Chapter 6
The Effect of Public and Private Quality Information on Consumer Choice in Health Care Markets

Jonathan T. Kolstad

Abstract Information-based policy interventions have become increasingly common in health care markets. The rationale for such interventions is to correct a market failure in which consumers are asymmetrically informed about relevant attributes of a health care provider (e.g., quality). The magnitude of this market failure and the effect of public intervention on welfare depend on whether there exists market-based information on quality that alters consumer choice. To better understand such effects, I study consumer response to information provided by *U.S. News and World Report* hospital rankings and hospital reputation before and after the release of report cards on surgeon quality in Pennsylvania's market for cardiac bypass surgery. I estimate a model of consumer demand for surgeon quality (mortality) that integrates market-based information and quality reporting while controlling for the role of insurers and referring physicians in consumers' choice. The role of public versus market-based learning is identified using the interaction of the intertemporal change in information induced by the release of report cards with differences across providers in market-based information on those providers' quality. I find that market-based mechanisms impact patient response to quality prior to the release of report cards. After public release of information, the response to surgeon quality increases significantly. However, existing *U.S. News and World Report* rankings reduce consumer response to surgeon quality.

Keywords Consumer choice • Health care • Matching • Quality reporting • Hospital competition

J.T. Kolstad (✉)
The Wharton School, University of Pennsylvania, Philadelphia, PA, USA
e-mail: jkolstad@wharton.upenn.edu

R. Laxminarayan and M.K. Macauley (eds.), *The Value of Information: Methodological Frontiers and New Applications in Environment and Health*,
DOI 10.1007/978-94-007-4839-2_6,

6.1 Introduction

Market structure and function in the health care industry depend critically on the availability of information. Arrow (1963) demonstrated that information structure alone can explain many of the unique institutions that set health care delivery apart from other markets (e.g., the dominant role of not-for-profit providers, physician agency, insurance). Predicated, at least in part, on this idea, policymakers have sought to improve efficiency in health care markets by changing the way in which consumers use information by gathering, analyzing and providing health care "report cards." Whether such efforts improve welfare depends on the available mechanisms for consumers to learn about quality (and other asymmetrically held attributes of providers) in the absence of government intervention; this is called market-based learning (Dafny and Dranove 2008).

For example, U.S. News and World Report ranks hospitals in a number of specialties without any policy intervention. If such existing information sources have already informed consumers about quality, then public provision of quality data will be of little value. Alternatively, patients may rely on the advice of a physician agent (e.g., cardiologist) in choosing a specialist or may be constrained by their insurance in the set of available choices. The effect of both will be to alter the effect of report cards on observed consumer choice.

Motivated by these observations, I seek to answer two questions. First, how much do market-based learning and private information alter consumer choices in the absence of public reporting? Second, are privately provided information sources complements or substitutes for information-based public policy initiatives?

To answer those questions and to better understand the role of public and private information provision, I estimate a model of demand for cardiac bypass surgeons in Pennsylvania. Using detailed individual and provider observables, I first explore what factors alter consumers' choice of surgeons in the absence of public reporting. I estimate patients' response to a latent measure of a surgeon's quality, his or her risk-adjusted mortality rate (RAMR), and to cross-sectional variation in surgeons' attributes as reported in a privately provided information source, U.S. News and World Report.

I then turn to the effect of public reporting efforts. Changes in response to RAMR after intertemporal changes in information availability due to the release of report cards identify the effect of quality reporting. Differences in response across surgeons with differing privately provided quality estimates (measured by U.S. News and World Report rankings) allow difference-in-difference estimates for whether private and public reporting are complements or substitutes for each other.

I also include demand shifters observable to agents (but not patients)—the quality of the match between patients and surgeons given the prior types of patient treated by the surgeon. Incorporating this measure into demand allows me to characterize the role of agency in choice overall and on the effect of public reporting.

The model also allows the choice set to vary based on the breadth of the network offered to each patient based on the type of insurance they have, such as Medicare fee for service (FFS), Medicare health maintenance organization (HMO), or private HMO. In this way, the demand model accounts for two of the major agents in patient choice- referring physicians and health insurance- and isolates the impact of information with and without these effects.

The chapter proceeds as follows. Section 6.2 provides background on CABG surgery and the Pennsylvania setting. Section 6.3 introduces the data used. Section 6.4 develops an empirical model of patient choice with multiple information sources. Section 6.5 presents results and discussion, and Sect. 6.6 concludes and suggests avenues for future research.

6.2 Background and Setting

6.2.1 CABG Surgery

When a patient's blood flow to the heart is compromised by narrowing of the coronary arteries, coronary artery bypass graft (CABG) surgery is one of a range of available treatment options. Diagnosis and treatment of a patient with coronary disease are an integrated process requiring effort from both a primary-care physician and a cardiologist to diagnose the problem and to select a treatment regime. If a decision for surgical intervention is made, the patient must then choose between angioplasty and CABG and select a cardiac surgeon.

To perform CABG surgery, the surgeon opens the chest wall and creates a bypass around the blocked coronary artery, using either internal mammary arteries or arteries from the leg. The process is highly invasive, typically requiring a heart-and-lung bypass machine to support the patient during the procedure and a stay of several days in the hospital intensive care unit (ICU).

It has been well documented that production in cardiac surgery exhibits a volume-outcome relationship—that is, quality rises with the number of surgeries performed by a surgeon (Ramanarayanan 2007; Gowrisankaran et al. 2006; Gaynor et al. 2005; Huckman and Pisano 2005; Arrow 1963). This is generally attributed to learning-by-doing, though the endogeneity of volume raises the possibility of an alternative mechanism, selective referral.

6.2.2 Public Reporting in Health Care Provider Markets

Currently, 37 states in the United States mandate some form of mandatory quality reporting for providers (Steinbrook 2006). The earliest and most studied provider-reporting initiatives are New York's and Pennsylvania's CABG quality report cards.[1] Reporting of RAMR for CABG began in 1989 with New York State's release of risk-adjusted performance measures for hospitals and cardiac surgeons.[2] Beginning in 1990, the Pennsylvania Health Care Cost Containment Council (PHC4), a public-private partnership, began collecting discharge data on outcomes and patient comorbidities. The first widely available report card was released in May 1998 and included data for 1994–95.[3]

Studies generally find evidence for consumer response to the release of public information, though the economic magnitude varies substantially (Kolstad and Chernew 2008). There is evidence that higher-quality (lower-RAMR) hospitals and surgeons in New York saw increased demand after the release of quality information (Mukamel and Mushlin 1998; Cutler et al. 2004). Decomposing this effect, Cutler et al. (2004) find a statistically significant reduction of five surgeries per month (10% of the average hospital's volume) following a low quality indication but little effect of being flagged as a high-quality hospital. There is also evidence that quality reporting may lead the supply side of the market (e.g. surgeons) to improve quality solely due to their intrinsic incentives to do so (Kolstad 2010).

The only paper to date that explicitly considers market-based learning in the context of provider report cards is Dranove and Sfekas (2008). The authors estimate a discrete choice model that accounts for consumers' beliefs about provider quality prior to the release of report cards. They find a significant effect of *new* information on hospital market share. A one-standard-deviation improvement in reported RAMR results is approximately a 5% increase in market share. Dranove and Sfekas (2008) do not, however, decompose the way in which prior beliefs are established. This study extends their work by estimating a model that decomposes prior learning among private information sources, agency, and insurance.

