Reacting to Rankings: Evidence from "America's Best Hospitals and Colleges" *

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Abstract

Rankings and report cards have become a popular way of providing information in a variety of domains. In this study, I estimate the consumer response to rankings in two important areas: hospital and college choice. Analyzing the consumer reaction to these rankings can help answer important economic questions such as whether or not patients respond to changes in perceived hospital quality. In order to identify the causal effect of the rankings on consumer decisions, I exploit the available, underlying quality scores on which the rankings are based. Using aggregate-level data and flexibly controlling for the quality scores, I find that hospitals and colleges that improve their rank are able to attract significantly more patients and students resulting in a higher revenue stream for hospitals and a stronger incoming class for colleges. A further discrete-choice analysis of individual-level hospital decisions allows for a comparison between the effects of perceived quality (as reflected by the rankings) and hospital location. I discuss the heuristic that many consumers use when making their choices – reacting to ordinal rank changes as opposed to focusing strictly on the continuous quality measure. Limited attention and cognitive costs can explain why consumers use this shortcut. I provide bounds on how high processing costs must be in order for the use of the ordinal rankings as a rule of thumb to be optimal.

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1 Introduction

Rankings and report cards have become a common way for firms to present a range of options to consumers as well as synthesize detailed information into a format that can be easily processed. Some popular examples include rankings of colleges (e.g. US News and World Report), restaurants (e.g. Zagat), companies (e.g. Fortune 500), bonds (e.g. Moody's), and hospitals (e.g. US News and World Report). Additionally, Consumer Reports ranks a wide variety of consumer products each year. Many ranking systems provide an ordered list while others use letter grades (A, B, C, etc.), stars (4-stars, etc.), or alternative grouping methods.

In this analysis, I explore the consumer reaction to the widely-dispersed hospital and college (undergraduate and graduate) rankings published by U.S. News and World Report (USNWR) magazine. Released annually, these nationwide rankings anecdotally have a large influence on hospital and college choices. Obtaining empirical estimates of the impact that these rankings have on consumers is of interest for several reasons. Evidence of a large consumer response to these rankings suggests that the synthesis and public release of information in these markets is useful to many consumers. The magnitude of the response also illustrates the size of the (potentially perverse) incentives that hospitals and colleges have to improve their rank. A large consumer response to the hospital rankings has a further implication regarding competition in the hospital market. It has been argued that consumers of health care are unresponsive to changes in hospital quality because of restrictions such as distance from home, health plan networks, and doctor referrals. Limited evidence exists on this question in part because hospital quality is difficult to measure. Furthermore, measures that do exist of hospital quality typically change slowly across time, making within-hospital analyses difficult. Rankings provide an ideal setting where quality can be defined and measured. While it can be argued whether or not the USNWR hospital rankings reflect true quality, they provide an ideal setting in which consumer responses to changes in perceived quality can be measured, thus adding insight into the hospital competition and anti-trust literature.

A fundamental challenge in estimating the causal impact that rankings have on consumer behavior is the possibility of rank changes being correlated with underlying quality that is observed by individuals but not by researchers. Thus, an OLS relationship between rank changes and consumer behavior may result if changes in rank simply confirm what consumers already learned as opposed to providing new information. To circumvent this problem, I exploit a special feature of the USNWR hospital and college rankings: a continuous measure of quality is provided for each hospital and college along with the ordinal ranks. The rankings are completely determined by simply ordering the continuous quality scores. If the rankings are not affecting consumer decisions, variables that indicate the ability that a hospital or college has to attract patients or students should be smooth rather than discontinuous as one hospital or school barely surpasses another in rank. While flexibly controlling for the underlying quality score, any jumps in patient volume or student applications that occur when a hospital or college changes rank can be considered a lower bound on the causal effect of the rankings.

Employing this identification strategy, I estimate the effect of the hospital rankings on patient volume and hospital revenues. The data used for this section of the analysis consist of all hospitalized Medicare patients in California (1998-2004) and a sample of other hospitals around the country (1994-2002). I begin by aggregating the data to the hospital-specialty level. Using a fixed-effects framework, and while flexibly controlling for the underlying quality scores, I find that an improvement in a given hospital-specialties' rank leads to a significant increase in both the number of non-emergency patients and the total revenue generated from non-emergency patients treated by the hospital in that specialty. The point estimates indicate that an improvement in rank by one spot is associated with an increase in both non-emergency patient volume and revenue of approximately 1%. As a robustness check, I demonstrate that changes in rank have no effect on emergency patient volume or revenue generated from emergency patients.

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. Under this framework, I estimate the distribution of preferences over hospital quality (as represented by the hospital rankings) and geographic proximity. The results demonstrate that both the 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. The results suggest that rank changes have the largest impact on patients who live more than 50 miles from the hospital that experienced the rank change.

Overall, the results offer evidence that the USNWR hospital rankings have had a large effect on the hospital choices made by consumers of health care.[1] Assuming the sample of hospitals used in this analysis to be representative of the nation as a whole, 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 changing hands over the past ten years.

A similar aggregate-level analysis is conducted to analyze the impact of USNWR college rankings on the ability of schools to attract high-quality students. Controlling for the underlying quality score, I find that improvements in rank have a significant effect on the acceptance rates and the quality of incoming students (as measured by SAT, GMAT, LSAT, MCAT, and GRE test scores) for undergraduate research and liberal arts schools and for graduate programs of business, law, and medicine. I find no effect of the rankings on graduate programs of engineering. The results suggest that a lower bound of 100,000 applications have been affected by the rankings since 1990.

An interesting finding of this analysis is that many consumers are paying attention to the ordinal rankings when a more informative measure of quality is available. This simple heuristic adds to an expanding literature suggesting that consumers often use rules of thumb or shortcuts when making complex decisions (Kahneman and Tversky, 1982). The fact that many consumers use the ordinal ranking even in the presence of the continuous quality score helps to explain the stylized fact that many magazines and other companies often provide information in a ranking or report card format as opposed to less aggregated quality measures at their disposure.

Are consumers acting optimally by using the ordinal ranks as a shortcut when making hospital or college choices? A consumer who uses only the ordinal rankings when making a decision may choose a hospital/college that, had the more informative quality score been used, is inferior in expected utility to another. While this "suboptimal"

[1] While I frequently refer to hospital-choice decisions being made by consumers, I cannot rule out the possibility that doctors, rather than patients, use the rankings when making referral decisions.

outcome may occur, it may still be rational for a consumer to strictly use the ordinal rankings if there are cognitive costs involved with using the more informative quality measure (Simon, 1955). This issue is very difficult to resolve, however, one question that I address in this study is how much information exists in the continuous quality score that is being ignored when consumers only use the ordinal ranks. Answering this question implies bounds on how high the processing costs of information must be in order for consumers to optimally consider only the ordinal ranking when making their decisions. I find that the processing costs must be such that it is worth ignoring a change in the number of physicians who consider the hospital to be one of the top five in a given specialty of 1.3%. Similar bounds can be placed on the processing costs faced by college applicants who use only the ordinal rankings in the decision process.

