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# Learning and the value of information: Evidence from health plan report cards

Michael Chernew<sup>a,d</sup>, Gautam Gowrisankaran<sup>b,d,\*</sup>, Dennis P. Scanlon<sup>c</sup>

<sup>a</sup>Department of Health Care Policy, Harvard Medical School, Boston, MA, USA

<sup>b</sup>Department of Economics, University of Arizona, Tucson, AZ, USA

<sup>c</sup>Department of Health Policy and Administration, Center for Health Care Policy Research, The Pennsylvania State University, PA, USA

<sup>d</sup>National Bureau of Economic Research, Cambridge, MA, USA

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## Abstract

This paper develops a framework to analyze the value of information in the context of health plan choice. We use a Bayesian learning model to estimate the impact and value of information using data from a large employer, which started distributing health plan ratings to its employees in 1997. We estimate the parameters of the model with simulated maximum likelihood, and use the estimates to quantify the value of the report card information. We model both continuous specifications with Gaussian priors and signals, and discrete specifications with Beta priors and Binomial signals. We find that the release of information had a statistically significant effect on health plan choices. Consumers were willing to pay about \$330 per year per below expected performance rating avoided, and the average value of the report card per employee was about \$20 per year. We find large variation in valuations across different performance domains, but no significant evidence of heterogeneity based on observable employee characteristics or unobservable dimensions.

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## 1. Introduction

In many markets, products vary substantively in terms of quality. However, quality is often not readily observable. Failure to capture full information can result in a lack of equilibrium or incomplete markets (Akerlof, 1970; Rothschild and Stiglitz, 1976) and may diminish welfare in a variety of ways (Stiglitz, 1989). Certainly, markets capture some information through informal mechanisms such as reputation, but it is uncertain how well these mechanisms work. In particular, it is often hard to develop markets for information because information is hard to value before it is known and often has characteristics of a public good.<sup>1</sup> For

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\*Corresponding author. Department of Economics, University of Arizona, PO Box 210108, Tucson, AZ 85721 USA. Tel.: +1 520 621 2529.  
E-mail address: [gautam\\_gowrisankaran@nber.org](mailto:gautam_gowrisankaran@nber.org) (G. Gowrisankaran).

<sup>1</sup>For example, Arrow (1963) comments on the “elusive character” of information as a commodity.

these reasons, economists have long been interested in understanding the impact of information in markets with products of heterogeneous quality.

This paper develops a framework to analyze the value of acquiring potentially noisy information. We apply our model to the market for health insurance plans, evaluating the value and impact of report card information for this market. Our analysis is based on a “report card” dissemination effort in which the General Motors Corporation (GM) began distributing ratings of Health Maintenance Organization (HMO) health plans to its non-union employees for the 1997 open enrollment period. GM has been a leader in creating health plan report cards and was one of the first companies to provide such information directly to employees. For each offered HMO, the GM ratings listed the performance in a variety of dimensions as one of four levels: superior, average, and below expected performance, and no data (which indicates that the HMO did not provide the information necessary to assess performance). Our data include employee plan choice before and after the release of the report card (i.e., from 1996 and 1997) and thus can explain the extent to which information affects choice.

Understanding the role of information in the health insurance market is important since the market is notoriously plagued by a variety of information imperfections (Arrow, 1963). Information about the quality of HMOs is particularly relevant since these plans provide a mechanism for individuals to commit to a package of benefits and style of care before an illness. To the extent that increased information about HMOs will increase enrollment in these plans, report cards can potentially result in the more efficient provision of healthcare.<sup>2</sup> In contrast, report cards that do not measure quality perfectly may create perverse incentives for firms to exploit selection.<sup>3</sup>

We develop a formal Bayesian learning model of health plan quality, estimate the parameters of the model with simulated maximum likelihood, and use the estimated model to quantify the value of the report card information. In our model, each employee chooses one of the offered health plans each year in order to maximize her expected utility. Expected utility is a function of plan price, benefits, perceived quality, and idiosyncratic unobserved components. In 1996, employees have priors regarding plan quality; they use these priors and the signal from the ratings to form posterior distributions of quality in 1997.

We specify two different functional forms for the learning process: a specification with continuous quality levels that uses Gaussian priors and signals and another with discrete quality levels that uses Beta priors and Binomial signals. We model prior mean quality levels via fixed effects for each plan in each market, and we examine the impact of ratings using a variety of different specifications and for different subgroups. These methods allow us to evaluate the robustness of our findings to functional form and to obtain results that are consistent with heterogeneous priors and responses. As GM is a national employer, our data contain over 100 HMOs and approximately 70,000 employees observed over 2 years across many different markets. This provides us with a large amount of variation in ratings, plan attributes, and plan choices that is useful in identifying the value of different types of information.<sup>4</sup>

This study builds on a literature on report card ratings for health plans (Beaulieu, 2002; Chernew et al., 2004; Dafny and Dranove, 2006; Jin and Sorensen, 2006; Sorensen, 2006; Scanlon et al., 2002; Wedig and Tai-Seale, 2002)<sup>5</sup> and on a literature that has estimated formal Bayesian learning models for goods ranging from yogurt to prescription drugs (Akerberg, 2003; Crawford and Shum, 2005; Erdem and Keane, 1996). We believe that the study makes two related contributions. First, it shows how to apply a Bayesian learning model to detailed panel data on health plan choices, rather than standard discrete choice specifications as used in the prior literature. The Bayesian learning model gives a different picture of the value of information than would be obtained by simply estimating a standard discrete choice model. This is because the Bayesian learning

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<sup>2</sup>For instance, Cutler et al. (2000) find that managed care plans have 30–40% lower expenditures than traditional health plans, and with similar outcomes.

<sup>3</sup>Dranove et al. (2002) find empirical evidence of such behavior for hospital report cards.

<sup>4</sup>One limitation of the study design is that everyone in our sample received ratings in 1997. Because the US experienced a general trend towards HMOs in this period (see InterStudy, 1996/1997), we would not want to attribute any trend towards HMOs at GM solely to the release of ratings. As we detail in Section 3, we use supplementary data to control for this limitation.

<sup>5</sup>Scanlon et al. (2002) is based on the same report card release as this study, but uses data only on HMO enrollees, and only for those HMOs which reported ratings. This study furthers Scanlon et al. (2002) by estimating formal Bayesian learning models that quantify the value of information and by allowing for more heterogeneity in responses to information.

model incorporates the fact that information is valuable to the extent that it causes people to switch choices, and thus both positive and negative signals are valuable. Second, the study shows how to estimate a discrete learning specification. A discrete specification is a natural fit for models where the information release is discrete, which includes many types of product evaluations. To our knowledge, this is the first estimation of this type of learning process; the Bayesian learning literature cited above employs continuous specifications.

The remainder of this paper proceeds as follows. Section 2 describes the data. Section 3 specifies the model and estimation. Section 4 provides results. Section 5 concludes.

## 2. Data

### 2.1. Sample

During the late 1990s, GM provided health insurance and benefits for over 1.6 million active employees, retirees, and dependents in the US. Our analysis is based on the 1996 and 1997 health plan enrollment decisions for the approximately 70,000 active, non-union US GM employees.<sup>6</sup> Table 1 provides a list of the data elements that we use in our analysis; some are measured at the employee level, while the others are measured at the plan level.

Employees could choose from four different coverage tiers: single, employee and spouse, employee and children, and employee and family. In addition to the coverage tier, employees could choose from a menu of different health plans. In both periods, all employees could choose from fee-for-service basic (FFSB) and fee-for-service enhanced (FFSE) plans, with additional HMO and Preferred Provider Organization (PPO) options. To ensure that plans provided adequate local coverage, GM determined the set of available PPOs and HMOs based on the employee's zipcode of residence. The set of available plans was very similar across the 2 years. Benefits were standardized within each of the four plan types, although they varied across types. FFSB coverage included the highest deductibles and copays, with lower deductibles and copays for FFSE and the lowest deductibles and copays for HMOs. PPOs offered variable copays and deductibles depending on whether treatment was in-network or not. In addition to plan choice, coverage tier and zipcode of residence, our employee data include the age and gender of the employee, tenure at GM, and ages and relations of dependents.