6.3 Data

The data include 89,406 observations, consisting of every isolated CABG surgery performed in Pennsylvania in 1994–1995, 2000 and 2002–2003 (PHC4 1994, 1995, 1999, 2002, 2003). Table 6.1 presents summary statistics for the pre- and post-report

[1] Similar report card programs for cardiac surgery are now in use in many states, including California, Massachusetts, Florida, and New Jersey, as well as at the country level in the United Kingdom (Steinbrook 2006).

[2] Initially the project was undertaken by the state Department of Health to gather and measure outcomes only at the hospital level. However, *Newsday* sued the State under the Freedom of Information Act, leading to the public release of the data in the form of surgeon- and hospital-level quality reports.

[3] Reports based on 1990–1993 data were constructed and released between 1992 and 1995. However, these reports are no longer available, and discussions with experts suggest that these data and the reports were not widely observed. Schneider and Epstein (1996) present survey evidence consistent with very low exposure for the early paper versions of the report cards.

Table 6.1 Summary statistics

Total number	1994–1995	2000 and 2002 (Q1,2)
Hospitals	43	63
Surgeons	201	208
Teaching hospitals	19	19
U.S. News hospitals	9	9
Average		
Surgeon RAMR	3.52	2.36
Hospital RAMR	3.18	2.41

card periods. Every observation includes surgeon and hospital identifiers, patient demographics, a set of patient comorbidities, the patient's home zip code, data on the payer type, and a set of outcome variables.[4] The outcome of interest in this chapter is inpatient mortality.

In addition to the data from PHC4, I introduce data from the American Hospital Association (AHA) annual survey of hospitals in 2000. Hospitals are matched based on the name reported to PHC4 and AHA. For a small number of hospitals whose reported names could not be found in the AHA data, I match street address reported in the AHA survey with the hospital address based on each hospital's website. The AHA data include detailed information on hospital size, service offerings, teaching status, and insurance contracts.

I also merge data from the *U.S. News and World Report* rankings of hospitals. The magazine began providing ratings in 1993 and issues ratings across a range of specialties; it ranks the top 25–50 hospitals in United States in a given specialty (the number ranked varies by year). Based on the name of the hospital in the rankings and that reported in the PHC4 data, I merge data on the Pennsylvania hospital rankings in each year in either cardiology or cardiac surgery. Of the 63 total hospitals with bypass programs in Pennsylvania, nine receive a ranking in the top 50 hospitals between 1994 and 2002. These rankings range from the 22nd hospital to the 50th hospital in the country. Hospitals that received a ranking in 1994 tend to continue to be included in the list. For example, of those ranked in 1994, 82% were also ranked in 2000. Given the small number of hospitals being ranked, the variation in the actual number of the rank over the time period, and the stability of hospital inclusion, I collapse the ranking to a dummy variable equal to 1 if a hospital receives a *U.S. News and World Report* ranking at any point during the sample period. The model also includes a control for the numerical ranking of the hospital. The number of ranked hospitals as well as the number of teaching hospitals is consistent over the pre- and post-report card period (see Table 6.1).

To compute a measure of surgeon quality, I use a measure of risk-adjusted performance. Each observation includes a dummy variable equal to 1 if a patient

[4] Patient characteristics include age, indicators for cardiogenic shock, concurrent angioplasty, complicated hypertension, dialysis, female sex, heart failure, and prior CABG or valve surgery.

died in the hospital during or immediately following surgery. The log probability of death is computed as follows:

$$\ln\left(\frac{\Pr(MORT_{i,s,h}=1\mid x_i)}{1-\Pr(MORT_{i,s,h}=1\mid x_i)}\right)=\beta_0+\beta_1\cdot X_i+\varepsilon_{i,s,h} \tag{6.1}$$

where i indexes patient, s surgeon, and h hospital. MORT is the indicator variable that equals 1 if the patient died in the hospital. This model is estimated for each report card period (1994–95, 2000, 2002, and 2003) (Pennsylvania Health Care Cost Containment Council 1998, 2002, 2004, 2005). The fitted values are obtained for each patient to form a predicted probability of death: the expected mortality rate (EMR). For each surgeon I then compute the risk-adjusted mortality rate:

$$RAMR_{s,h}=\left(\frac{OMR_{s,h}}{EMR_{s,h}}\right)OMR_{PA} \tag{6.2}$$

where the risk-adjusted, expected, and observed mortality rates for each surgeon s or hospital h are RAMR, EMR, and OMR respectively. These measures are computed as:

$OMR_{s,h}=\sum_{i|s,h} MORT_i$ and $EMR_{s,h}=\sum_{i|s,h} EMR_i$, where the summation is over patients i conditional on choosing surgeon s and hospital h, MORT is measured as above and EMR_i is equal to the fitted value for probability of death for patient i. Risk adjustment is accomplished by dividing the actual number of fatalities by the expected number of deaths conditioning on the actual patients selecting surgeon s or hospital h. This ratio is then normalized by multiplying this ratio by the statewide average mortality rate.

6.4 A Model of Patient Choice

6.4.1 Patient Utility

Each patient selects from the set of surgeons, $j \in J$, defined by the available set of surgeons in the hospital referral region (Wennberg et al. 1999). The utility for patient i from choosing a given surgeon s is a function of cost (both monetary and time costs), expected health improvement (capturing all components of quality and the ability of the patient to observe them), and an error term.

Indirect utility to consumer i who selects surgeon s is

$$u_{i,s,h}=g(X_i,\eta_i,\mu_i,Z_{s,h},\theta_{s,h};\rho)+\varepsilon_{i,s,h} \tag{6.3}$$

where X_i and η_i are vectors of observed and unobserved patient characteristics and μ_i is a vector of physician agent characteristics, all of which lead to differences in taste.

$Z_{s,h}$ is a K-dimensional a vector of hospital and surgeon characteristics not directly related to expected health. $\theta_{s,h,t}$ is the expected quality (beliefs about the gains in health) of surgeon s at hospital h. Finally, $\varepsilon_{i,s,h}$ is an iid error term distributed type-1 extreme value and ρ is a vector of parameters.

Learning about quality from different sources enters in the way in which a patient determines $\theta_{s,h,t}$. Each patient is assumed to infer quality from all available information sources in each period *t*. The model of expected quality for surgeon s at hospital h in period t is

$$\theta_{s,h,t} = \beta_1 RAMR_{s,t-1} + \beta_2 RAMR_{s,t-1} * Post_t + \beta_3 \varphi_{s,h,t} + \beta_4 \varphi_{s,h,t} * RAMR_{s,h,t-1} + \beta_5 \varphi_{s,h,t} * Post_t + \beta_6 \varphi_{s,h,t} * RAMR_{s,t-1} * Post_t \tag{6.4}$$

The effect of formal reporting is identified by changes in patient choices between the pre- and post-report card period (1994–95 compared with 2000 and the first two quarters of 2002), captured by the dummy variable$Post_t$that takes a value of 1 if an observation in period t is after 1995.

Equation (6.4) models two main effects. The first is the average response to quality, given available information. The coefficient β_1 is a measure of the average response to surgeon RAMR with only market-based learning. β_2 captures the average differential response to quality following the release of report cards. The second is the effect of market-based learning on choice. The coefficient β_3 is a measure of patient response to privately supplied information on quality. The term on the interaction of $\varphi_{s,h,t}$ with surgeon RAMR,β_4, is an estimate for the differential effect of each component of $\varphi_{s,h,t}$ on an individual's response to latent surgeon quality. Interacting $Post_t$ with $\varphi_{s,h,t}$ captures the effect of report cards on patient response to privately supplied quality information. Finally, the coefficient β_6 captures the effect of quality reporting on the response to quality, given market-based signals about quality.