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

2 Literature Review

Empirical Literature. There is an emergent literature that has documented consumer and/or firm responses to published rankings and report cards in a variety of markets (Figlio, 2004, Jin and Leslie, 2003, and Pope and Pope, 2006). More specifically related to this paper, several studies have attempted to estimate the effects of rankings in college and health-care markets.

In the health-care industry, several studies have addressed 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, and Dafny and Dranove, 2005). The majority of these studies find a small, positive consumer response to health-plan ratings. Unlike health-plan choices, however, there is reason to question whether hospital choices can be influenced by quality ratings. Arguably, location is more of a factor to consumers in the hospital market than in the health-plan market. Furthermore, many individuals are restricted in their hospital choices to those referred to them by their primary-care physician or that are within their health plan's coverage. Because of these potential constraints, the hospital industry has received a considerable amount of attention in the competition and anti-trust literature (see Gaynor and Vogt (1999) and Gaynor (2006) for reviews of the literature on hospital competition). However, even with these restrictions, anecdotal and survey evidence suggest that hospital decisions may be affected by quality rankings. For example, a survey in 2000 by the Kaiser Family Foundation found 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).

By far, the most studied hospital ratings system has been the New York State Cardiac Surgery Reporting System. Released every 12 to 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. Studies estimating the consumer response to these ratings have produced mixed results. Cutler, Huckman, and Landrum (2004) demonstrated a significant decrease in patient volume for the small percentage of hospitals that were flagged as performing significantly below the state average. However, they found no evidence that hospitals flagged as performing significantly above average had any impact on patient volume. 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.

One further issue 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 able to be identified by looking at patient volume. Keeler and Ying (1996) argued that due primarily to technological advances through the 1980s, hospitals had substantial excess bed capacity. Evidence that hospitals continue not to be capacity constrained can be inferred from the fact that even the best hospitals are advertising for additional patients on a regular basis. In a recent study, Larson, et al. (2005), contacted 17 of the hospitals that were ranked most highly by USNWR and asked them if they advertise for non-research patients. 16 of the 17 hospitals reported that they advertise to attract non-research patients.

While strong anecdotal evidence exists regarding the impact of rankings in the college market, there are few empirical studies that have attempted to estimate the magnitude of these effects. Ehrenberg and Monks (1999) provided the first thorough empirical investigation into whether students respond to USNWR college rankings by using data on a subset of schools that were ranked as undergraduate research or liberal arts schools. While their paper did not attempt to identify exogenous changes in rank, it provided strong evidence suggesting that students responded (applications, yield, and SAT scores) to changes in school rankings. Meredith (2004) extends the analysis of Ehrenberg and Monks by looking at a wider range of scores and variables.

Why Aggregate Information? A further question regarding this literature involves the reason why firms would choose to present information in a ranking or report-card format. Even when more detailed information about a set of options is available, firms will often synthesize the information into a much simpler rank or final score (Moody's bond ratings give letter-grade scores such as AA+ rather than a more detailed score, composite SAT/ACT exam scores are given as opposed to the score received on each section of the exam, best-seller rankings are provided rather than the actual number of products sold, etc.). There exist several explanations for why consumers may prefer to receive information that has been aggregated into a single, easy to understand statistic as opposed to receiving more detailed information.

First, due to cognitive costs, consumers may prefer information at a higher aggregation level because it is easier to process. It has been argued that consumers often use shortcuts or rule of thumbs when making complex decisions (Kahneman and Tversky, 1982). Another reason why consumers may prefer to receive information in an aggregated form is that they trust "experts" to put the proper weight on individual product attributes. Gains to specialization may result from a few people deciding what is best for everybody else. This explanation is especially feasible when preferences across product attributes are homogeneous. The recent literature on limited attention suggests a third reason why consumers might be attracted to information presented in a rankings or groupings format. Agents with limited attention are expected to pay attention to information that is relatively salient in some way (Fiske and Taylor, 1991). Thus, the basic prediction of the theory of limited attention is that agents will pay too much attention to salient stimuli (Barber and Odean, 2004 and Huberman and Regev, 2001) and too little attention to non-salient stimuli (Fishman and Pope, 2006 and DellaVigna and Pollet, 2006). Synthesizing information into a simple, salient rank may be more likely to capture the attention of consumers than a complicated, more detailed presentation of the information.

3 Rankings Methodology

"America's Best Hospitals". In 1990, 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.[2] This study focuses on the specialties that are ranked using characteristics beyond simply a survey of hospital reputation.[3]

USNWR claims that the rankings are determined in the following manner. First, USNWR identifies 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 each year considers to be important. Each year about 1/3 of the approximately 6,000 hospitals in the US meets one of these three criteria. These hospitals are then assigned a final score, 1/3 of which is based on a survey of physicians, 1/3 by the hospital-specialty's mortality rate, and the final 1/3 by a combination of other observable hospital characteristics (nurses-to-beds ratio, board-

[2] 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.

[3] 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 the identification strategy 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.

certified M.D.'s to beds, the number of patients treated, and the specialty-specific technologies and services that a hospital has available).[4] 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. Figure 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.

To more fully understand how the rankings are determined, 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). 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, even the sign on risk-adjusted mortality rates is in the wrong direction. While USNWR claims that each of these variables represent 1/3 of the final score, since the variables are not normalized, reputation scores (which are much more variable than risk-adjusted mortality rates) are basically driving all the rankings. Thus, the continuous quality score that is provided for each hospital can be essentially thought of as an affine transformation of the reputation score.

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

[4] 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.

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, and Hill, Winfrey, and Rudolph 1997). A tour of major hospital websites illustrates that hospitals actively use the rankings as an advertising tool (for example see www.clevelandclinic.org and www.uchospitals.edu). 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.

"Best Colleges and Graduate Schools". In 1983, USNWR began publishing undergraduate college rankings in their weekly magazine. Beginning in 1987, the magazine annually ranked the top 25 national research universities and the top 25 national liberal arts colleges. In 1995, the top 50 schools in each of these two categories were ranked. In 1987, USNWR also began using data in order to rank graduate schools of law, business, medicine, and engineering. Throughout the 1990s they began to rank graduate programs of other disciplines.[5] This analysis focuses on the undergraduate research and liberal arts school rankings along with the graduate programs rankings in law, business, medicine, and engineering between 1990 and 2006.[6]

USNWR uses data on students and faculty along with a survey of academics to compute their undergraduate and graduate school rankings. While the exact methodology employed varies across disciplines and has changed over time, the final rankings are generally computed by taking a weighted average of several sub-rankings that are created.[7] Depending on the discipline, sub-rankings may include: academic reputation, retention rate, faculty resources, student selectivity, financial resources, alumni giving, graduation-rate, and student placement outcomes. After a ranking is given to each of these categories, weights are placed on each sub-score ranking to generate a continuous

[5] The majority of the recent graduate school rankings rely solely on a survey of department reputation as opposed to using detailed data like that used for the law, business, medicine, and engineering rankings.
[6] Prior to 1990, a continuous quality score was not provided along with the ordinal rankings making it impossible to employ the identification strategy used in this paper. Rankings were analyzed for up to the top 50 schools in each of these categories when available.
[7] A detailed report of the current methodology used can be found on USNWR's website at http://www.usnews.com/usnews/edu/college/rankings/about/06rank_brief.php.

quality score for each school (where the top school each year is given a quality score of 100% and every other school's score is related to that of the top school). The final rank is then computed by ordering the continuous quality score. The final ranks and continuous quality scores are then published in the magazine along with a subset of the individual variables used in the rankings process.