We defined an HMO or PPO plan to be in the choice set for a zipcode if it was allowed by GM for that zipcode and chosen by at least one person in that zipcode in both years.<sup>7</sup> We aggregated zipcodes into geographic areas, where every zipcode in a geographic area contains the same choice set. While geographic areas are mutually exclusive, plans may serve multiple geographic areas. To create our final sample, we dropped employee/year observations with missing or obviously incorrect zipcode information, observations where the chosen plan was not in the choice set, observations with missing price or ratings data, and observations in zipcodes for which no one chose an HMO or PPO. In all cases, these adjustments were minor, resulting in few dropped observations. We define a market to be a particular geographic area/coverage tier combination and then excluded markets with fewer than five employees in either year. The GM data contain 150,089 employee-year observations for active, non-union US employees, and our final estimation sample includes 133,383 observations (89%).

Table 2 details the number of employees by coverage tier and plan type kept in our sample for both years. 37.6% of employees chose an HMO in 1996, a number that rises to 40.7% in 1997. In 1997, HMOs were the most popular type of plan for employees selecting coverage for themselves and their children, while FFS plans dominated for employees without coverage for children. Table 2 also examines the extent to which employees switched plans and plan types across years, using the set of employees who were observed in both years. In spite of the ratings, most employees do not switch plans or plan types. For instance, 87.2% of employees who

<sup>6</sup>We did not analyze dependents separately because they almost always made the same choice as the employee. We excluded retirees because they are frequently eligible for Medicare, making the nature of plan choice different than for the non-Medicare population. We excluded union employees because we lacked detailed enrollment data for them.

<sup>7</sup>This restriction will result in the choice set for some individuals appearing smaller than it actually is, but only 2.2% of employees chose a plan that was not allowed for their zipcode, according to the data (likely due to errors in coding information such as employee zipcode). In addition, only 0.22% of the employee/year/plan observations have no employee in the employee/plan cell for the other year of the data.

Table 1  
Data elements used in analysis

Data element	Values
<i>For each active, salaried US GM employee</i>	
Employee ID	Unique 9-digit number assigned to each employee
Year of observation	1996, 1997
Gender of employee	Male, female
Employee age	Age in years of the employee
Tenure at GM	Number of years working for GM
Relation and age of dependents	Relation: spouse or child; age in years
Plan chosen	One of 105 HMOs, 26 PPOs or 2 FFS plans
Coverage tier	Employee (1), emp./spouse (2), emp./child (3), family (4)
Flex dollars for insurance spending	\$1,764, \$3,528, \$3,048, \$4,812 for tiers 1–4, respectively
Zipcode of residence	Subset of US zipcodes
<i>For each offered plan</i>	
Plan type	HMO, PPO, FFSB, or FFSE
Out-of-pocket premium	Varies by year and coverage tier (see Table 3 for details)
Report card ratings	For HMOs in 1997 only (see Fig. 1 and Table 3 for details)
Plan copays and deductibles	Varies by year and plan type
Set of zipcodes in which available	Subset of US zipcodes for HMOs and PPOs only

Table 2  
Employees by coverage tier and plan type and by prior plan type

	HMO	PPO	FFS	Total
1996	25,275 (37.6%)	10,768 (16.0%)	31,204 (46.4%)	67,247 (100%)
1997	26,903 (40.7%)	10,110 (15.3%)	29,123 (44.0%)	66,136 (100%)
Tier 1 (employee)	11,295 (33.8%)	5100 (15.3%)	17,002 (50.9%)	33,397 (100%)
Tier 2 (employee/spouse)	11,213 (34.5%)	5876 (18.1%)	15,448 (47.5%)	32,537 (100%)
Tier 3 (employee/child)	3780 (44.1%)	1685 (19.7%)	3103 (36.2%)	8568 (100%)
Tier 4 (family)	25,890 (44.0%)	8217 (14.0%)	24,774 (42.1%)	58,881 (100%)
	1997 HMO	1997 PPO	1997 FFS	1997 same plan
1996 HMO	21,733 (95.5%)	263 (1.16%)	766 (3.37%)	19,836 (87.2%)
1996 PPO	474 (4.86%)	8679 (89.0%)	598 (6.13%)	8599 (88.2%)
1996 FFS	1713 (6.10%)	611 (2.17%)	25,778 (91.7%)	24,682 (87.8%)

Note: The universe is all active non-union employees kept in sample. Percentage of row in cells is in parentheses beside the numbers.

chose a managed care plan in 1996 chose the same one in 1997, while only 6.10% of employees who chose a FFS plan in 1996 chose an HMO in 1997.

## 2.2. Report cards ratings and prices

We now summarize the report card ratings and prices; details are included in Scanlon et al. (2002). GM determined out-of-pocket premiums that employees were charged for each plan. During the open enrollment period for 1997, which occurred in the Fall of 1996, non-union GM employees were given report cards with ratings for each of the HMOs in their choice set. GM's human resources consultant distributed the report card ratings via the mail in a booklet called the 1997 Enrollment Decision Guide that was personalized by location. The booklet also contained information about the flex dollars provided to the employee, and the out-of-pocket prices employees had to pay for each benefit option. The mailing also included a 20-page booklet entitled 1997 GM Medical Plan Guide for Salaried Employees that detailed the construction of the report card and outlined GM's philosophy towards employee benefits. Ratings covered all HMOs, but not FFS or PPO



### COMPARING YOUR 1997 GM MEDICAL OPTIONS

The following table shows the rating of the HMO option(s) available in eight selected quality measures. The ratings are based on historical data and therefore may not necessarily represent the quality of care you will receive in the future. GM does not endorse or recommend any particular medical plan option. The medical plan you elect is your personal decision.

For a more complete description of the eight selected quality measures, see the *GM Medical Plan Guide*.

	NCQA Accredited?	Benchmark HMO?	Operational Performance	Preventive Care	Medical/Surgical Care	Women's Health	Access to Care	Patient Satisfaction
0001 Basic Medical Plan	Information Currently Not Available							
0002 Enhanced Medical Plan	Information Currently Not Available							
PPO 2190 Blue Preferred Plus	Information Currently Not Available							
HMO 2103 Health Alliance Plan	Yes	No	▲▲▲	▲▲▲	▲▲▲	▲▲▲	▲▲▲	▲
HMO 2104 BCN Southeast Michigan	Yes	No	▲▲▲	▲	▲▲▲	▲	▲▲	▲
HMO 2106 SelectCare HMO	Yes	No	▲	▲	▲	▲	▲	▲▲
HMO 2109 OmniCare Health Plan	Yes	No	▲	ND	ND	▲	ND	▲▲▲
HMO 2119 Care Choices HMO	Yes	No	▲▲	▲▲▲	▲▲	▲▲▲	▲▲	▲▲▲

**Key:** ▲ =below expected performance    ▲▲ =average performance    ▲▲▲=superior performance  
 ND=no data was available from this plan

HMO and PPO options are based on the plan service area. Eligibility is determined by zip code. You may not be eligible for any or all options listed. You may be eligible for other options if you live near a state line. See your enrollment information for your available options.

Michigan - Detroit

Fig. 1. Example information sheet.

plans because the measures used to construct the ratings are only collected for HMOs. GM did not distribute report cards to union employees.

Fig. 1 provides a simulated sample report card. HMOs were rated in six domains: operational performance, preventive health-care services, medical and surgical care, women’s health issues, access to care, and patient satisfaction. In each domain, an HMO could obtain one of four ratings: below expected performance, average performance, superior performance, or no data. Employees were informed that the plans with “no data” ratings did not provide sufficient information and hence we treat a “no data” rating differently from no rating.