β_6 is a triple differences estimate for the role of each component of market-based information on individuals' response to RAMR after it is made public following quality reporting. If public information is a substitute for private information (and vice versa), estimates will be positive and significant. That is, given prior information from private sources that a provider is of high quality, patient response to surgeon quality (RAMR) after public release is smaller. On the other hand, if market-based learning complements public reporting, I expect that the interaction of RAMR with market-based information will have a (weakly) negative coefficient.

6.4.2 Prices and Insurance

Indirect utility in (6.3) is derived directly from a quasilinear utility function without wealth effects or prices. Typically, demand models include price in indirect utility. In this case, however, we do not observe the out-of-pocket price facing a patient undergoing CABG. For a procedure as expensive as CABG, the out-of-pocket cost for an insured patient is unlikely to vary in any meaningful way between surgeons. On the other hand, for patients not covered by traditional Medicare or private fee-for-service plans, network constraints can limit their choice of surgeon. To deal with this issue, I model the patient's specific network constraints for each surgeon.

Implementing this empirically is hampered by a common difficulty in estimating patient choice models in health care: data on patients' specific plans and the hospital and surgeon networks available within those plans in each period are not available. Because I do not directly observe network participation by hospitals or surgeons or a patient's specific plan brand (e.g., Blue Cross Blue Shield preferred provider organization, Aetna HMO), I infer the network constraints facing individual i using data on the general type of insurance for each patient (Medicare, Medicare HMO, private FFS, private HMO, Medicaid, and uninsured). A patient's choice probability is computed as a function of the likelihood that a given surgeon is available to that patient in period t based on observed market outcomes for that surgeon in the prior period.

Consider a specific plan (e.g., an Aetna HMO) that is included in insurance type z (Private HMO). The probability that a surgeon s is included in individual i's choice set is the joint probability that surgeon s is included in any type z network and, conditional on inclusion in type z network, the probability that the plan is included in the type z plans in market h. I assume that surgeons and hospitals prefer to serve the most profitable patients and that prior-period profitability is correlated with current-period profitability for a patient with insurance type z as follows:

$$\pi_{i,z,t} = v\pi_{i,z,t-1} + u_{i,z,t} \tag{6.5}$$

where v is a coefficient capturing the intertemporal correlation in insurer type profitability and $u_{i,z,t}$ is mean zero error term. When $v>0$, we expect the more profitable a given insurance type was in period t-1, the more likely a surgeon is to contract with that insurance type again in period t. Conditional on a surgeon's being included in any plan of type z, the probability that the plan is included in the set of type z plans in market h is $\tau_{z,h,t} \sim N(b, W)$. Under these assumptions, the share of patients in plan type z treated by surgeon s in the prior period is a measure of the relative profitability of those patients. Thus the probability that patient i will have the option of selecting a surgeon s is a function of the lagged share of patients of insurance type z seen by surgeon s weighted by the (unobserved) probability that the plan is included in the set z for surgeon s. Assuming that the error in (6.5) is distributed normally, we subsume the error into the distribution of $\tau_{z,h,t} \sim N(b, W)$.[5] Thus the probability that a surgeon s is included in the network is

$$\tau_{i,s}\left(v_z PayorShare_{z,t-1}\right) \tag{6.6}$$

[5] Distributing τ and taking the plim of the error term $\tau * u_{i,z,t} = 0$.

In this way, network constraints are captured by reducing the probability that a patient can substitute an alternative surgeon who served a smaller share of patients of the same insurance type in the prior quarter. In estimation I also interact the prior-quarter payer share with the number of HMO contracts at hospital h to allow a more flexible response.

6.4.3 Agency

No studies to date have been able to estimate a model of consumer choice that separates the role of a physician agent from patient choice in responding to information (Pope 2009). To identify the role of agency in patient choice, I rely on a demand shifter that is unlikely to be observable to an individual patient but should be known by a cardiologist: the match between a patient with a given severity and the types of patients each surgeon usually treats. That is, a referring physician is better informed regarding different surgeons' performance in treating patients with differing types of disease and severity. By conditioning demand on such a measure, I can control for the role of the physician agent in demand.

I model this match value as a function of the absolute value of the deviation between a patient's severity (measured by predicted mortality) and the lagged mean patient severity for surgeon i in period t-1 (the prior quarter). This measure is used on the assumption that patients with more comorbidities are likely to be (both observably and unobservably) more difficult cases and be better suited to surgeons who have more experience in treating complex cases. Thus agency enters demand as a (potentially nonlinear) function:

$$\mu_i = \gamma_1 f\left(\left|EMR_i - \overline{EMR}_{s,t-1}\right|\right) \tag{6.7}$$

The subscript i remains because realized behavior is the manifestation of the joint decision process of patient and agent, and I do not observe any information on the identity of the referring physician. In some specifications I also allow agency to depend on the unobserved term η_i. This accounts for unobserved patient willingness to take the advice of her agent as well as unobserved variation in the degree to which patient-surgeon matching alters the agent's referral patterns.

6.4.4 Likelihood and Estimation

A patient selects surgeon s at hospital h if and only if

$$u_{i,s,h} > u_{i,j,h} \forall j \neq s \tag{6.8}$$

Incorporating Eqs. (6.4), (6.6), and (6.7) and substituting back into (6.3), the patient's utility function is now

$$
\begin{aligned}
u_{i,s,h} = {} & X_i + \gamma_1 f(|EMR_i - \overline{EMR}_{s,t-1}|) + \lambda_1 PayorShare_{i,z,t-1} + \beta_1 RAMR_{s,h,t-1} \\
& + \beta_2 RAMR_{s,h,t-1} * Post_t + \beta_3 \varphi_{s,h,t} + \beta_4 \varphi_{s,h,t} * RAMR_{s,h,t-1} + \beta_5 \varphi_{s,h,t} * Post_t \\
& + \beta_6 \varphi_{s,h,t} * RAMR_{s,h,t-1} * Post_t + \varepsilon_{i.s.h}
\end{aligned} \tag{6.9}
$$

Note that in (6.9) I do not include unobserved taste components. I begin by estimating (6.9) as a standard multinomial logit model (McFadden 1974). I then turn to a model that incorporates unobservable patient responses to quality, market-based information, and agency as well as unobserved network constraints. Individual utility in this model is

$$
\begin{aligned}
u_{i,s,h} = {} & X_i + [\gamma_1 f(|EMR_i - \overline{EMR}_{s,t-1}|) + \beta_1 RAMR_{s,h,t-1} \\
& + \beta_2 RAMR_{s,h,t-1} * Post_t + \beta_3 \varphi_{s,h,t} + \beta_4 \varphi_{s,h,t} * RAMR_{s,h,t-1} + \beta_5 \varphi_{s,h,t} * Post_t \\
& + \beta_6 \varphi_{s,h,t} * RAMR_{s,h,t-1} * Post] * \eta_i + \lambda_1 \tau_{i,s}\left(v_z PayorShare_{i,z,t-1}\right) + \varepsilon_{i.s.h}
\end{aligned} \tag{6.10}
$$

Individual choice is a function of observed (to the econometrician) patient and surgeon attributes as well as a set of unobserved factors: insurer network constraints, random tastes for and use of report cards, and the role of agency in this choice. I incorporate the unobserved terms as random coefficients (Berry et al. 1995; Nevo 2001; Train 2003).