For the year 2000, Table 2 reports the regression of the continuous quality score for the undergraduate research universities on the set of variables provided in the magazine. While the reputation scores are very important in determining the final scores, unlike the hospital rankings, there are other variables that also have significant impacts.

4 Data & Empirical Strategy

Hospital 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/emergency), diagnosis-related group (DRG), length of stay, outcome (released/transferred/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 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. Except for patient zip codes, the NIS data contain similar information about each patient and hospital visit as the California data.

I primarily focus on Medicare patients in this analysis. There are three main reasons why Medicare patients are an attractive group to consider when testing for a consumer response to USNWR rankings. First, Medicare patients represent over 30% of all inpatient procedures. Second, Medicare prices are constant and cannot be adjusted by individual hospitals. Thus, focusing on just Medicare patient volume allows me to eliminate any confounding effects that may result from hospitals changing their prices in response to rank changes. Third, in contrast to privately insured individuals (who may want to react to changes in a hospital's rank but can't because of network-provider limitations), Medicare patients have flexible coverage. While I focus on Medicare patients for these reasons, Appendix Table 1 contains information regarding the effect of USNWR rankings on non-Medicare patients. The impact of the rankings on Non-Medicare patients, while smaller and less significant, is qualitatively similar to the effect found for Medicare patients. The sample of inpatient discharges is further restricted to patients who were admitted as non-emergency patients.[8] I assume that emergency patients should not be affected by the rankings since many of them arrived by ambulance or, for other emergency reasons, did not have the time to compare hospitals. While this analysis focuses on non-emergency patients, the effect of the rankings on emergency patients is reported as a robustness check. Table 1 provides a breakdown of the aggregate-level observations that are used in this analysis by state, year, and specialty. Table 2 presents the average number of patients that each hospital treats by specialty and patient type.

College Data. The data used in the college analysis are gleaned from the information published by USNWR in their annual rankings issues. For most years, USNWR provides statistics on the average test scores of the incoming class (SAT, LSAT, GMAT, MCAT, and GRE) and the acceptance rates for the colleges that are ranked.[9] In this analysis, I use these two available variables as outcome measures representing a college's ability to attract and enroll students. Lower acceptance rates and higher incoming test scores both reflect an increase in demand for a particular college. Table 3 provides summary statistics for the schools that are used in the college analysis.

Empirical Strategy. 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. In order to circumvent this bias, I use an approach similar to a regression discontinuity design (Thistlewaighte and Campbell, 1960, Campbell, 1969,

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[8] 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."

[9] The statistics that come out report information for the incoming class and acceptance rates two years prior to the publication year. For some tests, USNWR only reported the 25th and 75th percentiles rather than the average incoming student test score. The average of the 25th and 75th percentile scores was used to represent average test score in these cases.

Angrist and Lavy, 1998, Hahn, Todd, and van der Klaauw, 2001, and Lee, 2001). I begin by considering the following econometric specification for the hospital case

$$(1) \qquad Pat_{jt} - \overline{Pat_j} = \alpha_t + \beta Rank_{jt-1} + \varepsilon_{jt}$$

where $Pat_{jt} - \overline{Pat_j}$ represents the deviation in the number of patients that hospital-specialty j was able to attract in year t from its average, $Rank_{jt-1}$ represents the Rank of hospital-specialty j that is used by individuals during year t, and ε_{jt} is an error term representing all other observable and unobservable determinants of $Pat_{jt} - \overline{Pat_j}$. For now I assume that the effect of rank on the deviation in patient volume is linear and can be represented by β.

The key feature to the strategy of regression discontinuity is that a deterministic function of $Rank_{jt-1}$ is known and observed. In the case of the USNWR rankings, $Rank_{jt-1}$ is completely determined by the continuous quality score given to each hospital-specialty. Without loss of generality, consider the situation where only two hospital-specialties exist: j and k. $Rank_{jt-1}$ is determined by the following function

$$(2) \qquad Rank_{jt-1} = \begin{cases} 1 & \text{if Quality Score}_{jt} > \text{Quality Score}_{kt} \\ 2 & \text{if Quality Score}_{\mathrm{jt}} < \text{Quality Score}_{\mathrm{kt}} \end{cases}$$

A simple comparison between the hospital-specialty that was ranked first and the hospital-specialty that was ranked second is

$$(3) \qquad E[Pat_{jt} - \overline{Pat_j} \mid Rank_{jt-1} = 1] - E[Pat_{jt} - \overline{Pat_j} \mid Rank_{jt-1} = 2] = \beta + Bias_t$$

where

$$(4) \qquad Bias_t = E[\varepsilon_{jt} \mid \text{Quality Score}_{\mathrm{jt}} > \text{Quality Score}_{\mathrm{kt}}] -$$

$$E[\varepsilon_{jt} \mid \text{Quality Score}_{\mathrm{jt}} < \text{Quality Score}_{\mathrm{kt}}]$$

The key assumption in the regression discontinuity approach is that the bias approaches zero when comparing deviations in patient volume for hospitals that are just barely ranked differently than each other. I assume that ε_{jt} is continuous as the quality scores for the hospital specialties near each other

$$(5) \qquad E[\varepsilon_{jt} \mid \text{Quality Score}_{\mathrm{jt}} \to \text{Quality Score}^{+}_{\mathrm{kt}}] =$$

$$E[\varepsilon_{jt} \mid \text{Quality Score}_{\text{jt}} \rightarrow \text{Quality Score}_{\text{kt}}^{-}]$$

or more generally, I assume that

(6) $E[\varepsilon_{jt} \mid \text{Quality Score}_{\text{jt}}] = g(\text{Quality Score}_{\text{jt}})$

where $g(\text{Quality Score}_{\text{jt}})$ is continuous everywhere.

In this paper, I assume Equation (6) is true and therefore, control for a flexible parameterization of the quality score when estimating the impact of a rank change on patient volume. Flexibly controlling for the continuous quality score will control for changes in hospital quality that are observed by individuals but not by the researcher and allow for the identification of breaks that occur in the dependent variable when a hospital changes rank.

It is worth noting that the estimates that this analysis obtains for the effect of USNWR rankings represent a lower bound of the impact that these rankings have on consumer's hospital and college choices. I am unable to identify how many decisions are made by consumers who are paying attention to the continuous quality score in the decision process. After controlling for the rankings, it is impossible to parse out whether any remaining predictive power that the continuous quality score has on patient volume is due to omitted variable bias or the direct reaction of individuals to the continuous quality score.