The performance ratings were mostly based on measures computed using the technical specifications from the Health Plan Employer Data and Information Set (HEDIS), maintained by an independent and impartial data source, the National Committee for Quality Assurance (NCQA). HMOs used these specifications to collect the measures for their plan populations, and then provided the results to GM. GM picked a subset of the HEDIS measures and then aggregated them by computing z-scores for each of the measures for each

Table 3  
Summary of price and ratings characteristics

	All plans: (HMO/PPO/FFS)				
	<i>N</i>	Mean (\$)	Std. dev. (\$)	Min (\$)	Max (\$)
1996 annual Tier 1 (employee) price	133	481	179	0	708
1997 annual Tier 1 price	133	476	193	0	732
1996 annual Tier 4 (family) price	133	1325	494	0	1956
1997 annual Tier 4 price	133	1312	528	0	2004
Difference between Tier 1 prices, 1997–1996	133	–4	137	–468	252
Difference between Tier 4 prices, 1997–1996	133	–13	432	–1608	960
	HMO plans				
	<i>N</i>	Mean	Std. dev	Min	Max
Number of superior ratings	105	2.18	1.79	0	6
Number of average ratings	105	1.91	1.27	0	5
Number of below expected performance ratings	105	1.41	1.31	0	5
Number of no data ratings	105	0.50	1.09	0	5
	<i>N</i>	Yes	No		
Accreditation	105	74 (70%)	31 (30%)		
Benchmark plan	105	15 (14%)	90 (86%)		

Note: Annual prices reflect the difference between the GM employee price-tag and the allotted flex dollars.

domain, and then equally weighting these *z*-scores to produce a domain-specific score.<sup>8</sup> Plans were then sorted based on the domain-specific scores to assign the labels (i.e., superior, average, and below expected performance) contained in the report card. The underlying HEDIS data used for the HEDIS-based ratings include rates of utilization of selected services, rates of medically appropriate procedures for relevant sub-populations of plan membership (e.g., mammographies, cardiac catheterizations and prenatal visits, as appropriate), and measures of access to physicians. The ratings did not include risk-adjusted outcomes data, which are seldom found in health plan report cards and are not available in HEDIS. GM also included two performance domains in the report card that are not from HEDIS data: operational performance, constructed by GM based on information collected from site visits to HMOs; and patient satisfaction, based on a standardized HMO member survey administered to a sample of plan members by a survey research vendor. The report card also included two binary indicators: whether the plan was accredited by the NCQA and whether GM designated the plan as a “benchmark” HMO (a positive designation) based on quantitative data and a qualitative assessment. We do not use the benchmark designation in our specifications since Scanlon et al. (2002) found that it had little impact on choice and since it only applies to a small number of plans.

The employees paid for health plans using “flex dollars” that could be allocated across several benefit categories (e.g., health insurance, life insurance, disability insurance, and dental insurance) as well as out-of-pocket pre-tax dollars. The price for every health plan was at least as high as the amount of flexible benefit dollars received. We define price as the difference between the annual out-of-pocket price and the allotted flex dollars.

Table 3 provides summary statistics on health plan prices by coverage tier and ratings during our 2-year period. Although the mean out-of-pocket prices for plans stayed relatively constant from 1996 to 1997 there is substantial variation in the change in price between 1996 and 1997; for instance, for Tier 4 (family) coverage, the standard deviation of the price difference is \$432 relative to a mean price of \$1312. Starting in 1997, GM assigned plans to a small number of “efficiency groups” and assigned each plan in an efficiency group the same out-of-pocket plan price by coverage tier. According to the *Medical Plan Guide* booklet, GM determined the

<sup>8</sup>At the time, methods for health plan report card construction were in their infancy. The GM approach was similar, in terms of measures and aggregation methods, to other contemporaneous approaches (see Scanlon et al., 1998 for details).

efficiency groups based on plans' quality and cost. Specifically, GM chose lower out-of-pocket premiums for plans with higher quality and lower costs in order to encourage its employees to choose high quality and efficient plans.

### 3. Model and estimation

#### 3.1. Model

We consider a Bayesian learning model where individual  $i$  resides in market  $m$  at time period  $t$ , and must choose among a set of plans  $j$ .<sup>9</sup> Individuals care about plan attributes including the perceived quality of care that the plan will provide them. We assume that individuals have von-Neumann Morgenstern utility functions (and hence care about expected utility), are well informed about the price that they pay for the plan, as well as general plan coverage characteristics, such as copays and deductibles, but that they may lack information about the quality of care that they would receive if enrolled in the plan. For instance, individuals may not know how easy it is to find a specialist affiliated with the plan who will accept new patients; they may not know whether the health plan and its physicians are good at recommending medically appropriate treatments ranging from diagnostic procedures such as mammographies to invasive surgeries; they may not know the extent to which a serious illness would be accompanied by long waits to see physicians; and they may not know the quality of surgical care provided by doctors and hospitals affiliated with the plan. We let  $q_{ijm}$  denote plan quality expressed in utility units.

We specify the expected utility function at time  $t$  for the individual as

$$u_{ijmt} = E_t[q_{ijm}] - \alpha P_{jmt} + \delta_{jmt} + \varepsilon_{ijmt}, \quad (1)$$

where  $E_t$  is a conditional expectation at time  $t$ ,  $P_{jmt}$  is price,<sup>10</sup>  $\alpha$  is a parameter,  $\delta_{jmt}$  are other plan attributes, and  $\varepsilon_{ijmt}$  is a component of utility that is not systematically related to plan quality and is unobservable to the econometrician.<sup>11</sup> Because we assume that prices enter linearly in utility, we are implicitly assuming that consumers are risk neutral over the range of health plan prices observed in the data. As in Table 3, this range is relatively small. Differences in the quality of medical care can plausibly have much bigger differences in utility, and there is no assumption of risk neutrality over that range.

Following Cardell (1997) and Berry (1994), we assume a nested logit error structure for  $\varepsilon_{ijmt}$  which allows for correlated unobservables within a plan type. Specifically, we let

$$\varepsilon_{ijmt} = \varepsilon'_{ig(j)mt} + \lambda \varepsilon''_{ijmt}, \quad (2)$$

where  $\varepsilon'$  and  $\varepsilon''$  are independent,  $\lambda$  is a parameter,  $g(j)$  indexes the type of health plan  $j$  (i.e., HMO, PPO, or FFS),  $\varepsilon''$  is distributed extreme value, and  $\varepsilon' \sim C(\lambda)$ . As shown in Cardell (1997),  $C(\lambda)$  is the unique distribution that makes  $\varepsilon$  extreme value given  $\lambda$  and the distribution of  $\varepsilon''$ . If  $\lambda = 1$ , then the model will be identical to the logit model and the unobservable will be i.i.d., while if  $\lambda = 0$ , the unobservable will be perfectly correlated within a group. We estimate a nested logit because this specification provides a natural way to estimate the extent to which consumers are willing to switch between types of plans.

We consider individuals at two time periods, 0 and 1 (i.e., 1996 and 1997, respectively). Signals, which are derived from health plan report cards for HMOs, are given to individuals immediately before they make their choice of health plan at time 1. The conditional distribution of quality at time 0 (i.e., the prior) is a function of reputation and experience, while the conditional distribution of quality at time 1 (i.e., the posterior) is a

<sup>9</sup>Our plan choice model builds on a number of papers that have estimated the impact of price (though not quality) on the choice of health plans (Buchmueller and Feldstein, 1997; Cutler and Reber, 1998; Royalty and Solomon, 1999).

<sup>10</sup>Since (1) includes price, it is an indirect utility function. The underlying direct utility function that generates this would specify overall utility to be the sum of the utility from the health plan and from some numeraire good, which costs \$1 per unit and gives a constant utility  $\alpha$  per unit.

<sup>11</sup>Although consumers may learn about plan quality from experiences while enrolled in the plan, we assume there is sufficient noise in the learning process that consumers do not consider the value of learning when choosing a health plan. With this assumption, consumers will choose the health plans that maximize their current expected utilities (1). We believe that "sampling" plans are very uncommon, and therefore that this assumption is reasonable.

function of both the prior and the signal. We estimate two specifications for the learning model, one with continuous quality levels and the other with discrete quality levels. These specifications will approximate the true, unknown, densities in different ways, and thus add to the robustness of our findings. We now discuss both of these specifications in turn.

### 3.2. Continuous quality levels

This specification assumes that the support of  $q_{ijm}$  is continuous with Gaussian priors and signals, specifically that the prior distribution is  $N(\tilde{q}_{jm}, h_{1i}^{-1})$  and the distribution of the signal,  $s_{ijm}$ , is  $N(q_{ijm}, h_{2i}^{-1})$ , where  $\tilde{q}_{jm}$  are parameters, and  $h_{1i}$  and  $h_{2i}$  are precisions of the priors and signal, respectively. We assume that the priors and signals are uncorrelated across plans in a market. We let  $s_{ijm}$  be related to the published ratings  $r_j$  as

$$s_{ijm} = \tilde{\beta}_i r_j + \tilde{\sigma} v_{ijm}, \tag{3}$$

where  $\tilde{\beta}_i$  and  $\tilde{\sigma}$  are parameters and  $v_{ijm} \sim N(0, 1)$  captures other sources of health plan information obtained during period 0, e.g., media coverage. We include  $v_{ijm}$  to make the signal more continuous, in keeping with the assumption that its distribution is Gaussian. We index  $\tilde{\beta}_i$  by “ $i$ ” because we let  $\tilde{\beta}_i$  be a random coefficient for some of the results. For these results, we let the coefficients on the ratings be distributed around some mean  $\tilde{\beta}$ , i.e.,  $\beta_i = \tilde{\beta} + \tilde{\sigma} \tilde{v}_{ijm}$  with  $\tilde{\sigma}$  being a parameter and  $\tilde{v}_{ijm} \sim N(0, 1)$ . For other results, we include a fixed  $\tilde{\beta}$ .

