	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
R-squared	0.954	0.953	0.954	0.969	0.968	0.969
Observations	309	309	309	309	309	309

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of non-emergency Medicare patients (Columns (1)–(3)) or the log revenue generated from non-emergency Medicare patients (Columns (4)–(6)) that were admitted between January and June of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. State rank (lagged) represents the rank of the hospital-specialty relative to other hospital-specialties in the same state (e.g. a state rank of 2 means that there was one other hospital-specialty with a higher rank). Overall rank (not lagged) and state rank (not lagged) are similar except that they represent the rank that the hospital-specialty received the July or August after the January–June data. Hospital-specialty and year fixed effects are included. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 8
Robustness check: controlling for continuous quality score.

	Dependent variable: log volume and revenue of non-emergency Medicare discharges					
	Log number of patients			Log revenue generated from patients		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall rank (lagged)	0.0101(0.0033)***		0.0089(0.0035)**	0.0120(0.0034)***		0.0116(0.0038)***
State rank (lagged)		0.063(0.025)**	0.033 (0.026)		0.050 (0.029)*	0.012 (0.032)
Cont. quality score	−0.855 (0.768)	−0.015(0.645)	−0.952 (0.776)	−0.885 (0.820)	0.301 (0.717)	−0.919 (0.832)
Cont. quality score—squared	0.479 (0.402)	0.064 (0.343)	0.517 (0.405)	0.476 (0.427)	−0.101(0.366)	0.489 (0.432)
Cont. quality score—cubed	−0.069 (0.059)	−0.011(0.052)	−0.074 (0.060)	−0.065 (0.062)	0.016 (0.054)	−0.067 (0.063)
Hospital-specialty F.E.	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
R-squared	0.939	0.937	0.939	0.965	0.964	0.965
Observations	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of non-emergency Medicare patients (Columns (1)–(3)) or the log revenue generated from non-emergency Medicare patients (Columns (4)–(6)) that were admitted between January and June of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. State rank (lagged) represents the rank of the hospital-specialty relative to other hospital-specialties in the same state (e.g. a state rank of 2 means that there was one other hospital-specialty with a higher rank). Hospital-specialty and year fixed effects are included. A cubic polynomial of the continuous quality score that each hospital received is also included as a control. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

A cubic of this continuous score is included.[16] While including this continuous score increases the standard errors for most coefficients by 30–40%, the coefficient size remains very similar to those presented in Table 4. Furthermore, the majority of point estimates continue to be statistically significant at conventional levels. It is also of interest to note that the continuous quality score variable is never significant, suggesting that while USNWR readers pay attention to the ordinal rank of each hospital, attention is not given to the underlying continuous score that determines that rank.

Appendix Table A1 provides the results from several other specifications that one might consider. Specifically, I test for the effect of rank changes on non-emergency patient volume and revenue when the 3rd quarter patients are included and find similar results. I also test for the effect of log rank changes on volume and revenue. The log specification allows rank changes at the top of the list (moving from 5th to 3rd) to be more influential on consumer choices than rank changes at the bottom of the list (35th to 33rd). The fit of the model is about the same for the log rank specification as the linear rank specification. This suggests that consumers react slightly more to rank changes that occur at the top of the list, yet not to the degree that a log specification would imply. I present estimates from linear rank changes in our main specification for ease of interpretation and clarity. In Appendix A, I also present the effect of rank changes on private insurance and Medicaid patients. A priori, I thought that the effect of rank changes would be smaller

[16] A cubic function of this continuous variable is included in order to control for a possible nonlinear relationship between the continuous quality score and patient volume. Earlier versions of this paper included the continuous quality score linearly and in various polynomial forms. The author may be contacted for results when including different degrees of the continuous quality score polynomial.

Table 9
Mixed and conditional logit estimates of hospital choice.