Aggregate-Level Hospital Analysis. I begin by aggregating 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 is 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

[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.

specialties. 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.[11]

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, I restrict the data to individuals who were admitted between January and June of each year – nearly all of whom would have used the previous fall's rankings.[12]

The baseline econometric specification used is

$$Y_{jt} = \alpha_j + \delta_t + \beta Rank_{jt-1} + g(QualityScore_{jt-1}) + \varepsilon_{jt} \qquad (7)$$

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. A cubic polynomial of the continuous quality is included.[13]

The continuous quality scores included in both the hospital and college regressions are adjusted from those that are directly reported in the magazine. Since the scores are a percentage of the number-one-ranked hospital or college's score, the scores of all hospitals can shift up or down from year to year if the number-one-ranked hospital or college's score changes. This shifting across years adds noise to the continuous quality scores. So, rather than including the continuous quality scores as reported, I normalize each of the quality scores by dividing by the average quality score of the top 40 ranked hospital-specialties each year for the hospital regressions and by the average quality score of the top 25 colleges (by discipline) each year for the college regressions.

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[11] 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 treated very few inpatients and to be consistent with the results from the individual-level analysis, which also eliminates hospitals for which less than ten cases were treated.

[12] Appendix Table I 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.

[13] Regressions with higher-order polynomials of the continuous quality change have the same affect as a cubic.

Thus the regressions control for the relative continuous quality score of each hospital as they should.

Specifications other than Equation (1) may be relevant. For example, the effect of rank changes may not be linear. A specification using Ln(rank) might be more appropriate if a change in rank at one of the top few hospital-specialties has a larger effect than a change in rank elsewhere. The Ln(rank) results can be seen in Appendix Table 1. While Ln(rank) appears to have an equally good fit as linear rank, I include the linear rank in the main tables for ease of interpretation. It is possible that achieving a better rank than that of another hospital-specialty in the patient's state has a larger impact than surpassing the rank of a hospital that is on the other side of the country. Appendix Table 1 contains a specification that includes each hospital-specialty's state rank along with their overall rank. While the coefficient on state rank is in the direction hypothesized even when controlling for overall rank, due to the small amount of variation the estimates are imprecise. Estimates from specifications that control for the quality score even more flexibly (quality score interacted with year and specialty dummies as well as controlling for the standard deviation changes in quality scores as opposed to difference from the mean) are also provided in Appendix Table 2. While these specifications generally reduce the power of the regressions by including more variables that are highly correlated with rank, the overall rank effect is robust to these inclusions.

Aggregate-Level College Analysis. The baseline specification for the college analysis is

(8) $$Y_{jt} = \alpha_j + \delta_t + \beta Log(Rank)_{jt-1} + g(QualityScore_{jt-1}) + \varepsilon_{jt}$$

where Y_{jt} represents either the acceptance rate (in percentage terms) or the average test scores of the incoming class in year t for school j. $Log(Rank)_{jt-1}$ is the USNWR rank of college j in year t-1. A cubic polynomial of the continuous quality score is included.

In the college analysis, Ln(rank) fits the data much better than a linear specification. Once again, estimates from specifications that control for the quality score more flexibly (quality score interacted with year as well as controlling for the standard deviation change in quality scores as opposed to difference from the mean) are provided in Appendix Tables 3 and 4.

Individual-level Hospital Analysis. Using the individual-level inpatient data, I estimate a discrete choice model. 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). Unlike the conditional logit model, the mixed-logit model estimates random coefficients on the product characteristics in the indirect utility function. The allowance of random taste variation eliminates the need for assuming the independence of irrelevant alternatives 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 (see for example Berry, Levinsohn, and Pakes, 1995, Train 2006, Nevo 2001, Hastings, Kane, and Staiger 2005).

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

$$(8) \qquad P_{ijt} = \int \left(\frac{e^{\beta x_{ijt}}}{\sum_j e^{\beta x_{ijt}}}\right) f(\beta) d\beta$$

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 Equation (8) 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 data set 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 1998-2004. 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.

5 Results

Aggregate-Level Hospital Results. Following the specification in Equation (7), Table 6 presents the first set of results from the aggregate hospital-level analysis. Column (1) reports the effect of a hospital-specialties' lag rank on the log number of non-

[14] This is done by using the latitude and longitude of the patient and hospital's zip-code centroids.

[15] I chose the heart specialty for two reasons. First, 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).

emergency Medicare patients treated by that hospital-specialty. 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 rank by one spot for a particular hospital-specialty on average increases the number of non-emergency patients treated at that hospital-specialty by .88%. Column (2) illustrates the positive relationship between log patient volume and the linear continuous quality score. When both rank and the linear continuous quality score are included in Column (3), the point estimate for the continuous quality score is cut to 1/3 of its previous level while the coefficient on rank continuous to be about 1% and significant. Column (4) includes a cubic of the continuous score without affecting the size or significance of the coefficient on rank. Columns (5)-(8) analogously present the effects of rank and continuous quality score on emergency Medicare patients. There is no evidence suggesting that rank changes are associated with changes in emergency patient volume. Table 7 presents similar results when the dependent variable is the log total revenue generated from either non-emergency or emergency Medicare patients. Once again, an improvement in rank by one spot is associated with approximately a 1% increase in total revenue for non-emergency patients even after flexibly controlling for the continuous quality score. No effect is found on emergency patient revenue.

Table 8 presents the effect of rank changes on non-emergency Medicare patient volume by each of seven specialties (the gynecology specialty drops out due to insufficient observations). The results indicate that no single specialty is driving all of the results presented in Tables 6 and 7. While almost no estimates are significant due to the small samples, the specialties with the largest point estimates are cancer and urology.

Individual-Level Hospital Results. Table 7 contains the results from the mixed-logit model using the individual-level hospital data. Column (1) provides estimates for the mean effect of the overall 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 $1/10^{th}$ 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 .2%. This result is consistent with the aggregate-level results presented in the previous section.

Aggregate-Level College Results. Following the specification in Equation (8), Table 10 reports the effect of the USNWR college rankings on college admission outcomes. Panel A of Table 10 presents the simple OLS results while the regressions in Panel B controls for the continuous quality score (cubic). The odd numbered columns indicate the effect of rank changes on the following year's acceptance rates while the even numbered columns indicate the effect of rank changes on the following year's incoming test scores. Looking at Column (1) of Table 10, changes in lag overall rank have a significant effect on the acceptance rates of undergraduate research schools.

Interpreting the log rank, a school that is able to cut its rank in half (e.g. 10^{th} to 5^{th} or 4^{th} to 2^{nd}) is on average able to reduce its acceptance rate by just over 2%. The effects of rank changes on acceptance rates are smaller but still significant for undergraduate liberal arts, law, and business schools and insignificant for schools of medicine and engineering. Interpreting the effect of rank changes on average incoming SAT scores in Column (2) indicates that a school that cuts its rank in half is able to increase the average incoming SAT test score by approximately 6 points. Similar calculations can be performed to interpret the effect of rank changes on test scores from other college types. The test score results are significant for all college types with the exception of engineering (whose results are, if anything, in the opposite direction). The results in Panel B of Table 10 are very similar to those found in Panel A. With the exception of schools of medicine, including the cubic continuous quality score does not significantly reduce the estimated effect of the rankings on acceptance rates or average incoming test scores.