For the continuous specification, the prior mean quality is  $E_0[q_{ijm}] = \tilde{q}_{jm}$ . Using (3) in conjunction with standard Bayesian updating formulas, the posterior mean quality is

$$E_1[q_{ijm}] = \frac{h_1 \tilde{q}_{jm} + h_2 (\tilde{\beta}_i r_j + \tilde{\sigma} v_{ijm})}{h_1 + h_2} \tag{4}$$

for plans which receive ratings.

We require certain normalizations in order to identify our model. In particular, since utility is not observable, we normalize the FFSB plan to have expected prior quality 0 for every market. We normalize FFSB because it does not have published ratings, is homogeneous and is offered in every market. We also cannot jointly identify the precisions,  $h_1$  and  $h_2$ , since proportional increases in both do not affect expected utility (as in (4)) and employees maximize expected utility. We estimate instead  $h \equiv h_1 / (h_1 + h_2)$ . Defining  $\sigma = \tilde{\sigma} h_2 / (h_1 + h_2)$  and  $\beta_i = \tilde{\beta}_i h_2 / (h_1 + h_2)$ , expected utility for a rated plan at time 1 can then be expressed as

$$u_{ijm1} = h \tilde{q}_{jm} + \beta_i r_j + \sigma v_{ijm} - \alpha P_{jm1} + \varepsilon_{ijm1}. \tag{5}$$

### 3.3. Discrete quality levels

This specification assumes that the support of  $q_{ijm}$  is discrete with mass on two points,  $v_l$  (low quality) and  $v_h$  (high quality).<sup>12</sup> We assume that the prior density of the probability that  $q_{ijm}$  is  $v_h$  is distributed  $\text{Beta}(a_{jm}, b_{jm})$ .<sup>13</sup> Thus, the prior probability that  $q_{ijm}$  is  $v_h$  is  $a_{jm} / (a_{jm} + b_{jm})$  and

$$E_0[q_{ijm}] = v_l \frac{b_{jm}}{a_{jm} + b_{jm}} + v_h \frac{a_{jm}}{a_{jm} + b_{jm}}. \tag{6}$$

We assume each report card rating is a Binomial signal of either  $v_l$  or  $v_h$ . Let  $R_{jl}$  and  $R_{jh}$  denote the number of low- and high-quality ratings for plan  $j$ ,<sup>14</sup> respectively. Using standard Bayesian updating formulas, the posterior density of the probability that  $q_{ijm}$  is  $v_h$  is distributed  $\text{Beta}(a_{jm} + R_{jh}, b_{jm} + R_{jl})$  and hence the expected posterior probability that  $q_{ijm}$  is  $v_h$  is  $(a_{jm} + R_{jh}) / (a_{jm} + b_{jm} + R_{jh} + R_{jl})$ .

<sup>12</sup>Note that we could specify a Dirichlet prior and a multinomial signal and expand our specification to allow for four values for quality (instead of two) to fully exploit the fact that there are four ratings. While it is straightforward to evaluate the posterior for this model, we still cannot identify more than one coefficient implying the need for more normalizations, many of which might be unintuitive.

<sup>13</sup>It is standard to define a Binomial on the set  $\{0,1\}$  and a Beta over the interval  $[0,1]$ . We renormalize to  $v_l$  and  $v_h$ , respectively, because this fits better with our utility framework.

<sup>14</sup>Section 3.4 provides details on how we transform the report card into these ratings.

As with the continuous case, we cannot identify both  $a_{jm}$  and  $b_{jm}$  for each plan in each market, because proportional increases in the two parameters would not affect the expected utility of quality. Accordingly, we estimate the  $a_{jm}$  parameters and one parameter  $\text{info} \equiv a_{jm} + b_{jm}$  in place of all the  $b_{jm}$  parameters. Also similar to the continuous model, we normalize the FFSB plan to have prior  $a_{\text{FFSB},m} = v_l \times \text{info} / (v_l - v_h)$ , which implies (from (6)) that the expected prior quality for this plan is 0. Analogous to (5), expected utility for a rated plan at time 1 can be expressed as

$$u_{ijm1} = v_h \frac{a_{jm} + R_{jh}}{\text{info} + R_{jh} + R_{jl}} + v_l \frac{\text{info} - a_{jm} + R_{jl}}{\text{info} + R_{jh} + R_{jl}} + \delta_{jmt} - \alpha P_{jm1} + \varepsilon_{ijm1}. \quad (7)$$

### 3.4. Parameterization

We allow prior mean quality to differ across markets and plans because of the local nature of information. Thus, we estimate  $\bar{q}_{jm}$  or  $a_{jm}$  (for the continuous and discrete specifications, respectively) as a separate parameter for each plan  $j$  and market  $m$ . Note that this assumption is similar to allowing plan-market fixed effects in a linear specification.

We specify several different functional forms for ratings. Our base specification for the continuous model assumes that the response to each of the six performance domains is the same and allows for four ratings (superior, average, and no data, with below expected performance excluded) and a dummy for whether or not the plan was accredited by the NCQA. We use this specification since consumers often use decision rules such as selecting plans with the most superior ratings or fewest below expected performance ratings (Hibbard et al., 1997) and evidence from laboratory settings is consistent with such decision rules (Hibbard et al., 2000). Other specifications for the continuous model allow for variation in the ratings coefficients across performance domains. Our discrete model is limited to two signals. Based on evidence from the continuous model below, we group superior with average and no data with below expected performance.

We also cannot identify non time-varying components of  $\delta_{jt}$  from choice data (since we estimate plan-market fixed effects) and so we only consider time-varying components. We include three plan-type interactions for time 1,  $\delta_{\text{FFSE},1}$ ,  $\delta_{\text{PPO},1}$ , and  $\delta_{\text{HMO},1}$ , designed to capture shifts in acceptance for different plan types over time; all are relative to the FFSB time trend. We expect that these trends might be important because of differences in coverage across plan types and changes in valuations over time. For instance, Lichtenberg (2001, 2002) finds that the value of drug coverage was increasing over this time period, and the HMO and FFSE plans provide lower copays for drug coverage than the FFSB plan. We particularly expect  $\delta_{\text{HMO},1}$  to be positive, since US HMO enrollment increased substantially between 1996 and 1997,<sup>15</sup> likely because of a relative increase in the value of HMO services.

It is important to model  $\delta_{\text{HMO},1}$  since we do not want to attribute an increase in GM HMO enrollment solely to ratings. Unfortunately, since every employee received ratings in 1997 for every HMO,  $\delta_{\text{HMO},1}$  is collinear with ratings, and hence we cannot estimate it. However, we obtained aggregate data from a similar Midwest-based Fortune 50 manufacturing company that did not distribute ratings. That firm experienced an increase in HMO enrollment of 1.99 percentage points (from 40.78% to 42.77%) among its non-union employees between 1996 and 1997. Thus, we choose  $\delta_{\text{HMO},1}$  to be the value that would have caused a 1.99 percentage point increase in GM HMO enrollment between 1996 and 1997 at the estimated parameters in the absence of ratings or any price or sample change. We also experimented with other values of  $\delta_{\text{HMO},1}$  and found similar results for nearby values.

Our base model assumes that the parameters are the same across individuals. However, we also examine several alternate specifications, which generalize this assumption. In particular, in some specifications we define subgroups based on observable characteristics (e.g., gender, presence of young children) and allow all the parameters to vary across subgroups. In addition, for some specifications of the continuous model, we allow for random coefficients for the ratings.

<sup>15</sup>InterStudy (1996/1997) reports that the number of “pure HMO” enrollees in the US increased from 52.5 to 58.8 million people during 1996.