Assume that the unobserved components of utility are distributed according to the distribution $\phi(\eta_i, \tau_i | b, W)$ that is known up to a mean and covariance, b and W, to be estimated. Thus the probability that a patient i chooses surgeon s is the closed form logit choice probability integrated over the distribution of the unobserved terms. The probability that patient i selects surgeon s given choice set j can be expressed as follows:

$$
P_{i,s} = \int \left(\frac{e^{\beta X_{i,s}}}{\sum_j e^{\beta X_{i,j}}} \right) \phi(\eta_i, \tau_i | b, W) d\lambda \tag{6.11}
$$

The integral over the unobserved components of utility does not have an analytical solution. However, I can estimate the model using simulated maximum likelihood (Train 2003). Estimates for the demand system are computed by solving analytically for the logit choice probabilities and integrating out the random taste distribution by taking draws from the joint distribution of unobserved terms. Using this numerical simulation, I compute the likelihood of observing the choices based on the observed and unobserved components of choice.

I draw n values of the unknown components η_i and τ_i from the normal distribution. For each draw I then compute the choice probability using Eq. (6.11). For n Halton draws, the simulated log-likelihood is

$$SLL = \sum_{i=1}^{I} \sum_{n=1}^{N} I[i = s] \ln \ddot{P}_{is} \tag{6.12}$$

where $I[i = s]$ is an indicator function taking the value 1 if individual i chose surgeon s and zero otherwise and $\hat{P}_{i,s} = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{e^{\beta X_{i,s}}}{\sum_j e^{\beta X_{i,j}}} \right)$. The coefficient vector that maximizes (6.12) is the maximum simulated likelihood estimator (Train 2003).

6.5 Results and Discussion

6.5.1 Base Model

Table 6.2 presents results from estimating the model using a multinomial logit specification. I return to estimation that includes unobserved terms below. The first column presents estimates for the demand parameters when patients are assumed to respond only to the latent measure of surgeon quality, prior-quarter RAMR. Distance enters, as expected, negatively and significantly over most ranges. The significant coefficient on distance squared suggests a nonlinear cost of travel. Turning to consumer quality elasticity of demand, parameter estimate for β_1 suggests a significant negative response to RAMR in the absence of public quality reporting. Estimates of β_2, however, are small and insignificant, suggesting little response to the release of quality report cards.

I next incorporate controls for market-based information sources *(U.S. News and World Report)* as well as controls for insurance and physician agency. The estimates for this version of the model are in column 2 of Table 6.2. Incorporating these additional "omitted variables" to the version of the model in column 1 gives parameter estimates for β_1 and β_2 that are negative and significant. The coefficients on surgeon RAMR suggest a response to mortality in the prereporting period as well as after report cards were released. The introduction of report cards led to a significantly larger disutility from seeing a surgeon who has a higher RAMR. Comparing estimates of β_2 in columns 1 and 2 suggests that, after controlling for market-based learning about high-quality providers, patients do respond to surgeon quality more with publicly provided data.

Estimates for β_5 suggest that consumers respond more positively to *U.S. News and World Report*–ranked hospitals in the post-reporting period. This finding is consistent with complementarities between private information sources and public reporting. The same effect also holds for hospital teaching status. Consumers increasingly value

Table 6.2 Multinomial logit estimates of patient demand parameters

	Dependent variable: Log probability patient i select surgeon s					
	(1)		(2)		(3)	
Travel cost:						
Distance (Miles) i, s	−0.093	(0.002)***	−0.088	(0.002)***	−0.088	(0.002)***
Distance squared (Miles) i, s	0.001	(0.000)***	0.001	(0.000)***	0.001	(0.000)***
Distance (Miles) i, s*Post RC	−0.014	(0.004)***	−0.012	(0.004)***	−0.012	(0.004)***
Distance squared (Miles) i, s*Post RC	0.000	(0.000)	0.000	(0.000)**	0.000	(0.000)**
Mortality (Quality):						
RAMR s, t-1	−0.012	(0.001)***	−0.009	(0.002)***	−0.006	(0.004)*
RAMR s, t-1*Post RC	−0.001	(0.003)	−0.010	(0.004)***	−0.022	(0.009)**
Market based information:						
US News top hospital			−0.649	(0.023)***	−0.630	(0.027)***
US News top hospital * Post RC			0.219	(0.034)***	0.053	(0.040)
US News ranking h			0.020	(0.002)***	0.018	(0.002)***
Top ranking US New hospital m			0.565	(0.077)***	0.504	(0.077)***
US News top hospital *RAMR s, t-1					−0.005	(0.004)
US News top hospital *RAMR s, t-1* Post RC					0.083	(0.009)***
Teaching hospital h			−0.563	(0.020)***	−0.559	(0.023)***
Teaching hospital h*Post RC			0.161	(0.034)***	0.156	(0.039)***
Teaching hospital h* RAMR s, t-1					−0.001	(0.004)
Teaching hospital h *RAMR s, t-1* Post RC					−0.009	(0.008)
Agency:						
|Pr Mort i- Pr Mort s, t-1|			−2.370	(0.397)***	−2.349	(0.398)***
|Pr Mort i- Pr Mort s, t-1|* Post RC			−0.020	(0.330)	−0.012	(0.330)
Insurance network:						
Payer share s, t-1, i			−0.006	(0.061)	−0.019	(0.062)
Payer share s, t-1, i*HMO Contracts h			0.006	(0.003)**	0.087	(0.112)
Payer share s, t-1, i* Post RC			0.039	(0.107)	0.007	(0.003)**

Payer share s, t-1, i*HMO Contracts h*Post RC			0.000	(0.006)	0.001	(0.006)
Medicare FFS i* RAMR s, t-1					0.000	(0.006)
Medicare FFS i* RAMR s, t-1*Post RC					−0.009	(0.009)
Medicare HMO i* RAMR s, t-1					−0.022	(0.015)
Medicare HMO i* RAMR s, t-1*Post RC					0.014	(0.018)
Private HMO i* RAMR s, t-1					−0.003	(0.006)
Private HMO i* RAMR s, t-1*Post RC					0.000	(0.011)
Observations	1,048,706		821,793		821,793	
Log likelihood	−133652.05		−105839.30		−105787.50	

*, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively

teaching hospitals in the post-reporting period. These complementarities may pick up greater awareness of variation in quality due to the release of public report cards; the release not only increases individuals' use of the report cards themselves but leads patients to seek out other available private information sources.

Physician agency and insurance network effects also enter choice significantly on average. However, the demand shifters that capture physician agency do not differentially alter choice after the release of quality reporting. This is perhaps not surprising if physician agents have relatively good information even in the absence of quality reporting. Insurance network effects enter choice significantly only in the pre-reporting period and only on the interaction of the number of HMO contracts at hospital h with the share of payer type at the surgeon level. This provides weak evidence that surgeons at hospitals who are more willing to contract with HMOs care for patients with relatively more restrictive networks. This effect is invariant to the release of report cards and, given the lack of a significant estimate for the effect of a surgeon's share of a given insurance type alone, I do not emphasize this result as conclusive.

Column 3 contains estimates for the fully interacted model, which allows market-based information to interact with latent surgeon quality and report card–induced learning. In this specification the patient's response to surgeons' RAMR is significant both before and after the release of report cards.

The parameter estimate of β_2 in the fully interacted model is larger than the estimates in both columns 1 and 2. In fact, the differential response to surgeon quality after report card release is more than double the estimated response that controls for the average role of market-based learning and insurance in choice (column 2). These findings suggest that the interaction of market-based and public information alter consumer choice. As a result, models that do not control for prior consumer learning likely underestimate the effect of public reporting on choice.