6 Discussion and Conclusion

Magnitude of Results. The results provide evidence that USNWR hospital-specialty rankings have had a significant effect on the hospital-choice decisions of consumers. In order to understand how many people's 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 multiply them by the number of patients and the percent of patients affected,

$$(9) \qquad \sum_{jt} 1\% * |(Rank_{jt} - Rank_{jt-1})| * \text{Non-emergency Patients(per year)}_{jt}.$$

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 Equation 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 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 1,788 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.

The magnitude of the college results are more difficult to interpret. Using the estimates of the effect of rank changes on acceptance rates, it is possible to obtain a lower bound on the effect of USNWR college rankings on applications.[16] I estimate as a lower bound that 100,000 applications were sent (or not sent) in response to changes in the rankings since 1990. However, perhaps the more important impact that the rankings have had is on the matriculation decisions made by accepted applicants (which is represented by the changes in average incoming test scores). Without individual-level data, I am unable to determine how many matriculation decisions were changed due to the rankings.

Individual Efficiency. Are individuals using the information revealed in the rankings in an efficient manner? An interesting finding in this analysis is that consumers are reacting to changes in ordinal rank as opposed to simply using the continuous quality score in their decisions. There are several reasons why an optimizing consumer may choose to ignore the more informative quality score. First, some consumers may receive information about the ordinal rank of a hospital or college without access to the

[16] I take the average log change in rank for research, liberal arts, business, and law schools each year between 1990 and 2006 and multiplying these average log changes by the estimated acceptance rate coefficients. Assuming that enrollment changes do not occur (acceptance rate changes solely reflect changes in applications) and by using the average number of applications received and acceptance rates by these schools during the years studied, I estimate the expected changes in applications that the rankings have caused over the last 15 years in these four specialties. This number is a lower bound since it does not reflect changes in applications for schools ranked outside of the top 50 or the effect of making it into the top 50 to begin with. It only reflects the number of applications affected by changes in rank by schools within the top 50.

continuous quality score (e.g. advertisements that only report the ordinal rank). Thus, the consumer would have to take extra time to find the magazine or look online to get the continuous scores. Second, some consumers may care about the rank itself above and beyond the quality of care/education that the rank represents. While this seems unlikely for the hospital rankings, it is very possible that high school students gain utility from the rank of the college even after controlling for the quality signal that it represents. Finally, even if the consumer has access to the continuous score and only cares about quality, the cognitive costs associated with processing the continuous score may be higher than the benefits. Understanding how much information consumers are ignoring by using only the continuous score can provide lower bounds on how high these processing costs must be.

On average, there is a 1.52% difference in the continuous quality score between each rank. A health-care consumer who uses only the ordinal ranking therefore on average neglects the amount of information that is able to adjust the continuous quality score by 1.52%. Using the estimates from column (2) of Table 1, it is possible to calculate exactly how much information about hospital reputation is neglected when a patient considers the ordinal rank as opposed to the continuous quality score. The coefficient in Table 1 suggests that a 1.52% change in the continuous quality score can be generated by a 1.3% difference in the number of physicians surveyed indicating that in their opinion the hospital is one of the best five hospitals in a given specialty. While it is difficult to say exactly how important a difference of 1.3% in reputation is, this serves as a measure of the amount of information being neglected.

A similar bound can be placed on the use of the ordinal rankings in the college data. 0.59% is the average difference in continuous quality score between each rank for undergraduate research universities. Using Table 2, a difference in continuous quality score of .59% can be generated by an increase in the average reputation of a school by .37, where reputation is the average score (between 1 and 5) given by presidents, provosts, and deans of universities. Similar calculations can be made using the estimates in Table 2 which illustrate how the 0.59% difference in continuous quality score can be driven by factors other than reputation that are used in the rankings process.

Conclusion. Overall, the results from this analysis suggest that USNWR rankings of hospitals and colleges have had a significant impact on consumer decisions. The estimates that are provided in this analysis are only a first step in determining the overall impact of these rankings on the college and 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 colleges and 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 and colleges to try to improve their rank. A separate implication of these findings is that hospital patients are affected by changes in perceived hospital quality. This response can provide insight to the hospital competition and anti-trust literature.

Finally, the analysis presented in this paper provides insights into consumer behavior. I find that consumers use a simple heuristic when making hospital and college decisions in that they ignore the most detailed information available. Future research may further consider how consumers make decisions when faced with information at different levels of aggregation.

References

Angrist, J.D., and Victor Lavy. "Using Maimondies' Rule to Estimate the Effect of Class Size on Scholastic Achievement." *Quarterly Journal of Economics* 114, 1998: 533-575.

Barber, Brad M. and Terrance Odean. "All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," mimeo, 2004.

Beaulieu, N.D. (2002). "Quality Information and Consumer Health Plan Choices." *Journal of Health Economics*, 21(1), 43-63.

Berry, S., J. Levinsohn, and A. Pakes 1995. "Automobile Prices in Market Equilibrium", Econometrica 63, 841-889.

Campbell, D.T. "Reforms as Experiments." *American Psychologist* 24 (1969): 409-429.

Chen J., Radford M., Wang Y., Marciniak T., and H. Krumholz. "Do 'America's Best Hospitals' Perform Better for Acute Myocardial Infarction?" *New England Journal of Medicine*, 340 (1999), 286-292.

Chernew, M., G. Gowrisankaran, and D.P. Scanlon (2004). Learning and the Value of Information: The Case of Health Plan Report Cards. Mimeo.

Cutler, David M., Huckman, Robert S., and Mary Beth Landrum, 2004. "The Role of Information in Medical Markets: An Analysis of Publicly Reported Outcomes in Cardiac Surgery," *American Economic Review*, 94(2), pp. 342-346.

Dafny, Leemore and David Dranove 2005. "Do Report Cards Tell Consumers Anything They Don't Already Know? The Case of Medicare HMOs," NBER Working Paper 11420, 2005.

DellaVigna, Stefano and Joshua Pollet, "Attention, Demographics, and the Stock Market", mimeo, 2006.

Dranove, D., Kessler, D., McClellan M., and M. Satterthwaite. "Is More Information Better? The Effects of 'Report Cards' On Health Care Providers," *Journal of Political Economy*, 2003, v111, 555-588.

Ehrenberg, Ronald and James Monks. "U.S. News and World Report's College Rankings: Why Do They Matter", Change, 31(6), 1999, 42-51.

Figlio D.N., and M.E. Lucas. "What's In a Grade? School Report Cards And The Housing Market," *American Economic Review*, 94 (2004), 591-604.

Fishman, Peter, and Devin Pope, "Punishment-Induced Deterrence: Evidence from the Video-Rental Market,", 2006, Mimeo.

Fiske, Susan T. and Shelley E. Taylor, "Social Cognition", New York: McGraw-Hill, Inc., 1991.

Gaynor, Martin. "What Do We Know About Competition and Quality in Health Care Markets?" NBER Working Paper 12301, 2006.

Gaynor, Martin and William Vogt. "Antitrust and Competition in Health Care Markets", NBER Working Paper 7112, 1999.