### 3.5. Identification

We first consider the identification of the coefficients on ratings ( $\beta_i$  for the continuous specification and  $v_l$  and  $v_h$  for the discrete specification) and price ( $\alpha$ ). These coefficients will be identified to the extent that plans with particular types of ratings are more likely to be chosen in 1997 than in 1996. We treat these variables as predetermined, and now explain why. Since we include a fixed effect for the prior quality of each plan in each market, endogeneity would occur only if particular ratings or changes in prices are correlated with changes in unobservable plan characteristics that might change market shares even in the absence of the changes in price or ratings.

We believe that endogeneity is unlikely for ratings because it is unlikely that particular ratings would change unobserved plan characteristics or vice versa. Specifically, ratings were provided only to non-union GM employees who formed a small subset of the enrollment base for any given health plan, suggesting that it is unlikely that plans would react to ratings by changing their unobserved characteristics. Moreover, the ratings, which were released in 1997, were based on 1995 plan performance, when most plans would not have anticipated the construction and release of the report card, suggesting that plans could not have endogenously influenced the ratings based on changes in their unobserved characteristics between 1996 and 1997. In addition, there is more direct evidence against endogeneity (or omitted variable bias) from Scanlon et al. (2002). This study included share among GM unionized employees as a control group, albeit at a more aggregate level,<sup>16</sup> and found virtually identical results. Since the union employees did not receive the report card information, this further suggests that any changes in enrollment among non-union workers that correlates with ratings is caused by the ratings.

The coefficient on price is similarly identified by the extent to which employees' switching of plans is correlated with changes in prices between 1996 and 1997. We also treat price as predetermined. Our prices are based on out-of-pocket costs charged to employees. Total prices might be endogenous in a market setting, varying positively with quality. However, changes in out-of-pocket prices between 1996 and 1997 were based largely on ratings, suggesting that it is reasonable to consider out-of-pocket prices to be predetermined. Moreover, as with ratings, Scanlon et al. (2002) find that the coefficient on price remains very similar when using union employees, who did not experience price changes, as a control group. Last, unlike ratings, several studies have measured the effect of price on health insurance plan-market shares, and, as we show in Section 4 below, our figures are similar to those in the literature.

Other parameters, including the parameters that are specific to the two learning models, are similarly identified from variation in the data that we believe to be consistent with our model. One parameter of note is the nested logit correlation parameter,  $\lambda$ . In the context of a fixed effects model, this parameter will be identified from changes in the attributes of the choices over time within a market. Since our data contain many such changes, they are useful in identifying this parameter.

### 3.6. Estimation and simulation

We estimate the parameters of the models using maximum likelihood. Each enrollee at each time period constitutes one observation. The likelihood for the observation is the probability that the chosen plan was selected, given the parameter vector. For the continuous specification, we simulate unobservable  $v_{ijm}$  and  $\bar{v}_{ijm}$  for the random effects specifications, and hence use simulated maximum likelihood.

To define the likelihood let  $y_{imt}$  denote the chosen plan for individual  $i$  in market  $m$  at time  $t$ , and let  $x_{mt}$  denote the exogenous variables in market  $m$  at time  $t$ , which include ratings, prices, and plan identities. Let  $\theta$  denote the parameters:  $\theta = (\bar{q}_{j,m} \forall j \text{ and } m, h, \beta, \sigma_v, \alpha, \lambda, \delta_{PPO,1}, \delta_{FFSE,1})$  for the continuous specification and  $\theta = (a_{j,m} \forall j \text{ and } m, v_l, v_h, \text{info}, \alpha, \lambda, \delta_{PPO,1}, \delta_{FFSE,1})$  for the discrete specification. Then, the log likelihood for an individual  $i$  for the continuous specification satisfies

$$\begin{aligned} \ln L(\theta|y, x) \\ = \sum_{i,m,t} \ln \left( \frac{1}{NS} \sum_s Pr(\text{Choice for enrollee } i, m, t \text{ is } y_{imt} | \theta, x_{mt}, v_{ijms}) \right), \end{aligned} \quad (8)$$

<sup>16</sup>We could not use union employees directly as a control group since the only available data are aggregate plan-market shares by state.

where NS is the number of simulation draws per individual,  $v_{ijms}$  is one simulation draw, and the probabilities of the observed choices are calculated using the nested logit model applied to the utility function specified by (5) in 1997 and a simpler utility function without ratings in 1996.

For the discrete specification, the log likelihood is analogous to (8) but uses (7) in place of (5), and does not include simulations over  $v_{ijms}$ . The likelihood for the random coefficients models is similar, but includes the parameter  $\bar{\sigma}$  and involves simulation over  $\bar{v}_{ijms}$ .

A few details about the estimation process are warranted. We estimate the model using a Newton–Raphson search. This derivative-based search converges reasonably quickly, which is necessary given that each estimation includes over 1500 parameters. We set NS to 20, and our conclusions are insensitive to estimates computed with 40 draws. As is generally done for simulated likelihood estimators, we use the same draws across parameter values.

One of our main goals is to measure the value of information. This is different than measuring the value of underlying product attributes. A drop in plan performance will lower utility. However, information about a drop in a plan’s performance may be valuable to the extent that it causes consumers to alter their behavior based on accurate information.<sup>17</sup> The textbook measure of the value of information when faced with subsequent decisions is given by DeGroot (1970, p. 197). DeGroot’s measure accounts for the fact that information is valuable exclusively to the extent that it causes people to make choices with higher ex-post utility. The measure of value is based on the ex-post utility of the plan that was chosen with the information, relative to the ex-post utility of the plan that would have been chosen without information.

It is entirely possible that information can be valuable but result in ex-post utility being worse than ex-ante utility. An example of this type of information would be a very bad signal for a plan. This information would be valuable because it would cause people to switch away from the plan with a bad signal. This might result in a reduction in utility, when compared to utility before the report cards were released, because the ex-post utility of the newly chosen plan could be lower than the ex-ante utility of the old plan. Specifically, this would occur when the report card information lowered the utility of the original plan, but the newly chosen plan provides less utility than the enrollee had before the information lowered the utility of the original plan.

To use the DeGroot measure in our context, let  $\mathfrak{I}_t$  denote the information set at time  $t$  (where  $t = 0$  indicates pre-information and  $t = 1$  post-information),  $Y_{im}(\mathfrak{I}_t)$  denote the optimal choice for person  $i$  in market  $m$  given an information set  $\mathfrak{I}_t$ , and  $U_{im}(\mathfrak{I}_t, Y)$  denote expected utility given information set  $\mathfrak{I}_t$  and choice  $Y$ . Then, the aggregate value of the information, expressed in utility units, is

$$V = \sum_m \sum_i [U_{im}(\mathfrak{I}_1, Y_{im}(\mathfrak{I}_1)) - U_{im}(\mathfrak{I}_0, Y_{im}(\mathfrak{I}_0))]. \tag{9}$$

In words, (9) states that the value of information is the difference in the ex-post utility between the ex-post choice and the ex-ante choice. In contrast, the value of a standard product attribute such as gas mileage for cars would be expressed as

$$V = \sum_m \sum_i [U_{im}(\mathfrak{I}_1, Y_{im}(\mathfrak{I}_1)) - U_{im}(\mathfrak{I}_0, Y_{im}(\mathfrak{I}_0))]. \tag{10}$$

Note that our measure of the value of information (9) is based on the ex-post distribution of signals. To find the per-capita value of information in dollar terms, we divide the value in utility units by the marginal utility of money,  $\alpha$ , and the number of people.

## 4. Results

### 4.1. Results from base continuous specification: Specification 1

This section details the estimates and implications of the model developed in Section 3. As discussed in Section 3, our base specification, Specification 1 in Table 4, groups ratings across performance domains. This

<sup>17</sup>Information may affect the behavior of health care providers or employers, which we do not account for. In addition, information may affect utility even if it does not alter behavior because it can reassure, or worry, consumers independent of any effects on plan choice. We follow the statistical literature and focus only on the portion of value generated as a result of behavior changes.