	Mixed logit		Conditional logit	
	Mean		S.D.	
	(1)	(2)	(3)	(4)
Rank (lagged)	0.0118(0.0068)*	0.0054(0.0041)	0.0125(0.0063)**	0.0386(0.0129)***
Rank × (less than 50 miles)				−.0231 (0.0128)*
Distance				
Less than 3 miles	12.62 (0.10)***	2.10 (0.09)***	12.34 (0.09)***	12.57 (0.09)***
3–6 miles	11.49 (0.09)***	1.42 (0.07)***	11.34 (0.09)***	11.57 (0.09)***
6–10 miles	10.21 (0.09)***	0.71 (0.08)***	10.06 (0.09)***	10.30 (0.09)***
10–20 miles	8.60 (0.09)***	0.22 (0.08)***	8.47 (0.09)***	8.72 (0.09)***
20–50 miles	6.48 (0.09)***	0.64 (0.08)***	6.47 (0.08)***	6.72 (0.09)***
50–100 miles	3.48 (0.08)***	0.24 (0.13)*	3.48 (0.08)***	3.58 (0.08)***
Cont. quality score (cubic)	X	X	X	X
Cont. quality score (cubic) × (less than 50 miles)				X
Alternative-specific constants	X	X	X	X
Log likelihood	−58,732	−58,732	−58,967	−58,711
# of individuals	28,647	28,647	28,647	28,647
# of observations	4,698,108	4,698,108	4,698,108	4,698,108

Notes: Each observation represents a unique patient–hospital pair. The observations represent all patient–hospital pairs from a 25% random sample of all Medicare, non-emergency, heart patients admitted between January and June between 1998 and 2004 to hospitals that treated at least 10 non-emergency patients. Columns (1) and (4) present results from a conditional logit model and Columns (2) and (3) present results from a mixed-logit model. The dependent variable is an indicator that equals 1 if the patient chose the hospital represented in that patient–hospital pair. Rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. The base group for the distance indicators is the hospital being located more than 100 miles from the individual's home. An alternative-specific constant was included for each hospital. The rank variable was inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).

* Significant at 10%.

** Significant at 5%

*** Significant at 1%.

for these groups since they are oftentimes more restricted in which hospitals their health plans allow them to visit and because hospitals can adjust their rates for these patients according to changes in demand. The coefficient on rank changes for these groups are only marginally significant and the coefficient size is approximately 30% smaller.

6.2. Individual-level results

Table 9 contains the results from the mixed-logit model using the individual-level hospital data. Column (1) provides estimates for the mean effect of the rank and distance-to-hospital variables. While controlling for alternative-specific constants and continuous quality scores (cubic), I find that a better rank is associated with individuals having a higher probability of attending the hospital. Column (2) provides estimates for the standard deviations of the random coefficients. For comparison, Column (3) provides conditional logit estimates for the rank and distance-to-hospital variables. The coefficients are very similar across the two models. Column (4) includes an interaction term between rank and the hospital being less than 50 miles away. The results suggest that individuals who live more than 50 miles away from a hospital that experiences an increase in rank are affected about three times as much as individuals living within 50 miles.

How does the effect of rank changes compare to the importance of distance for individuals making hospital decisions? Analyzing the coefficients in Column (1) (or Column (3)), an improvement in rank by ten spots is approximately equal to 1/10th of the value place on a hospital being less than three miles from an individual as opposed to 3–6 miles away. If the regression is run with a linear distance variable, a ten spot change in rank is approximately equal to the value of a hospital being 1 mile closer to the patient. One further comment on the size of the rank effect is that I am estimating the average response rate across all individuals. If only 10% of people actually use the USNWR rankings, then the value that those people place on the rankings is actually ten times higher than the interpretation given above.

Are the magnitudes of the effects found in the individual-level analysis comparable to the aggregate-level analysis? Interpreting the marginal effect of a rank change at the average values of the explanatory variables and at an average hospital yields an increase in probability of 0.000075 for an improvement in rank by one spot. Multiplying this probability increase by the total number of heart patients treated in California in a given year indicates that a hospital that improves its rank by one spot should expect approximately 1.5 more patients which is equivalent on average to an increase in heart patient volume by 0.2%.

7. Discussion and conclusion

Overall, the results from this analysis suggest that USNWR rankings of hospitals have a significant impact on consumer decisions. In order to understand exactly the number of people whose hospital choices were affected by these rankings, it is necessary to know how volatile the rankings are. On average, the rank of each of the hospital-specialties in my sample changes by 5.49 spots each year. Thus, the USNWR rankings on average account for a change in over 5% of non-emergency Medicare patients in each of these hospital-specialties each year. A precise count of the number of hospital switches that took place because of the rankings can be calculated by summing up the rank changes and multiplying them by the number of patients and the percent of patients affected,

$$\sum_{jt} 1\% \times |(Rank_{jt} - Rank_{jt-1})| \times \text{Non-emergency patients(per year)}_{jt}.$$

In order to estimate the exact number of people in this sample whose hospital-choice decisions were affected by the rankings, the resulting number from Eq. (9) should be divided in half because individuals that choose a higher ranked hospital over a lower ranked hospital are essentially being counted twice (a decrease

Table A1
The effect of USNWR hospital rankings on patient volume and total revenue—alternative specifications.