Gilbride, Timothy J., and Greg M. Allenby. "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening," *Marketing Science*, *23,* 2004, 391-406.

Goldschmidt P. "Are `America's Best Hospitals' America's best?" *Journal of the American Medical Association*, 278 (1997), 474-5.

Hahn, J., Todd P., and W. van der Klaauw. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica* 69, 2001: 201-209.

Hastings, Justine, Thomas Kane, and Douglas Staiger, "Preferences and heterogeneous Treatment Effects in a Public School Choice Lottery", NBER Working Paper 12145, 2006.

Hauser, John R., and Berger Wernerfelt. "An Evaluation Cost Model of Evoked Sets," *Journal of Consumer Research*, *16*, 1990, 393-408.

Hill C, Winfrey K, and B Rudolph. "`Best Hospitals': A Description of the Methodology for the Index of Hospital Quality." *Inquiry*, 34 (1997), 80-90.

Huberman, Gur, and Tomer Regev. "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar", *Journal of Finance,* 2001, Vol. 56, 387-396.

Jha, Ashish K., and Arnold Epstein, 2006, "The Predictive Accuracy of the New York State Coronary Artery Bypass Surgery Report-Card System." Health Affairs, 25(3), 844-855.

Jin, G., and P. Leslie. 2003 "The Effect of Information on Product Quality: Evidence From Restaurant Hygiene Grade Cards," *Quarterly Journal of Economics*, May 2003, *118(2)*, 409-451.

Jin G., and A. Sorensen. 2005. "Information and Consumer Choice: The Value of Publicized Health Plan Ratings" Mimeo.

Kahneman, Daniel, and Amos Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, New York, NY: Cambridge University Press.

Kaiser Family Foundation / Agency for Healthcare Research and Quality *National Survey on Americans as Health Care Consumers: An Update on The Role of Quality Information*, December 2000 (Conducted July 31-Oct. 13, 2000)

Keeler, T.E. and Ying, J.S., 1996. "Hospital Costs and Excess Bed Capacity: A Statistical Analysis." *Review of Economics and Statistics* 78, 470-481.

Larson R., Schwartz L., Woloshin S., and H. Welch. 2005 "Advertising by academic medical centers." *Arch Intern Med,* March 28, 165(6), 645-651.

Lee D.S. "The Electoral Advantage to Incumbancy and Voters' Valuation of Politicians' Experience: A Regression Discontinuity Analysis of Election to the U.S. House," NBER Working Paper 8441, 2001.

McFadden Dan "Conditional Logit Analysis of Qualitative Choice Behavior", in P. Zarembka, ed., Frontiers in Econometrics, Academic Press, New York, pp. 105-142.

McFadden Dan, and Kenneth Train, "Mixed MNL Models for Discrete Response," *Journal of Applied Econometrics*, 15(5) pp. 447-470, 2000.

Meredith, Marc. "Why Do Universities Compete in the Ratings Game? An Empirical Analysis of the Effects of the U.S. News and World Report College Rankings," *Research in Higher Education,* 45(5), 2004, pp. 443-461.

Mukamel D, Weimer D, Zwanziger J, Gorthy S, and A Mushlin. 2005 "Quality Report Cards, Selection of Cardiac Surgeons, and Racial Disparities: A Study of the Publication of New York State Cardiac Surgery Reports." *Inquiry*, *41*, 435-447.

Nedungadi, Prakash. "Recall and Consumer Consideration Sets: Influencing Choice without Altering Brand Evaluation," *Journal of Consumer Research*, *17*, 1990, 263-277.

Nevo, A. (2001). "Measuring Market Power in the Ready-to-Eat Cereal Industry", Econometrica 69, 307-342.

Pope, D. and J. Pope. 2006 "Understanding College Choice Decisions: How Sports Success Garners Attention and Provides Information," Mimeo.

Pope, J. 2006 "Limited Attention, Asymmetric Information and the Hedonic Model", Mimeo 2006.

Roberts, John H., and James M. Lattin. "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, *28*, 1991, 429-440.

Rosenthal G., Chren M., Lasek R., and C. Landefeld. 1996 "The annual guide to "America's best hospitals". Evidence of influence among health care leaders." *Journal of General Intern Med.,* Sept., 11(9), 569-570.

Scanlon, D.P., M.E. Chernew, C.G. McLaughlin, and G. Solon (2002). The Impact of Health Plan Report Cards on Managed Care Enrollment. *Journal of Health Economics,* 21(1), 19-41.

Schauffler, Helen, Mordavsky, Jennifer. 2001. “Consumer Reports in Health Care: Do They Make a Difference?”, Annual Review of Public Health, 22, pp. 69-89.

Simon, H. 1955. “A Behavioral Model of Rational Choice”, Quarterly Journal of Economics, 69, pp. 99-118.

Schneider, Eric, and Arnold Epstein. 1996. “Influence of Cardiac-Surgery Performance Reports on Referral Practices and Access to Care – A Survey of Cardiovascular Specialists”, New England Journal of Medicine, 335(4), 251-256.

Thistlethwaite, D., and D. Campbell. “Regression-Discontinuity Analysis: An alternative to the ex post facto experiment.” *Journal of Educational Psychology*, 51, 1960: 309-317.

Train, Kenneth, “Discrete Choice Methods with Simulation”, Cambridge University Press, 2003.

Train, Kenneth and Cliff Winston “Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers”, Mimeo 2006.

Wedig, G.J. and M. Tai-Seale (2002). “The Effect of Report Cards on Consumer Choice in the Health Insurance Market.” *Journal of Health Economics,* 21(6), 1031-1048.

Figure 1.

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

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Table 1. Estimating the Components of the Continuous Quality Score - Hospitals

	Dependent Variable: Continuous Quality Score (%)		
	(1)	(2)	(3)
Reputation (%)	1.17	1.16	
	(.01)***	(.01)***	
Risk-Adjusted Mortality Rate	-6.10		2.64
	(.81)***		(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%

Table 2. Estimating the Components of the Continuous Quality Score - Undgraduate Research Universities

	Dependent Variable: Continuous Quality Score (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Reputation (%)	0.951	1.605							
	(.123)***	(.158)***							
Freshman Retention (%)	0.261		1.712						
	(.187)		(.211)***						
5-Year Graduation Rate (%)	0.306			.858					
	(.084)***			(.090)***					
Student-Faculty Ratio	-0.228				-1.26				
	(.124)*				(.248)***				
Classes Under 20 Students (%)	0.171					.412			
	(.037)***					(.089)***			
Classes Over 50 Students (%)	0						-.299		
	(.082)						(.202)		
Average SAT	-0.002							.081	
	(.008)							(.008)***	
Alumni-Giving Rate (%)	0.035								.425
	(.042)								(.087)***
R-Squared	0.953	0.695	0.593	0.67	0.365	0.324	0.047	0.698	0.347
Observations	47	47	47	47	47	47	47	47	47

Notes: Observations are at the college level. The dependent variable is the continuous quality score (%) reported in the US News and World Report's Best Colleges issue in 2000. Data for reputation and other ranking factors were also taken from the magazine issue.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. 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, overall rank (lagged).