Table 4  
Base coefficient estimates and estimated value of information

	Continuous quality, four ratings (1)	Continuous quality, two ratings (2)	Discrete quality, two ratings (3)
Rated (base: below exp.; col. (2) below exp. and no data)	-.091** (.023)	-.140** (.034)	
# Superior ratings	.040** (.005)		
# Average ratings	.047** (.006)		
# No data ratings	-.034** (.006)		
# Average and superior		.053** (.011)	
Not accredited	.041* (.017)		
Prior weight ( $h$ )	.929** (.012)	.935** (.012)	
Std. dev. param. ( $\sigma$ )	.015 (.013)	.016 (.014)	
Utility from avg. and sup. ( $v_h$ )			2.75** (.708)
Util. from below exp. and no data ( $v_l$ )			-2.15** (.671)
Prior draws (info)			86.0** (5.18)
Price (thousands per year)	-\$ .141** (.024)	-\$ .124** (.031)	-\$ .125** (.031)
Nested logit param. ( $\lambda$ )	.330** (.030)	.348** (.070)	.349** (.070)
PPO-year 1 dummy ( $\delta_{\text{PPO},1}$ )	.036* (.018)	.037* (.019)	.037* (.019)
FFSE-year 1 dummy ( $\delta_{\text{FFSE},1}$ )	.027** (.008)	.028** (.010)	.028** (.010)
HMO-year 1 dummy ( $\delta_{\text{HMO},1}$ )	.127	.128	.128
Log likelihood	-183,641	-183,667	-183,665
Willingness to pay per below exp. rating changed to average	\$332 (\$71)	\$428 (\$105)	\$458 (\$122)
Average value of information per employee	\$19 (\$6)	\$22 (\$7)	\$21 (\$7)

Note: Standard errors in parentheses. All specifications include 1527 plan-market prior dummies. The symbols “\*” and “\*\*” indicate significance at the 5% and 1% levels, respectively.

specification reveals a coefficient on price that is negative and statistically significant. Since we only observe employee out-of-pocket premiums and these vary widely across employers, it is not meaningful to compare our price elasticity to those from other studies. We instead compare the semi-elasticity of price, defined to be the average percent change in the probability of choosing a plan given a \$100 increase in the annual price. We find that the \$100 increase in price would result in a reduction in plan share of 2.7% (standard deviation .45%) on average across plans.<sup>18</sup> The literature on health plan choice finds values ranging from 2.5% to 4%, which is consistent with our value.<sup>19</sup>

We find that superior and average ratings are both significantly positive (relative to below expected performance) and similar in magnitude. A “no data” rating is significantly worse than below expected performance, though smaller in magnitude than the other two ratings. The implication is that consumers react to ratings primarily by staying away from plans with below expected performance ratings or no data. The table, which reports magnitudes of the coefficients in dollar units by dividing the ratings coefficient by the coefficient on price, shows that one extra average rating in place of a below expected performance rating would increase the willingness to pay for 1 year of plan coverage for a given plan by \$332 (standard deviation \$71).

<sup>18</sup>We obtain this standard deviation and all other reported standard deviations by simulating from the variance/covariance matrix of the estimated parameters using 100 Monte Carlo draws.

<sup>19</sup>Cutler and Reber (1998) find an elasticity of  $-2$  for Harvard employees, which is equivalent to a semi-elasticity of 4% per \$100 increase given that the average gross premium is roughly \$5000 in their study. Royalty and Solomon (1999) report price elasticities of  $-1$  to  $-1.8$  for Stanford employees. Using the midpoint of  $-1.4$  and noting that their average gross premium is roughly \$4000, this implies a semi-elasticity of 3.5% per \$100 price change. Buchmueller and Feldstein (1997) report that an increase in net price from \$120 to \$240 reduced plan share by 4% for University of California employees, and that a further \$120 increase reduced the plan share by 3%. Scaling these down to \$100 increments yields semi-elasticities of between 2.5% and 3.3% per \$100 price change. Because they allow a discrete jump in response associated with any positive change in price, Buchmueller and Feldstein (1997) find much larger price elasticities, which we do not replicate, when the price changes from \$0 to \$120.

We estimate the nested logit parameter,  $\lambda$ , to be .330 with a small standard error of .030. The standard error allows us to easily reject the logit model, which imposes  $\lambda = 1$ , and thus, we do not present results from the logit model. Nonetheless, we estimated the logit model and obtained similar results to our base specification. The estimated value suggests that there are substantial correlations in preferences, in the sense that people with a high unobserved affinity for a PPO (for example) are likely to have a high unobserved affinity for another PPO.

This specification includes 1527 plan-market prior dummies, as do all specifications that use the full data set. In the interest of brevity, we do not list these coefficients. However, their magnitudes are much larger than the magnitudes of the ratings coefficients: the absolute value of these parameters has a mean of .774 and a standard deviation of .568. We estimate the prior weight coefficient,  $h$ , to be .929 and significantly different from both 0 and 1. This implies that the posterior precision of plan quality is only about 8% higher than the prior precision. The estimated values of  $h$  and the plan-market prior dummies together imply that prior information is much more important than the signal in determining the posterior.

We estimate a value of the standard deviation for the unobserved shock in the signal,  $\sigma$ , that is small (e.g., less than half the magnitude of any ratings coefficient) and statistically insignificant. Recall that  $\sigma$  indicates the magnitude of the information that consumers obtain during the first period from sources other than the report card. Thus, this suggests that most of the *learning* about plan quality between the 1996 and 1997 place choice decisions came from the report card.

Our model includes three plan type-year interaction variables for 1997, all relative to FFSB. The estimated  $\delta_{\text{FFSE},1}$  and  $\delta_{\text{PPO},1}$  coefficients are both positive and significant. FFSE differed from FFSB only in that it had lower copays and deductibles, and thus the positive sign on  $\delta_{\text{FFSE},1}$  must be due to an increase in value from these features. We believe that the reasons why  $\delta_{\text{PPO},1}$  is positive are similar to the reasons why HMO market share was increasing over time nationally, noted in Section 3.

As discussed in Section 3, the HMO-time interaction term,  $\delta_{\text{HMO},1}$ , cannot be estimated since ratings are distributed to all employees for all HMOs in 1997, but rather is chosen to generate an increase in HMO market share of 1.99 percentage points at the estimated parameters between 1996 and 1997, to match an aggregate control group. In keeping with the increase in market share, we find a positive value of  $\delta_{\text{HMO},1}$  that is larger than either the PPO or FFSE interactions. We cannot obtain a standard error for the parameter. Note that  $\delta_{\text{HMO},1}$  is perfectly collinear with the “rated” parameter and hence its value will not affect any of the other parameter estimates. However, a higher value of  $\delta_{\text{HMO},1}$  will result in a lower value of “rated” which will then attribute more of the 1997 increase in market share for HMOs to ratings and less to plan acceptance. This will in turn affect the value of information. The sign of this latter effect is not clear, since both good and bad information is useful. In practice, we found that reasonable values of  $\delta_{\text{HMO},1}$  gave very similar numbers for the value of information.

Using our estimated parameters and (9), we compute the value of the information contained in the report card. We find a reasonably modest value of information, an average of \$19 per employee (standard deviation \$6). In contrast, if we had estimated the value of information using (10) as though information were a standard product attribute, we would have obtained a figure of \$87 per employee (standard deviation \$53). This underscores the importance of modeling information acquisition via a formal learning process.

We believe that the evidence that the impact of information is modest is well-substantiated in the data: the report cards did not get too many people to switch plans. In particular, only 12.4% of employees in our sample in both years switched health plans between 1996 and 1997. Some of that is due to ratings and some to other factors, such as price changes, changes in geographic location, and changes in unobserved components. Our base specification implies that ratings caused only 3.89% of employees to switch plans (standard deviation .27%).<sup>20</sup> Moreover, the HMO market share increased by a net of only 3.1 percentage points between 1996 and 1997. Our model attributes only 1.0 percentage points of that change to ratings, and the rest to greater HMO acceptance and changes in pricing and other plan attributes.

Our modest value of information occurs in spite of the reasonably large willingness to pay to avoid below expected performance or no data ratings. The substantiation in the data for this dichotomy is that people did not often switch plans because of either price changes or ratings, and the willingness to pay figures are

<sup>20</sup>We derive this figure using 1997 plan attributes.

essentially a ratio of how willing people are to switch plans for better ratings to how willing they are to switch plans because of a lower price. Note that among the 3.89% of employees who switched plans as a result of ratings, the ex-post utility was on average \$488 higher than the ex-post utility of their ex-ante choice.