	Dependent variable: log patient volume or total revenue generated from non-emergency Medicare patients by type							
	Log patient volume				Log total revenue			
	Medicare (1)	Medicare (2)	Insurance (3)	Medicaid (4)	Medicare (5)	Medicare (6)	Insurance (7)	Medicaid (8)
Rank (lagged)	0.0084(0.0023)***		0.0062(0.0040)	0.0059(0.0044)	0.0079(0.0024)***		0.0082(0.0046)*	0.0074(0.0054)
Log (rank) (lagged)		0.192(0.050)***				0.235(0.065)***		
Including 3rd quarter	X				X			
Hospital-specialty F.E.	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X
R-squared	0.946	0.938	0.969	0.927	0.968	0.965	0.973	0.942
Observations	446	446	446	444	446	446	446	444

Notes: Observations are at the hospital-specialty-year level. Robust standard errors clustered at the hospital-year level are reported in parentheses. The dependent variable is the log number of non-emergency Medicare patients, insurance patients, and medicaid patients (Columns (1)–(2), (3), and (4) respectively), or the log revenue generated from non-emergency Medicare patients, Insurance patients, and Medicaid patients (Columns (5)–(6), (7), and (8), respectively) that were admitted between Jan. and Jun. of the observation year. Overall rank (lagged) represents the rank that the hospital-specialty received the July or August before the January–June data. Log(rank) (lagged) represents the log of the rank (lagged) variable. Hospital-specialty and year fixed effects are included. The rank variable is inverted such that an increase in rank by one should be interpreted as an improvement in rank (e.g. 8th to 7th).
**Significant at 5%.
* Significant at 10%.
*** Significant at 1%.

in patient volume in the lower ranked hospital and an increase in patient volume at the higher ranked hospital). This calculation results in an estimated 1788 non-emergency Medicare patients in my sample who adjusted their hospital choice because of the rankings. A similar calculation can be done to calculate the amount of revenue affected by the rankings. An estimated 76 million dollars of revenue was transferred from hospitals in my sample whose rank decreased to hospitals whose rank increased. Given that my sample only represents a small portion (about 10%) of all of the USNWR rankings, the effect that these rankings have had on patients nationwide is likely much higher. Assuming my sample to be representative of the other hospitals ranked by USNWR, I estimate that these rankings have influenced over 15,000 hospital decisions made by Medicare patients and 750 million dollars in revenue between 1993 and 2004.

However, the estimates that are provided in this analysis are only a first step in determining the overall impact of these rankings on hospital markets. While it is beyond the scope of this paper, these rankings may also induce a measurable firm response. To understand the entire impact of these rankings, it is necessary to know whether the response of hospitals to the rankings is efficiency increasing or decreasing. This paper provides a first step in understanding how strong the incentives may be for hospitals to try to improve their rank.

Overall, I find that USNWR hospital rankings have a large impact on hospital-choice decisions. Why is it that this ranking system has a large impact on decisions while many other rankings and measures of hospital quality do so little to affect choices?[17] While there may be several answers to this question, I posit three plausible explanations. First, unlike many studies of hospital quality, our paper focuses on non-emergency Medicare patients. Due to the availability of time to make a decision and a flexible health-care plan, these patients are the most likely to be affected by hospital quality. Our estimates would be substantially smaller if they represented the impact of USNWR rankings on the average patient. Second, the simplicity of the USNWR quality measure – ordinal ranks – may be easier for consumers to understand and respond to than other more complicated measures of hospital quality. Recent work in behavioral economics suggests that the simplicity of information content is an important factor in consumer behavior (see for example, Bertrand et al., 2005). As evidenced by the popularity of both its hospital and college rankings, USNWR seems to have come up with a system to which consumers are able to easily grasp. Finally, the fact that these rankings come out in a popular national magazine may give them better coverage and/or make them seem more reliable to the general public than other measures of hospital quality.

While it can be argued whether changes in these rankings reflect true changes in hospital quality, at the very least, consumers are willing to respond to changes in *perceived* hospital quality. This has implications regarding the competitiveness of hospital markets and further suggests that the release and dissemination of believable information regarding hospital quality can affect consumer hospital-choice decisions.

[17] An exception to this is Cutler et al. (2004) that find that hospitals that are flagged as high mortality in New York experience a 10% reduction in patient volume—an effect similar in magnitude to that found in our paper.

Appendix A.

Table A1.

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