The interaction of consumers' response to surgeons' RAMR with the type of insurance they have does not produce any significant effects. However, after incorporating these terms, there is a significant coefficient on the interaction of lagged payer share and the *Post* dummy variable, suggesting some increase in the constraints of networks after reporting. Because identification is coming from intertemporal changes, this finding may also be due to the rise of managed-care networks over the time period. This further underscores the need to account for the effect of insurance network constraints when estimating the effect of quality reporting on choice. Decomposing patients' response to RAMR across Medicare FFS, Medicare HMO, and private HMO patients suggests little differential effect of insurance on quality demand. Taken together, these results suggest that insurance network constraints play a relatively small role in a patient's choice of CABG surgeon, and to the extent that they do influence choice, this seems to be unrelated to surgeon quality.[6]

[6] In a set of unreported regressions I re-estimate the model allowing patient response to *U.S. News and World Report* to vary with the type of insurance a patient has. Consistent with the lack of response to RAMR, I find no differential response to private information provided by *U.S. News* between Medicare FFS patients and those in managed care (both Medicare and private).

The other relevant coefficient in the full model is β_6, the differential response to quality reporting given the market-based beliefs about a provider. The results in Table 6.2 suggest that *U.S. News and World Report* is a substitute for the information provided by PHC4. Teaching status and insurance do not differentially alter patients' response to quality information after the inception of reporting. The parameter estimates for the interaction of a *U.S. News and World Report* ranking and lagged surgeon RAMR is 0.083 and is significant at the 1% level. The response to new quality data within hospitals that have *U.S. News* rankings is substantially less after the release of report cards than among surgeons at hospitals that do not have such information available.

6.5.2 Incorporating Unobserved Effects

I next turn to estimating a version of the model that allows unobserved taste variation to enter as random coefficients in demand. This allows the effect of agency and the use of market-based information to vary in the population because of unobserved factors and the likelihood of a patient's being able to choose a given surgeon to vary because of unobserved insurance network constraints. The results of estimating Eq. (6.10) using maximum simulated likelihood are presented in Table 6.3. The first two columns contain mean and standard deviations for the parameters in the model, including market-based learning but with interacting private information with patient response to RAMR. Columns 3 and 4 present mean and standard deviation estimates for parameters in the fully interacted model.

The biggest change between the random coefficients and the base model is that estimates for the response to quality information (RAMR) are no longer significant in either specification. This is true both for the average effect and for the marginal increase due to quality reporting. However, in the fully interacted model (column 3) the estimate for the mean of β_2 is of a similar magnitude to the estimates in column 3 of Table 6.2, though the coefficient is not significant at conventional levels (p-value = .12). The estimates for the variance of the parameters on response to surgeons' RAMR are not significant in either version of the model.

I next turn to patients' response to a hospital's being ranked by *U.S. News and World Report*. These mean coefficient estimates are significant, both statistically and economically, in both specifications. The estimated standard deviation of patients' response to being ranked by *U.S. News and World Report* is large and significant in both versions. This lends further support to the idea that a subset of patients value *U.S. News* rankings highly while a larger group not only do not value (or access) this information but appear to avoid these hospitals, perhaps reflecting other rationing mechanisms or top hospitals' efforts to price-discriminate among patients.[7]

[7] I use the term price discrimination, but as discussed, this is more likely to be non-price-based efforts to ration care across patients with a different willingness to pay for *U.S. News* rankings.

Table 6.3 Random-coefficients estimates of patient demand parameters

	Dependent variable: Log probability patient i selects surgeon s							
	Mean		S.D.		Mean		S.D.	
Travel cost:								
Distance (Miles) i, s	−0.181	(0.004)***			−0.182	(0.004)***		
Distance squared (Miles) i, s	0.003	(0.000)***			0.003	(0.000)***		
Distance (Miles) i, s*Post RC	−0.022	(0.007)***			−0.019	(0.007)***		
Distance squared (Miles) i, s*Post RC	0.000	(0.000)***			0.000	(0.000)***		
Mortality (Quality):								
RAMR s, t-1	−0.004	(0.003)	0.000	(0.004)	−0.001	(0.004)	0.000	−0.007
RAMR s, t-1*Post RC	−0.003	(0.009)	0.001	(0.008)	−0.015	(0.010)	0.000	−0.017
Market based information:								
US News top hospital	−0.541	(0.033)***	0.543	(0.111)***	−0.535	(0.036)***	−0.606	−0.174***
US News top hospital * Post RC	0.396	(0.046)***	−0.005	(0.089)	0.273	(0.052)***	0.003	−0.013
US News ranking h	0.022	(0.002)***			0.021	(0.002)***		
Top ranking US New hospital m	0.657	(0.081)***			0.607	(0.081)***		
US News top hospital *RAMR s, t-1					−0.004	(0.005)	0.003	−0.177
US News top hospital *RAMR s, t-1* Post RC					0.059	(0.010)***	−0.002	−0.008
Teaching hospital h	−0.177	(0.026)***	−0.002	(0.052)	−0.159	(0.028)***	0.022	−0.028
Teaching hospital h*Post RC	0.034	(0.045)	−0.006	(0.085)	0.010	(0.049)	−0.016	−2.108
Teaching hospital h* RAMR s, t-1					−0.005	(0.004)	0.001	−3.134
Teaching hospital h *RAMR s, t-1* Post RC					−0.005	(0.009)	−0.003	−0.200
Agency:								
|Pr Mort i- Pr Mort s, t-1|	−4.980	(0.632)***	−0.093	(1.037)	−4.955	(0.633)***	−0.090	(1.030)
|Pr Mort i- Pr Mort s, t-1|* Post RC	2.266	(1.259)*	−0.064	(1.929)	2.314	(1.270)*	0.562	(1.886)
Insurance network:								
Payer share s, t-1, i	−0.045	(0.073)	0.018	(0.097)	−0.036	(0.073)	−0.011	(0.096)
Payer share s, t-1, i*HMO contracts h	−0.123	(0.150)	0.038	(0.271)	−0.107	(0.151)	0.034	(0.284)
Payer share s, t-1, i* Post RC	0.011	(0.033)***	0.002	(0.006)	0.011	(0.003)***	−0.001	(0.006)

Payer share s, t-1, i*HMO contracts h*Post RC	−0.003	(0.007)	0.001	(0.013)	−0.002	(0.007)	−0.002	(0.014)
Medicare FFS i* RAMR s, t-1					−0.001	(0.004)		
Medicare FFS i* RAMR s, t-1*Post RC					−0.007	(0.011)		
Medicare HMO i* RAMR s, t-1					−0.048	(0.018)***		
Medicare HMO i* RAMR s, t-1*Post RC					0.038	(0.022)*		
Private HMO i* RAMR s, t-1					−0.003	(0.007)		
Private HMO i* RAMR s, t-1*Post RC					0.000	(0.013)		
Observations	459,870				459,870			
Log likelihood	−65,398				−65,372			

*, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively

The estimated mean effect of patient-surgeon matching on choice—the role of physician agents—is significant not only before (as in the prior estimation) but also after the release of report cards. The variance in the population of agency is not significant for either the baseline effect or the marginal effect after reporting.

I find that allowing random coefficients to enter the model of insurance network constraints makes some difference in the estimated influence of network constraints. The estimated coefficients suggest a significantly larger mean effect after report cards, as before, though the variance of the estimate is not significant. In the fully interacted model the estimated response to quality by patients in Medicare HMOs is relatively larger (more negative) prior to the release of report cards. However, this effect is eliminated by the post-reporting period (I fail to reject the hypothesis that the sum of the coefficients on Medicare HMO* RAMR + Medicare HMO*RAMR*Post is equal to zero). Despite this finding, I do not interpret this as strong evidence for a role of Medicare HMO networks as agent in specialist choice based on quality. Given the volatility of payments and regulation as well as selection behavior in Medicare Part C markets and the fact that these factors were changing over time, I am concerned about omitted variables in my intertemporal identification.