Our evidence that ratings have an impact on choice is consistent with survey data that suggest that measures such as these are salient for potential health plan enrollees (see Hibbard and Jewett, 1996; Tumlinson et al., 1997). Our willingness-to-pay figures are also consistent with Scanlon et al. (2002) who find comparable numbers using similar data but a different model. Our results on employee switching and the value of information are also broadly consistent with other studies (see Beaulieu, 2002; for Harvard University employees, Jin and Sorensen (2006), for federal employees; and Dafny and Dranove (2006), for Medicare beneficiaries) who all find a small, but significant, amount of consumer switching resulting from report cards.<sup>21</sup>

#### 4.2. Impact of discrete learning process: Specifications 2 and 3

We next examine the discrete learning specification, Specification 3, also in Table 4. Recall that we assume a two-point support for the distribution of quality and group together superior and average ratings and no data and below expected performance ratings, because of the similarity of these coefficients in Specification 1. We use the six performance domains as the sources of information for this specification, and do not include accreditation. For comparison purposes, Specification 2 (also in Table 4) provides estimates for the continuous model with the ratings aggregated into two groups as in the discrete specification.

We find that the discrete learning specification provides very similar results to the continuous specification to the extent that they are comparable. In particular, the value of information, willingness to pay to avoid low ratings, the price coefficient, nested logit correlation and time interactions are almost identical across the two specifications. These results should add evidence that the results from the continuous model are not largely driven by functional form.

The discrete model also shows that prior information is very important relative to the signal from the report card ratings. In particular, we estimate the parameter “info” to be 86.0. This suggests that prior information about plan quality was equivalent to 86 ratings measures, some good and some bad. In contrast, the report card information contained only six measures, and hence contributed much less to the posterior.

#### 4.3. Effect of specific performance domains: Specifications 4 and 5

In order to understand further which performance domains contribute value, Table 5 presents specifications where the signal from the report card is allowed to vary across domains. We use only continuous specifications here since our discrete model restricts the ratings to take one of two values. We estimate a specification (Specification 4) where we allow each of the 19 individual ratings to have a separate coefficient, and one where we allow for variation in the coefficients across performance domains but group together superior and average ratings and no data and below expected performance ratings, as in Specification 2.

Specification 4 generally results in ratings coefficients that are not very precisely estimated and do not have a consistent pattern. We believe that the reason for this is that we are trying to estimate 19 ratings coefficients from data on only 105 HMOs, and hence there is not enough variation in the ratings to identify these coefficients. Indeed, one of the domains, operational performance, has no HMOs with a “no data” rating, and hence this parameter is excluded.

In contrast, Specification 5 shows a pattern that is more internally consistent and also consistent with Table 4. In particular, consumers’ value average or superior ratings for five of the six domains positively, and in four of these five cases, the coefficients are statistically significant. Moreover, a likelihood ratio test would allow us to reject the hypothesis that individuals respond equally to all ratings. It is useful to analyze responses

<sup>21</sup>Jin and Sorensen (2006) and Dafny and Dranove (2006) report smaller effects of switching than we do. However, there is no reason to expect the magnitudes to be the same since the value of information and extent of switching behavior is dependent on the type of ratings information, preferences and prior knowledge of the population studied, and choice sets, all of which vary between our study and these studies.

Table 5  
Estimates with heterogeneity across performance domains

	Four ratings (4)	Two ratings (5)
Rated (base: below exp.; col. (5) below exp. and no data)	-.025 (.028)	-.008** (.021)
Operational performance superior	-.027 (.021)	
Op. perf. avg.; col. (5) avg. and superior	-.048** (.017)	-.031** (.012)
Operational performance no data		
Preventive care superior	.076* (.035)	
Prev. care avg.; col. (5) avg. and superior	.027 (.023)	.032** (.012)
Preventive care no data	-.007 (.026)	
Medical/surgical care superior	.077** (.024)	
Med./surg. avg.; col. (5) avg. and superior	.119** (.029)	.112** (.021)
Medical/surgical care no data	-.083* (.034)	
Women's health superior	-.035 (.036)	
Women's avg.; col. (5) avg. and superior	-.020 (.016)	.011 (.010)
Women's health no data	.131* (.063)	
Access to care superior	.028 (.017)	
Access avg.; col. (5) avg. and superior	.034 (.018)	.046** (.013)
Access to care no data	.014 (.029)	
Patient satisfaction superior	.028 (.017)	
Pat. sat. avg.; col. (5) avg. and superior	.032 (.020)	.052** (.012)
Patient satisfaction no data	-.007 (.026)	
Not accredited	-.010 (.019)	
Prior weight ( $h$ )	.933** (.013)	.940** (.013)
Std. dev. param. ( $\sigma$ )	.011 (.010)	.011 (.010)
Price (thousands per year)	-\$0.098** (.029)	-\$0.096** (.023)
Nested logit param. ( $\lambda$ )	.247** (.052)	.235** (.044)
PPO-year 1 dummy ( $\delta_{PPO,1}$ )	.029 (.018)	.029 (.018)
FFSE-year 1 dummy ( $\delta_{FFSE,1}$ )	.020** (.007)	.019** (.006)
HMO-year 1 dummy ( $\delta_{HMO,1}$ )	.121	.120
Log likelihood	-183,567	-183,604
Average value of information per employee	\$29 (\$11)	\$26 (\$7)

Note: Standard errors in parentheses. All specifications include 1527 plan-market prior dummies. The symbols “\*” and “\*\*” indicate significance at the 5% and 1% levels, respectively.

to specific performance domains. However, we do this with the caveat that the probability that every conclusion below is accurate is less than the probability of any one of them being accurate.

We find that people value patient satisfaction and access to care measures, which is consistent with evidence from Chernew et al. (2004) and Dafny and Dranove (2006) for employers and Medicare beneficiaries, respectively. However, the strongest response is to the medical and surgical care rating. This is intriguing because these measures are so imprecisely measured to not even include outcomes, except for one readmission rate. The fact that employees respond to even imprecise information along this dimension suggests to us that there is much uncertainty about the quality of medical and surgical care and employees may trust these measures more than informed observers might. Nevertheless, the result suggests that there may be considerable value in creating better measures.<sup>22</sup> In contrast, the coefficients on preventive care and women's health measures were smaller (also consistent with the two studies above), perhaps because there are less information problems for these domains. Moreover, care in these domains is more in control of the enrollees. Interested employees could receive high value on these services through their own actions, with less need to rely on the plan for providing quality. We are unsure what to make of the negative response to better operational performance. Perhaps employees view plans as achieving operational performance at the expense of quality care (e.g., employees do not have to wait to see a doctor, but the doctor spends only five minutes

<sup>22</sup>See, for instance, Geweke et al. (2003) for an example of a study that attempts to create better measures of hospital quality.

Table 6  
Estimates with heterogeneous responses across groups

	Employees with covered women (6)	Employees age 50 or older (7)	Employees with child age 12 or under (8)	Employees at GM 5 years or less (9)
Rated (base: below exp. performance)	.011 (.030)	-.212* (.086)	.018 (.030)	-.097 (.079)
# Superior ratings (col. (6): women's hlth.)	-.025 (.037)	.065** (.024)	.014 (.011)	.049* (.024)
# Average ratings (col. (6): women's hlth.)	-.013 (.016)	.079** (.026)	.020 (.015)	.046 (.024)
# No data ratings (col. (6): women's hlth.)	.123 (.065)	-.055* (.028)	-.025 (.019)	-.027 (.016)
Not accredited	-.006 (.019)	.130* (.066)	.027 (.024)	.005 (.041)
Prior weight ( $h$ )	.931** (.014)	.939** (.022)	.878** (.021)	.882** (.031)
Std. dev. param. ( $\sigma$ )	.013 (.011)	.082 (.059)	.020 (.017)	.020 (.027)
Price (thousands per year)	-\$106** (.033)	-\$206 (.110)	-\$060 (.046)	-\$112 (.079)
Nested logit param. ( $\lambda$ )	.231** (.056)	.721** (.209)	.137 (.100)	.262* (.126)
PPO-year 1 dummy	.044* (.020)	.056 (.048)	.035 (.035)	-.044 (.057)
FFSE-year 1 dummy	.028** (.009)	.067 (.042)	.009 (.010)	.016 (.015)
HMO-year 1 dummy	.130	.182	.109	.096
Number of employee/year observations	114,482	38,804	39,184	18,225
Log likelihood	-155,834	-48,479	-54,906	-27,159
Willing. to pay per below exp. rating to average	n/a	\$384 (\$4,165)	\$331 (\$1,344)	\$411 (\$4953)
Average value of information per employee	\$24 (\$10)	\$16 (\$190)	\$41 (\$709)	\$54 (\$861)

Note: Standard errors in parentheses. All specifications include plan-market prior dummies. Specification (6) includes dummies for all other ratings as in specification (5). The symbols “\*” and “\*\*” indicate significance at the 5% and 1% levels, respectively.

with each of them). Or perhaps, they were simply unsure about the meaning of this measure, which is probably the hardest to understand of the six ratings, based on name alone.