Table 4. Summary Statistics - Hospital Data

	Mean	Standard Deviation	Minimum	Maximum
Total Medicare Patients Within a Specialty	342	308	26	1,942
Non-Emergency	120	104	10	1,334
Emergency	222	257	10	1,709
Total Medicare Patients By Specialty				
Cancer	122	53	26	342
Digestive	422	232	88	1,019
Gynocology	92	26	42	133
Heart	741	470	147	1,942
Neurology	321	134	69	671
Orthopedics	277	203	26	1,401
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, overall rank (lagged).

Table 5. Summary Statistics - College Data

	Mean	Standard Deviation	Minimum	Maximum	Observations
Undergraduate					
Research Schools					
Acceptance Rate	38.8	18.2	9	84	628
SAT Scores	1331.5	86.0	1105	1525	596
Liberal Arts Schools					
Acceptance Rate	42.7	13.5	18	78	560
SAT Scores	1305.8	66.2	1105	1470	546
Graduate					
Law Schools					
Acceptance Rate	24.2	9.0	5.6	55.9	563
LSAT Scores	163.3	3.6	155.5	173	590
Business Schools					
Acceptance Rate	28.9	11.8	6.6	74	548
GMAT Scores	652.4	29.9	570	730	592
Medical Schools					
Acceptance Rate	7.8	4.2	2.1	29.7	425
MCAT Scores	10.8	0.5	9.5	12.3	445
Engineering Schools					
Acceptance Rate	30.4	12.4	8.6	75.2	607
GRE Scores (Quant.)	754.0	15.8	678	791	426

Notes: Observations are at the college-year level. Observations are included for college-years that have a non-missing, overall rank (lagged). Acceptance rate and test score data are taken from US News and World Report's Best Colleges and Best Graduate Schools issues between 1990 and 2006.

Table 6. The Effect of USNWR Hospital Rankings on Patient Volume

	Dependent Variable: Log Number of Medicare Discharges by Type							
	Non-Emergency Patients				Emergency Patients			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank (Lagged)	0.0088		0.0084	0.0101	-0.0034		-0.0029	-0.0024
	(.0027)***		(.0029)***	(.0034)***	(.0036)		(.0036)	(.0036)
Cont. Quality Score		0.144	0.054			-0.106	-0.075	
		(.100)	(.102)			(.114)	(.108)	
Cont. Quality Score (Cubic)				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	0.939	0.936	0.939	0.939	0.971	0.971	0.971	0.971
Observations	446	446	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. The dependent variable is the log number of non-emergency Medicare patients (Columns (1)-(4)) or emergency patients (Columns (5)-(8)) 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 Jan. - Jun. data. Hospital-specialty and year fixed effects are included. The overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. The Effect of USNWR Hospital Rankings on Total Revenue

	Dependent Variable: Log Total Revenue Generated from Medicare Patients by Type							
	Non-Emergency Patients				Emergency Patients			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rank (Lagged)	0.0105		0.0100	0.0120	0.0015		0.0024	0.0030
	(.0031)***		(.0032)***	(.0036)***	(.0035)		(.0035)	(.0037)
Cont. Quality Score		0.177	0.069			-0.103	-0.129	
		(.106)*	(.107)			(.125)	(.126)	
Cont. Quality Score (Cubic)				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	0.965	0.963	0.965	0.965	0.973	0.973	0.974	0.974
Observations	446	446	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. The dependent variable is the log total revenue generated from non-emergency Medicare patients (Columns (1)-(4)) or emergency patients (Columns (5)-(8)) 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 Jan. - Jun. data. Hospital-specialty and year fixed effects are included. The overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. The Effect of USNWR Hospital Rankings on Non-emergency Medicare Patient Discharges - By Specialty

	Dependent Variable: Log Number of Non-emergency Medicare Patient Discharges by Specialty						
	Cancer	**Digestive**	**Heart**	**Neurology**	**Orthopedics**	**Respiratory**	**Urology**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank (Lagged)	0.0121	0.0040	0.0020	0.0091	0.0095	-0.0196	0.0157
	(.0072)	(.0077)	(.0133)	(.0045)*	(.0101)	(.0278)	(.0123)
Cont. Quality Score (Cubic)	X	X	X	X	X	X	X
Hospital_Specialty F.E.	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X
R-Squared	0.891	0.951	0.957	0.987	0.974	0.992	0.897
Observations	58	79	67	70	66	32	55

Notes: Observations are at the hospital-specialty-year level. 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 Jan. - Jun. data. Hospital-specialty and year fixed effects are included. The overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Mixed and Conditional Logit Estimates of Hospital Choice

	Mixed Logit		Conditional Logit	
	Mean	Stand. Dev.		
	(1)	(2)	(3)	(4)
Rank (Lagged)	0.0118	0.0054	0.0125	0.0386
	(.0068)*	(.0041)	(.0063)**	(.0129)***
Rank X (Less Than 50 Miles)				-.0231
				(.0128)*
Distance				
Less Than 3 Miles	12.62	2.10	12.34	12.57
	(.10)***	(.09)***	(.09)***	(.09)***
3 to 6 Miles	11.49	1.42	11.34	11.57
	(.09)***	(.07)***	(.09)***	(.09)***
6 to 10 Miles	10.21	0.71	10.06	10.30
	(.09)***	(.08)***	(.09)***	(.09)***
10 to 20 Miles	8.60	0.22	8.47	8.72
	(.09)***	(.08)***	(.09)***	(.09)***
20 to 50 Miles	6.48	0.64	6.47	6.72
	(.09)***	(.08)***	(.08)***	(.09)***
50 to 100 Miles	3.48	0.24	3.48	3.58
	(.08)***	(.13)*	(.08)***	(.08)***
Cont. Quality Score (Cubic)	X	X	X	X
Cont. Quality Score (Cubic) X (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. Overall Rank (Lagged) represents the rank that the hospital-specialty received the July or August before the Jan. - Jun. 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 overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10. The Effect of USNWR College Rankings on Admission Outcomes

Panel A: Without Continuous Quality Controls

	Undergrad-Research		Undergrad-Liberal		Law		Business		Medicine		Engineering	
	Acceptance	SAT	Acceptance	SAT	Acceptance	LSAT	Acceptance	GMAT	Acceptance	MCAT	Acceptance	GRE (Quant)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Rank (Lagged)	-3.09	8.66	-1.39	9.74	-2.66	1.18	-2.54	5.62	-0.40	0.26	1.36	-4.87
	(.84)***	(2.73)***	(.82)*	(3.74)***	(.84)***	(.24)***	(1.05)**	(2.34)*	(.51)	(.06)***	(1.39)	(2.58)*
College F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X	X	X
R-Squared	0.924	0.970	0.883	0.937	0.889	0.952	0.814	0.922	0.799	0.867	0.738	0.669
Observations	628	596	560	546	563	590	548	592	425	445	607	426