Despite some changes to the findings in the random coefficients model, the basic results remain. I do note, however, that the effect of reporting on patients' response to quality is diminished. Given the assumptions on the form of the unobserved terms necessary to estimate Eq. (6.10), I focus on the base specification for the primary results and sensitivity analysis.

6.5.3 Sensitivity Analysis

The empirical strategy relies on two assumptions: that RAMR is a reasonable measure of surgeons' latent quality and that changes over time in response to RAMR are solely due to reductions in information asymmetries resulting from the release of quality report cards. If, however, other factors that influence patients' choice are correlated with RAMR or other changes between the pre- and post-report card period, the model is misspecified. To test for such a situation, I reestimate the model including only patients who received CABG after initially receiving angioplasty on the same day. This situation occurs when a patient has a complication during the angioplasty procedure and must be rushed to a CABG surgeon. Because these patients chose a surgeon in an emergency situation, I expect their choices not to respond to surgeon quality or to the release of information. If, instead, I find that surgeon quality affects the choices by these patients, particularly interacted with the post-reporting period, I will be concerned that measures of quality and reporting are correlated with the error term and that this may be driving the prior findings. Table 6.4 presents results for this specification.

Distance continues to enter significantly, reflecting the fact that angioplasty patients also prefer to receive care closer to their home. In all specifications,

Table 6.4 Multinomial logit estimates of patient demand parameters including only patients receiving both angioplasty and CABG on same day

	Dependent variable: Log probability patient i select surgeon s					
	(1)		(2)		(3)	
Travel cost:						
Distance (Miles) i, s	−0.101	(0.010)***	−0.082	(0.010)***	−0.083	(0.011)***
Distance squared (Miles) i, s	0.002	(0.000)***	0.001	(0.000)***	0.001	(0.000)***
Distance (Miles) i, s*Post RC	0.008	(0.038)	−0.014	(0.041)	−0.015	(0.041)
Distance squared (Miles) i, s*Post RC	0.000	(0.001)	0.000	(0.001)	0.001	(0.001)
Mortality (Quality):						
RAMR s, t-1	−0.007	(0.007)	0.000	(0.009)	0.003	(0.015)
RAMR s, t-1*Post RC	−0.006	(0.038)	−0.035	(0.043)	−0.082	(0.097)
Market based information:						
US News top hospital			−0.483	(0.118)***	−0.554	(0.135)***
US News top hospital * Post RC			0.000	(0.009)	−0.184	(0.394)
US News ranking h			0.031	(0.014)**	0.030	(0.014)**
Top ranking US New hospital m			1.001	(0.502)**	0.980	(0.502)*
US News top hospital *RAMR s, t-1					0.021	(0.020)
US News top hospital *RAMR s, t-1* Post RC					0.090	(0.096)
Teaching hospital h			0.402	(0.347)	−0.574	(0.113)***
Teaching hospital h*Post RC			−0.550	(2.058)	0.383	(0.395)
Teaching hospital h* RAMR s, t-1					−0.022	(0.019)
Teaching hospital h *RAMR s, t-1* Post RC					−0.022	(0.092)
Agency:						
|Pr Mort i- Pr Mort s, t-1|			−0.550	(2.058)	−0.588	(2.061)
|Pr Mort i- Pr Mort s, t-1|* Post RC			−0.150	(1.288)	−0.227	(1.294)
Insurance network:						
Payer share s, t-1, i			0.091	(0.321)	0.099	(0.322)
Payer share s, t-1, i*HMO contracts h			0.019	(0.014)	0.715	(1.270)
Payer share s, t-1, i* Post RC			0.772	(1.204)	0.019	(0.014)

(continued)

Table 6.4 (continued)

	Dependent variable: Log probability patient i select surgeon s					
Payer share s, t-1, i*HMO contracts h*Post RC			0.004	(0.067)	0.004	(0.069)
Medicare FFS i* RAMR s, t-1					−0.005	(0.019)
Medicare FFS i* RAMR s, t-1*Post RC					0.039	(0.114)
Medicare HMO i* RAMR s, t-1					−0.010	(0.092)
Medicare HMO i* RAMR s, t-1*Post RC					0.059	(0.142)
Private HMO i* RAMR s, t-1					0.022	(0.025)
Private HMO i* RAMR s, t-1*Post RC					0.036	(0.122)
Observations	28,017		28,017		28,017	
Log likelihood	−4391.29		−3433.69		−3431.27	

*, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively

surgeons' RAMR does not enter significantly either before or after the release of report cards. None of the variables for physician agency or the role of insurance networks enter the choice model significantly, either. Because a patient who requires CABG after receiving angioplasty is likely to be moved quickly to any available bypass surgeon, this also validates that these measure are not capturing unobserved variables that affect choice. The only market learning variables that enter significantly in Table 6.4 are the dummy for teaching hospital and *U.S. News and World Report* variables that are not interacted with surgeons' RAMR. This is not surprising, however, given that *U.S. News* rankings are for either cardiology or cardiac surgery overall at the hospital, not only for CABG. It thus appears that angioplasty patients also learn from market-based information and respond in a similar way to CABG patients (if anything, the premium on being the highest-ranked *U.S. News* hospital in a market is large even for angioplasty patients). The interactions between surgeons' RAMR and *U.S. News* information and teaching status are not significant in columns 2 or 3 of Table 6.4, suggesting that CABG-specific market-based learning is not picking up unobserved hospital-level observables that change over time.

6.6 Conclusion

This chapter considers the effect of privately and publicly provided information on patients' choice of a cardiac surgeon. *U.S. News and World Report* rankings significantly alter consumer choice, though this effect varies substantially in the population, and in some cases, patients prefer hospitals that are not ranked.

After the state of Pennsylvania introduced quality reporting for cardiac surgery, patients' response to quality increased. Patients' beliefs about quality due to *U.S. News and World Report* rankings significantly altered this response to the release of report cards. I find that the role of quality in patient choice was differentially smaller after the release of report cards among hospitals that were ranked by *U.S. News and World Report*. This provides evidence that private and public reporting substitute for each other.

The results also suggest that evaluations of reporting efforts should incorporate prior market-based learning into the model. Without this the estimated effect of reporting is likely to be biased down. Given that many studies of privately provided information find only a small or nonexistent effect of information release on consumer choice (see Kolstad and Chernew 2008 for a review of the evidence), these findings argue for continued investigation in this area.

Taken together, my results also underscore the importance of considering existing mechanisms for consumers to learn about quality when formulating information-based policy interventions. The distributional impact of such policies is also likely to vary depending on consumers' *ex ante* knowledge of providers' quality. If some markets have substantially more information available through market-based sources, the effect of reporting may differ from that in relatively less informed markets, where the effect is likely to be larger.

Without additional detail, it is difficult to make strong normative conclusions regarding the value of the introduction of quality report cards in Pennsylvania. This is true both in terms of a general evaluation and in trying to understand the normative effect of *U.S. News and World Report* rankings and physician and insurer agency. Future work that can evaluate the relative welfare gains from privately provided information and public reporting would be highly informative for policy.

In addition to studying information interventions, this chapter has estimated a demand model that separates the role of physician agency in demand for specialized care. Future work that considers the degree to which agents make optimal decisions for patients could inform appropriate information-based policy interventions as well as alternative incentive mechanism (e.g., payment policy) to improve choices in health care markets.