Note that the mean estimated values of information for these specifications are somewhat higher than in Specification 1, which occurs because the point estimates for certain individual ratings are larger in magnitude than the base point estimates, suggesting more value from switching plans in response to ratings. Indeed, we find that 4.03% of employees switch plans as a result of ratings in Specification 4 (standard deviation .28%), as compared to the 3.89% figure from Specification 1.

#### 4.4. Heterogeneity in responses across employees: Specifications 6–11

Specifications 6–9 in Table 6 examine the extent to which there is a heterogeneous impact of ratings on different subgroups. Specification 6 presents results from the sample of employees with covered women (i.e., employees who were female or who had a covered female spouse). We allowed for the full 19 ratings as in Specification 4, but we report only the coefficients for the women's health performance domain. We find no evidence that this domain is valued. Indeed, the point estimates for superior and average ratings for this domain are negative here as in Specification 4, though somewhat less so, and not statistically different from zero. Thus, there is no evidence of heterogeneity along this domain.

Specification 7 reports the same model as in Specification 1, but for the sample of employees age 50 or older. Older people have higher mortality and morbidity rates, have lower managed care enrollment rates than younger people, and may have other reasons to value ratings more. We find that the ratings coefficients for this group are somewhat larger than in Specification 1 but that the price coefficient is also somewhat larger, though not statistically significant. Overall, this yields a slightly larger willingness-to-pay to avoid below expected performance ratings (\$384 vs. \$332) and a slightly smaller value of information. The coefficients, in particular price, are much less precisely estimated than in the base sample, resulting in a very large standard deviation on the estimated value of information.

Specifications 8 and 9 consider the same model as in Specification 1 but for employees with a covered child 12 years or younger and ones whose tenure at GM is 5 years or fewer, respectively. The coefficient estimates are generally similar to Specification 1, though with much less precision. The price coefficient for people with

Table 7

Estimates with unobserved heterogeneity in responses to ratings

	Random effects with four ratings (10)	Random effects with two ratings (11)
Mean: rated (base: below exp.; col. (11) below exp. and no data)	-.084** (.027)	-.140** (.034)
Standard deviation: rated	.004 (.013)	.006 (.014)
Mean: # superior ratings	.037** (.008)	
Std. dev.: # superior ratings	.002 (.004)	
Mean: # average ratings (col. (11): avg. and superior)	.044** (.010)	.053** (.011)
Std. dev.: # average ratings (col. (11): avg. and superior)	.005 (.007)	.006 (.014)
Mean: # no data ratings	-.032** (.008)	
Std. dev.: # no data ratings	.009 (.015)	
Mean: not accredited	.030 (.017)	
Std. dev.: not accredited	.125** (.040)	
Prior weight ( $h$ )	.931** (.012)	.935** (.012)
Std. dev. Param. ( $\sigma$ )	.013 (.013)	.016 (.014)
Price (thousands per year)	-\$ .131** (.034)	-\$ .124** (.031)
Nested logit param. ( $\lambda$ )	.306** (.064)	.347** (.070)
PPO-year 1 dummy ( $\delta_{\text{PPO},1}$ )	.034 (.019)	.037* (.019)
FFSE-year 1 dummy ( $\delta_{\text{FFSE},1}$ )	.025** (.009)	.028** (.010)
HMO-year 1 dummy ( $\delta_{\text{HMO},1}$ )	.125	.128
Log likelihood	183,637	183,665
Average value of information per employee	\$25 (\$9)	\$22 (\$7)

Note: Standard errors in parentheses. All specifications include 1527 plan-market prior dummies. The symbols “\*\*” and “\*\*\*” indicate significance at the 5% and 1% levels, respectively.

children is smaller in magnitude than in the base specification and not significant. People with children may have a lower income per person, suggesting more elastic demand. However, they may also be more likely to use healthcare, suggesting less elastic demand and hence a coefficient that is smaller in magnitude. The value of information for this group is higher than for the base specification, but these differences are not significant, since the price elasticities are not significantly different from 0.

Table 7 examines the extent to which there is a heterogeneous impact of ratings based on unobservable factors, by estimating a random coefficients specification. Specifications 10 and 11 duplicate Specifications 1 and 2 with the addition of random coefficients for all the ratings, respectively. Our findings reveal generally small point estimates on the standard deviations of the ratings coefficients. Indeed, of the seven standard deviation parameters across the two specifications, only one is statistically significant. All the other parameter estimates are similar to the base specifications, although we estimate a somewhat higher value of information with this specification. Thus, we find no compelling evidence of heterogeneity based on unobservables, and it appears that whatever heterogeneity exists does not affect our conclusions very much.

## 5. Conclusions

This paper assesses the value and impact of information on health insurance plans by applying a Bayesian learning model to a study design that includes panel data and fixed effects and that exploits a policy intervention (i.e., GM non-union employees were given health plan report cards). We find that information affects health plan choice in that consumers have a moderately large willingness to pay to avoid plans with bad ratings. Only about 3% of people switch plans as a result of the ratings, implying a moderate per capita value of the report card at about \$20. The results are robust across discrete and continuous specifications for the learning process. We find evidence of heterogeneity in responses across performance measures, with people valuing medical and surgical care quality, and satisfaction and access measures, the most. In contrast, we find no significant evidence of heterogeneity in responses across different employee groups.

While our model cannot provide definitive answers as to why the impact of the ratings was modest, it does allow us to draw some inferences. One possible explanation is that people already are reasonably informed

about health plan quality prior to the report card release. However, this is contradicted by the fact that individuals report that they would like to see ratings information (see Hibbard and Jewett, 1996).

Thus, our results suggest that the GM ratings are not fully informative. There is support for this explanation from the specifics of the ratings and results. For instance, there are few indicators in the ratings about the quality of the covered physicians and hospitals, which survey work has documented is information that consumers have reported wanting. In contrast, the ratings include measures such as the utilization rates for recommended age- or gender-specific preventive care or cancer screenings, but it is not clear that these ratings should influence one's choice of health plan, since the guidelines for this type of care are fairly straightforward (e.g., women over age 40, etc.) and receipt of preventive care depends on both patients' persistence and physicians' recommendations. This is also supported by the findings that people react to performance domains such as patient satisfaction. Last, it is supported by studies that find that consumers do not feel fully informed as a result of ratings.<sup>23</sup>

Thus, our results suggest that consumers might value other, more directly pertinent, ratings information much more strongly. To provide a more definitive answer as to the types of report card information that would add value, it ultimately might be necessary to understand which information impacts medical costs and medical utilization rates and ultimately employees' health. While we lack this type of data in this study, we feel that this is an important topic for future research.

Our results must be interpreted within the context of a model that specifies conditionally independent choices each period and does not explicitly model switching costs. Although our model does not incorporate a parameter capturing switching costs, the low estimated value of information is caused by the low level of switching in the data, and not by the absence of such a parameter. However, our interpretation of the relative weight of the prior and signal may be affected by our failure to estimate switching costs. Specifically, we interpret the lack of switching as indicating a strong prior. An alternative explanation would be high switching costs.

A credible estimation of switching costs would require observing data from the time that the employee made her first choice of health plan. This is beyond the scope of this paper, since we do not observe plan choices prior to 1996. Nonetheless, we believe that it is also an important avenue for future research. The presence of switching costs would provide an alternate explanation for why consumers do not switch plans more often, and thus imply that the ratings are more informative, but not necessarily more valuable, than we find.

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<sup>23</sup>See Hibbard and Jewett (1996), Hibbard et al. (2000), Robinson and Brodie (1997), Tumlinson et al. (1997).

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