Panel B: With Continuous Quality Controls

	Undergrad-Research		Undergrad-Liberal		Law		Business		Medicine		Engineering	
	Acceptance	SAT	Acceptance	SAT	Acceptance	LSAT	Acceptance	GMAT	Acceptance	MCAT	Acceptance	GRE (Quant)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Rank (Lagged)	-3.57	10.66	-2.65	8.76	-3.20	1.33	-1.62	4.70	0.01	0.13	0.03	-3.48
	(.84)***	(2.80)***	(1.15)**	(4.57)*	(.946)***	(.297)***	(.988)	(2.53)*	(.54)	(.07)*	(1.34)	(2.68)
College F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Cont. Quality Score (Cubic)	X	X	X	X	X	X	X	X	X	X	X	X
R-Squared	0.925	0.970	0.884	0.938	0.895	0.953	0.817	0.924	0.801	0.874	0.753	0.671
Observations	628	596	560	546	563	590	548	592	425	445	607	426

Notes: Observations are at the college-year level. The dependent variable is either the acceptance rate (%) or the average test score of incoming students. Overall Rank (Lagged) represents the rank that the college received the year prior to the data. College and year fixed effects are included. The overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 1. 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	Medicare	Medicare	Insurance	Medicaid	Medicare	Medicare	Medicare	Insurance	Medicaid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rank (Lagged)	0.0099	0.0089		0.0015	0.0043	0.0099	0.0116		0.0024	0.0045
	[.0033]***	[.0036]**		[.0043]	[.0047]	[.0034]***	[.0039]***		[.0053]	[.0060]
State Rank (Lagged)		0.033					0.012			
		[.032]					[.038]			
Log(Rank) (Lagged)			0.241					0.297		
			[.086]***					[.093]***		
Cont. Quality Score (Cubic)	X	X	X	X	X	X	X	X	X	X
Including 3rd Quarter	X					X				
Hospital-Specialty F.E.	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X
R-Squared	0.947	0.939	0.939	0.971	0.928	0.968	0.965	0.965	0.974	0.944
Observations	446	446	446	446	444	446	446	446	446	444

Notes: Observations are at the hospital-specialty-year level. The dependent variable is the log number of non-emergency patients (Columns (1)-(5)) or the log total revenue generated from non-emergency patients (Columns (6)-(10)) that were admitted between Jan. and Jun. of the observation year. Columns (1)-(3) and (6)-(8) use data from only Medicare patients. Columns (4) and (9) use data from patients with private insurance. Columns (5) and (10) use data from patients on Medicaid. Overall Rank (Lagged) represents the rank that the hospital-specialty received the July or August before the Jan. - Jun. data. Columns (1) and (6) include data from for each year between Jan. and Sept. of each year. Hospital-specialty and year fixed effects are included. The overall rank, log(overall rank), and state rank variables were inverted such that an increase in the rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 2. The Effect of USNWR Hospital Rankings on Patient Volume and Total Revenue - Detailed Quality Score Controls

	Dependent Variable: Log Patient Volume or Total Revenue Generated from Non-Emergency Medicare Patients									
	Log Patient Volume					Log Total Revenue				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rank (Lagged)	0.0110	0.0271	0.0062	0.0061	0.0194	0.0141	0.0140	0.0078	0.0038	0.0127
	(.0040)***	(.0295)	(.0041)	(.0049)	(.0320)	(.0042)***	(.0324)	(.0042)*	(.0052)	(.0373)
Cont. Quality Score (Cubic) X Specialties	X					X				
Cont. Quality Score (Cubic) X Specialties X Years		X					X			
Stand. Dev. Score (Cubic)			X					X		
Stand. Dev. Score (Cubic) X Specialties				X					X	
Stand. Dev. Score (Cubic) X Specialties X Years					X					X
Hospital-Specialty F.E.	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X
R-Squared	0.945	0.993	0.939	0.945	0.992	0.969	0.996	0.965	0.970	0.995
Observations	446	446	446	446	446	446	446	446	446	446

Notes: Observations are at the hospital-specialty-year level. The dependent variable is the log number of non-emergency Medicare patients (Columns (1)-(5) or the log total revenue generated from non-emergency Medicare patients (Columns (6)-(10)) 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 Jan. - Jun. data. Hospital-specialty and year fixed effects are included. For Columns (1) and (6) the cubic of the continuous quality score was included separately for each specialty. For Columns (1) and (6) the cubic of the continuous quality score was included separately for each specialty-year. For Columns (3)-(5) and (8)-(10), the continuous quality score for each school was converted into a score representing its standard deviation from the mean. A cubic of this score (also included separately for each specialty and specialty-year) was controlled for in these regressions. The overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).

* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 3. The Effect of USNWR College Rankings on Admissions Outcomes - Detailed Quality Score Controls

Panel A: With Standard Deviation Controls for Continuous Quality Scores

	Undergrad-Research		Undergrad-Liberal		Law		Business		Medicine		Engineering	
	Acceptance	SAT	Acceptance	SAT	Acceptance	LSAT	Acceptance	GMAT	Acceptance	MCAT	Acceptance	GRE (Quant)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Rank (Lagged)	0.02	2.25	-2.65	8.62	-1.57	1.18	0.52	3.45	-0.42	0.18	5.21	-9.01
	(1.26)	(4.00)	(1.19)**	(5.61)	(1.16)	(.35)***	(1.25)	(3.16)	(.63)	(.09)*	(2.00)***	(4.16)**
College F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Cont. Quality Score (Cubic) - Standard Deviation	X	X	X	X	X	X	X	X	X	X	X	X
R-Squared	0.926	0.971	0.884	0.938	0.897	0.952	0.818	0.923	0.801	0.869	0.746	0.672
Observations	628	596	560	546	563	590	548	592	425	445	607	426

Panel B: With Controls for Continuous Quality Scores X Year

	Undergrad-Research		Undergrad-Liberal		Law		Business		Medicine		Engineering	
	Acceptance	SAT	Acceptance	SAT	Acceptance	LSAT	Acceptance	GMAT	Acceptance	MCAT	Acceptance	GRE (Quant)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Rank (Lagged)	-0.64	7.07	-1.89	5.35	-0.88	0.46	1.45	-2.87	2.16	0.02	-1.26	-2.38
	(1.42)	(5.00)	(1.36)	(6.83)	(1.38)	(.48)	(1.37)	(4.03)	(1.15)*	(.15)	(2.45)	(5.92)
College F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X	X	X	X	X	X	X
Cont. Quality Score (Cubic) X Year	X	X	X	X	X	X	X	X	X	X	X	X
R-Squared	0.931	0.974	0.899	0.946	0.914	0.956	0.832	0.931	0.824	0.891	0.770	0.688
Observations	628	596	560	546	563	590	548	592	425	445	607	426

Notes: Observations are at the college-year level. The dependent variable is either the acceptance rate (%) or the average test score of incoming students. Overall Rank (Lagged) represents the rank that the college received the year prior to the data. College and year fixed effects are included. The continuous quality score for each school was converted into a score representing its standard deviation from the mean. A cubic of this score was controlled for in the regressions. Te overall rank variable was inverted such that an increase in overall rank by one should be interpreted as an improvement in rank (e.g. 8^{th} to 7^{th}).
* significant at 10%; ** significant at 5%; *** significant at 1%