Finally, I have not considered the underlying normative value of the information contained in private and public report cards. This is important in interpreting these results for application, particularly in light of the substitution between *U.S. News* rankings and Pennsylvania's report cards. If *U.S. News* rankings are less correlated with socially desirable outcomes (e.g., increases in quality-adjusted life expectancy), then the results here suggest that market-based learning may undermine the value of public intervention. Of course, the converse may hold. Future studies that address this issue would be valuable in health care as well as in the many other markets in which information-based policy interventions have been applied and frequently overlap with private information provision.

Acknowledgments The data used in this analysis were obtained from the Pennsylvania Health Care Cost Containment Council (PHC4), which requests the following disclaimer: The Pennsylvania Health Care Cost Containment Council (PHC4) is an independent state agency responsible for addressing the problem of escalating health costs, ensuring the quality of health care, and increasing access to health care for all citizens regardless of ability to pay. PHC4 has provided data to this entity in an effort to further PHC4's mission of educating the public and containing health care costs in Pennsylvania. PHC4, its agents and staff, have made no representation, guarantee, or warranty, expressed or implied, that the data – financial, patient, payor, and physician specific information – provided to this entity, are error-free, or that the use of the data will avoid differences of opinion or interpretation. This analysis was not prepared by PHC4. This analysis was done by Jonathan T. Kolstad. PHC4, its agents and staff, bear no responsibility or liability for the results of the analysis, which are solely the opinion of the author.

6. Commentary: When Information Becomes Useful

Kenneth L. Leonard and Timothy Essam

"The Effect of Public and Private Quality Information on Consumer Choice in Health Care," by Jonathan Kolstad, tests whether patients are using information available from different sources to choose doctors of high quality. The central question, "Can patients adapt their behavior to information about quality and, in so doing, improve their own health?" is important in the health care literature, and it is one that we have also tackled, though with data from developing countries. In the case of this contribution, patients (together with their primary-care physicians) are choosing where to seek cardiac bypass surgery, using data collected by the state of Pennsylvania and published in *U.S. News and World Report*. In addition to tackling an important and difficult question, this chapter uses complex statistical methodologies to significantly improve the strength of its findings. It thus represents an important contribution to knowledge. Its primary contribution to this volume, however, is as an illustration of the complexities involved in measuring the value of information in general.

In this discussion of the chapter, we are not going to focus on the immediate question posed and answered by the author, since that is best left to him. Instead we will focus on how the chapter relates to the broader question of this volume. In the case of information about medical care, how should one present data on multiple stochastic outcomes to consumers? How much preliminary processing is required before the data can be shown to the public? Do data such as these lead to any change in behavior? Does this make the consumers of the information better off? More importantly, does the information make the average person better off? Some of these questions should seem surprising, given that people always have the option to ignore information; how can it be that accurately collected and reported information could ever make people worse off? As we shall see, this is all too easy, and proving that information has not caused harm is part of the reason that Dr. Kolstad's chapter is as complex as it is.

6.C.1. Information Asymmetry in Health Care

Health care has traditionally been seen as an interesting economic case study because of the imbalance of power, particularly with regard to information. Even in settings in which patients are empowered to choose treatments, hospitals, or

K.L. Leonard (✉) • T. Essam
Department of Agricultural and Resource Economics,
University of Maryland, College Park, MD, USA
e-mail: kleonard@arec.umd.edu; tessam@arec.umd.edu

physicians, they have little information or experience with which to make these decisions; the knowledge about medicine and the patient's condition lies with the physician. This means that patients cannot choose a physician and hospital and then demand high-quality services once they arrive, since they don't know what services are necessary and cannot evaluate whether high-quality services were ever delivered. For economists, this is a particular problem because there cannot be a "market for quality." Instead, patients attempt to ensure they get what they need by choosing the right physician and hospital.

However, in exactly the same setting where patients know so little, we can collect copious quantities of information, which should be useful to patients when they make decisions. Outcomes are an excellent example of how these data can be useful, and they illustrate some additional interesting features of health care. Whereas patients are unlikely to know much about what they need, or even what is happening to them, they know a lot about the outcome of treatment. So every patient gets one very high quality observation each time he visits a doctor. The chapter focuses on bypass surgery, which is not a particularly good example here, so we should imagine a mother taking her child in for an earache. The patient (and parent) can decide whether they liked the doctor's manner, how long they had to wait, the condition of the waiting room and how the child felt after they left the office, how he felt the next day, and even the day after that. However, this one piece of high-quality data is not particularly useful to the patient because doctor quality is related to health outcomes as only one piece of a complex set of variables. Outcomes are stochastic, meaning that a doctor can do everything right and the patient will not feel better, or she can do nothing right and the patient will feel better. It is possible to survive surgery from a terrible surgeon, and it is possible to die under the knife of the best surgeon. This means that although one piece of information is better than nothing, it is not an absolute guide for patients. In reality, patients can learn much more by looking at many points of low-quality data. It is more useful for the patient to know the outcomes for 100 patients operated on by a particular surgeon, or to hear the experiences of 100 children who went to a particular pediatrician for earaches.

This is the goal of these data collection efforts: to collect information from enough different cases to display a pattern. Thus, theory suggests that information from large data sets should be extremely useful to patients. However, the one thing that people often forget about health care is that what is hidden from patients is not hidden from other doctors. Patients cannot directly evaluate their doctors, and data collectors are in the same situation, but doctors can much more easily assess the skills of their peers without access to large data sets. This is a point that Kolstad recognizes and talks about explicitly, but we will come back to it in this review. In general, we need to remember that large data sets make local trends transparent to outside observers who otherwise would know very little, but that frequently there are people who have always known more about local conditions than the data can ever reveal. These well-informed actors may never be able to see the larger picture, but that does not stop them from acting in a way that could make data collection redundant.

6.C.2. Public Information Versus Expert Opinion

Kolstad is careful to recognize that patients have access to many forms of information, notably privately gathered private information, privately gathered public information, and publically gathered public information. Individuals, for example, can learn from their own experience, the experience of others in their social networks (parents talking with other parents about their experience with pediatricians), and even web searches (looking for information from other private sources). In general, individuals have much smaller networks but are willing to share whatever information they do gather. Thus, things like the Internet are valuable not just because we can find what others say, but because others are willing to post what they have learned. Other types of private organizations that may seek information include physicians and insurance companies. These private organizations may be less willing to share the information they have gathered, particularly if it was costly for them to gather. Interestingly, some private entities have incentives to invest significant resources in gathering information but then make them essentially public. *U.S. News and World Report* makes information available to its subscribers, but almost anyone could get access to this information at very low cost: it is effectively public. Then, of course, there are state and federal government entities, which can collect much more information (using legal mandates) and will deliberately make this information available. Kolstad's contribution shows that patients behave as if they had access to the publicly available public information and that they also value a private body's attempt to repackage this same information.

Kolstad finds that consumers are reacting to the information in *U.S. News and World Report* even before it is published; they have access to the information in some other form. However, they respond to this information even more when it is released in public form by a private entity. This suggests that there is some value to the manner in which the data are presented, either by the vehicle (a magazine) or by the format (discrete lists of recommended locations).

Does this mean that we can conclude the data are useful? Unfortunately not. Patients, individuals, and households react to all sorts of information, some of which is useful and some of which is not. Advertising, name brand recognition, and superstition are all forms of information that are publicly available but actually impede the flow of good information. This chapter stands on strong ground because it shows that patients react to information that is objectively useful, not just any form of information. What is interesting is that patients appear to partially incorporate such information even before it is easily available. We have shown similar results in work done in Tanzania (Leonard 2007; Leonard et al. 2009). There, households are learning by gathering information from the experiences of other households and making decisions as if they had access to high-quality information about physician quality. In these studies, the researcher has access to objective and correct information about quality that patients cannot access, but we can show that patients act as if they have access to this information. Thus, households are engaging in a private process that approximates the information that would be available in a public process. As in the U.S. study, the public information is more useful to households than the privately gathered information, but the private information does have some value.

When we know that the data accessible to patients are objectively correct, we have a stronger test of the value of information. In the data analyzed by Kolstad, the available information causes some people to choose better physicians. This must be better for the individuals making the better choices, but is it better for the collection of households? Does it improve overall welfare? This depends on the nature of the goods or services being provided. The way that Kolstad analyzes the data ensures that, for the sample he is studying, the average patient is seeking a better physician. Thus, in this setting, average quality should improve, but this finding is not automatically true in other settings.

If the good or service is inelastically provided (there isn't that much of it to go around), then one person's gain is likely to be another person's loss. Imagine there are only 20 operating theaters available and there are 20 patients waiting to undergo operations. Information about high-quality providers is likely to change who gets which operation, but it doesn't change the number of operations or the average quality of operations provided. If the people who switch to the better theaters are wealthy, then overall, nothing has been gained. If the people who switch to the better theaters are the people who need better surgery, then there may be overall gains from switching.

On the other hand, if the supply of the good or service is elastic (there is plenty to go around), then we might see larger improvements. If there are 25 available theaters for 20 patients, the worst 5 can be left empty and the average should improve. Thus, at the very least, we want to avoid a situation in which information simply leads to a shuffling of who gets what without any overall improvement in quality or productivity. Some people will be better off, but others will be worse off.

In health care the real hope for improvement comes when we think about the long-term supply of something like high-quality operating theaters. If information means that the best theaters are always full and the worst ones are empty, shouldn't we expect more good theaters (and surgeons) over time and fewer poor theaters and surgeons? Again, there is no reason to expect this automatic reaction to increases in demand. It must be the case that the additional revenue from attracting more patients is worth the cost of providing higher quality. This is not to say that hospitals and doctors do not want to have high ratings, but rather that it is not obvious that they would invest significant resources to improve their scores so as to attract more patients. This is even truer if they can use advertising to attract patients without having to increase quality: yes, some patients will seek quality as measured in things like *U.S. News and World Report,* but it is cheaper to simply advertise to attract more patients.

This leads us to what is probably the most important aspect of the information gathered by the state of Pennsylvania and published by *U.S. News and World Report:* doctors may care more about the esteem of their peers than they do about the opinion of prospective patients. Doctors are part of a profession, and the ideals of the profession of medicine are commonly held among doctors; they tend to care what other doctors think of them. So it is possible that, even though better patients are coming because of the available data, doctors are motivated by the opinion of other doctors. This is a good thing, but it illustrates that the data we collect might even help improve quality through a completely different mechanism than the one we are studying.

In fact, in many settings the expert opinion of peers may be much better than data collected by outside aggregators of information. For the data that Kolstad is analyzing, doctors have no reason to try to manipulate the results. When the data are collected, doctors and hospitals have little reason to believe the information could affect their bottom line. However, if patients continue to react to *U.S. News and World Report* and if doctors and hospitals care about how they react, there will come a time when manipulating the data is to the advantage of many hospitals and doctors. This has already begun to happen with other forms of rankings published by newspaper and magazines. In general, it is harder to manipulate the opinions of peers because opinions are not calculated by a formula (which allows people to see the flaws) and are therefore highly flexible and would respond to any long-term attempt at manipulation.

6.C.3. Implications

Jonathan Kolstad has examined an application in a setting where a large data set aggregates local events, and he has shown that presenting this information in a particular format is useful to some people. This is despite the fact that the information is gathered entirely from the experiences of other individuals and that patients by themselves, with their social networks and in collaboration with their doctors, appear to have access to some of this information already. In health care there are two sources of information available to patients: the information they can gather themselves (on outcomes) and the information available to their doctors (on outcomes and inputs). As we have seen, in this setting, doctors are useful as agents or aggregators of information because they know significantly more about the field of medicine than do patients.

This type of situation—aggregation of information that already exists, combined with the presence of a previously existing system for aggregating and processing information—is increasingly common, and therefore we should be able to draw some general lessons. Together with Molly Brown at NASA, we have been working on data using Normalized Difference Vegetation Index (NDVI) observations on fields in the Sahel region in Africa, trying to model the agricultural output from this area.[8] The satellite images are a poor representation of what each farmer knows

[8] NDVI data were obtained from the NOAA Advanced Very High Resolution Radiometer (AVHRR) archive and processed by the Global Inventory Monitoring and Mapping Systems (GIMMS) group at the NASA Goddard Space Flight Center (Tucker et al. 2005). Previous research has shown that NDVI can be used to detect deviations in production conditions and is correlated with net primary production and crop yields (Tucker et al. 1981; Prince 1991; Fuller 1998).

about his own crops, but we can quickly analyze data over a very large area and get a good idea of what is happening. In this case the aggregating agent is the market. Within about 6 weeks of the harvest, local and national markets in this area have absorbed all the relevant information about output, and prices reflect the balance between supply and demand and the costs of transporting food. The data are useful to us because it is difficult for researchers to collect the market data: we see local market prices only with a significant delay. However, since farmers can already see both their own high-quality data and the local information about prices, is there any possible gain from presenting this information to them? What would they learn from knowing how the average farmer is doing, given that they already know how they are doing and can observe market prices, which should already reflect what others are doing?

Two lessons from Kolstad's chapter are that the data need to be processed to be useful, and that information can be valuable if it allows people to learn things more quickly than they would be able to do with normal aggregation agents (their own doctors) or devices (markets).

If the data are to be useful, the information should be presented by someone who is planning on selling the analysis for profit. No farmer in Burkina Faso is going to pay for a glossy magazine, but something produced by a government ministry or international aid agency is likely to fail because workers in these offices aren't promoted on the basis of their ability to show sales of the information. *U.S. News and World Report* synthesizes a lot of information in a list of recommended doctors; what would we tell farmers? It would need to be something along the lines of picking from among four or five phrases: the total national harvest is well below average, below average, average, above average or well above average.

In addition, the marketed data can be better than the raw data or the market data if the information is timely. In the Sahel region of West Africa there is a short window (probably 8 weeks) between when the farmer knows he has a successful crop and when the markets have assimilated all the information from other farmer's crops. We are finding that a satellite image can potentially close this window, perhaps shortening it by 4 weeks. The farmer could use this information to decide how much of his crop to store, sell, or even leave in the field. In this case, although farmers are likely to benefit, traders and anyone with access to current information may suffer from the fact that their information is no longer private. Since traders use this information to move food around (potentially helping people) and they are more likely to move food if they can earn profits from their information, it is not clear that hurting traders is a useful strategy. It does seem likely that the farmers would benefit overall, and to the degree that the farmers are the poor people and that they have access to technologies to effectively store their crops (waiting for better prices they know will come), it is possible that, overall, such information would enhance development (poverty-fighting) objectives.

One interesting feature of satellite images is that it might be very hard to manipulate the data. A hospital has access to many tools for reclassifying patients and changing the definitions of services that could be used to make their outcomes seem better to agents like *U.S. News and World Report*. Farmers would have a much harder time trying to falsify the information that a satellite could observe from space. We cannot confidently say that it is not possible, but it seems to us to be very unlikely.

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